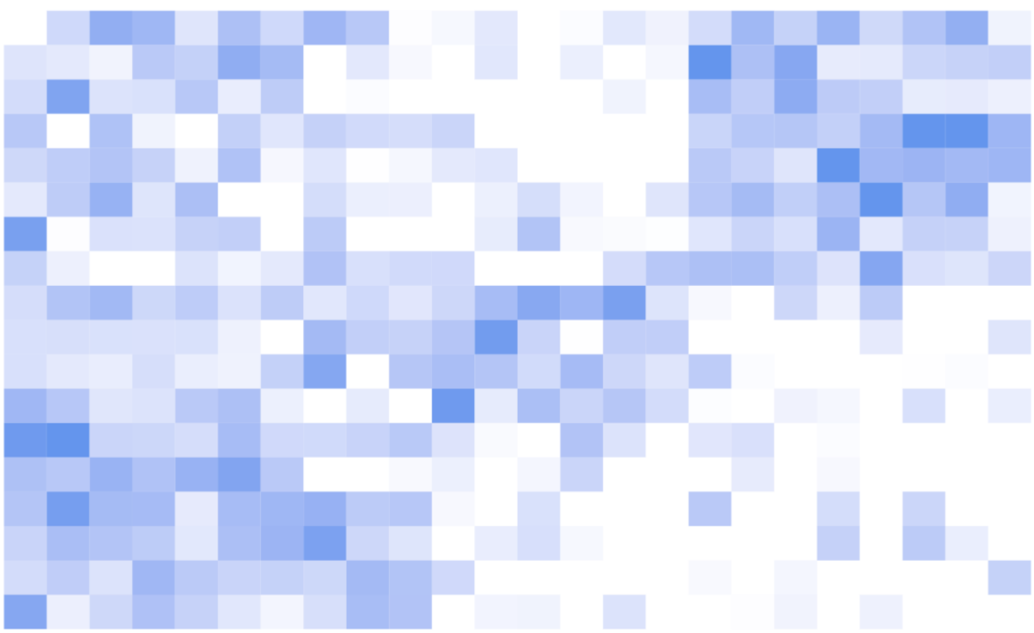
Data Visualization, Dashboards, and Evidence Use in Schools:

Data Collaborative Workshop Perspectives of Educators, Researchers, and Data Scientists

Edited by Alex J. Bowers



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Teachers College, Columbia University

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About the Book

Educators globally are continually encouraged to use data to inform instructional improvement in schools, yet while there have been many recent innovations in data visualization and data science, educators are rarely included in dashboard co-design. On December 5 and 6, 2019, the Education Data Analytics Collaborative Workshop was held at Teachers College, Columbia University in New York City with approximately 80 participants. This workshop was part of the final phase of the collaborative National Science Foundation funded research project (#1560720) "Building Community and Capacity for Data-Intensive Evidence-Based Decision Making in Schools and Districts", a research practice partnership (RPP) on data use and evidence-based improvement cycles in collaboration with Nassau County Long Island BOCES (Board of Cooperative Education Services) and their 56 school districts in Nassau County Long Island, New York, USA. This edited book details the results from the workshop through 28 chapters from authors who were attendees, including educators, data scientists, and researchers. We aimed to achieve three goals through a collaborative workshop: (a) to bring educators together with data scientists in collaborative co-design to build conversation, workflows, visualizations, and pilot code; (b) to train educators and data scientists around data use in schools using the current data systems available and focusing on educator problems of practice; and (c) to publish open-access code as well as educator perceptions of this intersection of data use, visualization, and education data science to inform evidence-based improvement cycles for instructional improvement in schools.

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This book represents the culmination and final phase of the National Science Foundation grant funded collaborative research project titled *Building Community and Capacity for Data-Intensive Evidence-Based Decision Making in Schools and Districts (*NSF #1560720). I thank the NSF for funding this project. As a multi-year collaboration between Teachers College, Columbia University and the Nassau Board of Cooperative Services (BOCES) in Nassau County Long Island New York, I want to thank the Nassau BOCES administration, management, and staff for their long-term vision, tireless work and commitment to this project, and thought-partnership throughout the collaboration including Valerie D'Aguanno, Meador Pratt, Jeff Davis, Elizabeth Young, Robert Feihel, and Byron Ramirez. I also want to thank the administrators and teachers from across the many Nassau County school districts who participated in this project and the workshop discussed throughout this book.

This book discusses the outcomes from the 2019 Education Data Analytics Collaborative Workshop, which could have only happened through the hard work of the planning team in the Education Leadership Data Analytics (ELDA) research group at Teachers College, Columbia University (TC). I thank Seulgi Kang for her many months of hard work organizing and managing the logistics of the event, and Kenneth Graves for co-designing, co-orchestrating, and co-leading the workshop. I also thank the many members of the ELDA research group who volunteered to help out before, during, and after the workshop in making sure it was a successful event, including Luronne Vaval, Megan Duff, Sarah Weeks, and Burcu Pekcan. Beyond the ELDA group, I also want to thank Andrew Krumm for being a great thought-partner and his contributions to the design of the workshop. I also thank the Smith Learning Theater staff at Teachers College, Columbia University, for their guidance and hard work throughout the planning and delivery of the workshop, including Abdul Malik Muftau and Andrew Visser.

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SECTION I

Education Data Analytics Collaborative Workshop Organization and Studying the Event Itself

CHAPTER 1

Introduction: Dashboards, Data Use, and Decision-making: A Data Collaborative Workshop Bringing Together Educators and Data Scientists

Alex J. Bowers
Teachers College, Columbia University

Introduction

This edited book volume is about bringing educators who do the important work of using evidence and data to inform their daily practice in schools together with data scientists, data dashboard researchers, and industry experts, to collaboratively build visualizations and computer code that addresses the data use issues that teachers and administrators say are the issues that matter most to them, issues that address their central problems with data visualization in their practice. Schools and districts are inundated with data, as not only do they collect state assessment data and data to report for policy, such as student attendance, discipline, and graduation data, but schools collect ever increasing amounts of data including interim assessments, socio-emotional behavioral data, and more recently, education technology and automated tutoring system data, in addition to data such as grades, student extra-curricular activity participation and much more. Research and policy encourage teachers and administrators to use these growing sets of data in their practice to motivate and inform instructional improvement, such as through "plan-do-study-act" cycles, data-driven decision making, and evidence-based improvement cycles. Over the last decade especially, data warehouse and data dashboard systems have come to the fore as a central technology to help organize and visualize these ever-growing amounts of data to help teachers and administrators do this work. Yet, research to date has shown that on average, teachers and administrators rarely use data dashboards in their daily work. Unsurprisingly then, while individual case studies suggest the potential of data dashboard use in school improvement, recent large-scale research has to date shown little impact of dashboard and instructional data use on school improvement and teacher practice.

The central motivation for the project that the chapter authors throughout this book speak to is the observation that data scientists and data dashboard designers rarely engage in in-depth discussions with educators around what data and visualizations would be most useful to the daily practice of educators in schools. Fewer still are examples of data scientists collaborating together with educators to focus on the data visualization needs of those educators to create the digital tools and visualizations that educators collaboratively design with data scientists. Through the generous funding of the National Science Foundation (NSF #1560720 *Building Community and Capacity for Data-Intensive Evidence-Based Decision Making in Schools and Districts*) and a multi-year collaboration between educators, data scientists, and education researchers, the contributing authors throughout this book reflect on the issues, successes, and challenges of data use in schools that surfaced from their participation at the 2019 Data Collaborative Workshop, held at the Smith Learning Theater, at Teachers College, Columbia University in New York City, USA. Chapter authors include teachers and administrators, county-level data analysts who manage and run the shared data warehouse across 56 school districts in Nassau County Long Island New York, national-level data scientists, education researchers, and data dashboard experts.

The 2019 Data Collaborative Workshop was designed to create an interactive design-based experience where over two days, educators were matched to national-level data scientists into what we termed "datasprint" teams. Importantly, about half of the event attendees were educators, including teachers and school and district administrators. The eleven datasprint teams (each less than 10 people) heard from a variety of education researchers and data scientists (who were also participants), and had the opportunity to experience multiple cutting-edge education data dashboard solutions, and then worked collaboratively using an iterative set of design-based protocols to build data visualizations together (Reimann, 2011; Sedlmair, Meyer, & Munzner, 2012) in open source code using the data formats currently available in the educators' central county-level instructional data warehouse provided through the Nassau Board of Cooperative Education Services (Nassau BOCES). The event organizers collected a range of data, from pre-event and post-event surveys, to participatory location tracking and attention data collected in the Learning Theater, to pictures and video from the event, to the written artifacts including contributions, drawings, code, visualizations, and notes from the participants. Participants were invited to contribute chapters to this edited book volume reflecting on the issues surfaced throughout the event that they found most compelling to discuss that relates to their practice as educators, administrators, researchers, and data scientists. Thus, this book represents an attempt to capture current conceptions of educators and data scientists around the successes and challenges of visualizing and using data in schools through data dashboard technologies. Much of the previous research in this domain focuses either exclusively on educators, or data scientists – rarely offering opportunities for collaborative work and reflection on co-design opportunities.

The chapters throughout this volume are organized into three parts of Part 1) chapters on research and practice in data use, collaboration, and visualization, including an overview of the design of the data collaborative event; Part 2) chapters from datasprint teams, representing the reflections on the collaborative work from the multiple perspectives of educators, data scientists, and education researchers; and Part 3) research papers focusing on important issues in data use in education surfaced through the discussions at the Data Collaborative Workshop.

Across the chapters, there are three main conclusions from the multiple authors who attended the workshop. First, the work of data use in schools is part of the ongoing practice of educators, yet having the opportunity to discuss the issues of data use is an important and formative experience in thinking about and designing possible solutions at the classroom, school, and district level collaboratively between educators who understand their data needs, data scientists who understand what data are available, how it is stored and can be organized through the database, and how to create data visualizations using open source code, and education researchers who understand the broader issues of data use and education policy and the issues of how to bring together needs from classroom to policy. Second, while the participants agree that data use in schools is an important domain to pursue, there are a broad range of perspectives about what the focus should be for data use, how to leverage the technologies and data that are available, and how best to support the work of teachers in instructional improvement through useful data dashboard improvements. And third, there is a disconnect between what educators want and what data scientists can create. Throughout the event, data scientists reported that while they could create quite elaborate and interactive visualizations that they thought addressed a central issue for the educators, teachers and administrators continually noted that they were not looking for fancy visualizations, but rather they wanted to discuss what data were most important for their current problems of practice, and how they could access useful summaries, metrics, comparisons, and visualizations that help support actions and next steps for instructional and organizational improvement. Thus, across the chapters, the authors provide a thoughtful discussion of these issues, and together, point to multiple next steps for this work at the intersection of data use, data visualization, data science, and evidence-based improvement cycles in schools.

Data Visualization, Dashboards, and Evidence Use in Schools

For decades across the US, teachers, and school and district administrators have been encouraged through recommendations from policy, research, and practice to continually use data and evidence to help inform instructional decisions and improvement throughout their work, with calls and attention to data use and data driven decision-making increasing especially over the last 20 years (Boudett, City, & Murnane, 2013; Datnow, Choi, Park, & St. John, 2018; Farley-Ripple & Buttram, 2015; Grabarek & Kallemeyn, 2020; Halverson, 2010; Mandinach & Schildkamp, 2021; Marsh, 2012; Piety, 2013; Schildkamp, 2019; Schildkamp, Poortman, Luyten, & Ebbeler, 2017; Wachen, Harrison, & Cohen-Vogel, 2018). To serve these data needs, a parallel set of research, policy, funding, and recommendations has generated data systems not only for policy reporting for accountability but with the purpose in mind to also inform teacher and administrator instructional decisions and student interventions to promote increased student learning, student persistence, and overall positive outcomes, systems which include instructional data warehouses (IDWs), data dashboards, and data visualization systems which provide ever increasing amounts of information to stakeholders (Agasisti & Bowers, 2017; Ahn, Campos, Hays, & Digiacomo, 2019; Bowers, 2021; Bowers, Bang, Pan, & Graves, 2019; Coburn & Turner, 2011, 2012; Krumm & Bowers, in press; Krumm, Means, & Bienkowski, 2018; Lacefield & Applegate, 2018; Streifer & Schumann, 2005; Wayman & Stringfield, 2006).

Evidence-based School Improvement Cycles

In the logic model of data driven decision making and evidence-based improvement cycles in schools (see Figure 1.1), these data system resources feed into a continuous improvement cycle that starts with the data, data which is then organized, filtered, and analyzed to generate information, which combined with teacher and administrator expertise generates knowledge that is applied to a response and action which leads to outcomes which then feedback with new data for subsequent iterations of the “plan-do-study-act” model of organizational improvement in schools (Bowers & Krumm, in press; Coburn & Turner, 2012; Ikemoto & Marsh, 2007; Jimerson, Garry, Poortman, & Schildkamp, in press; Mandinach, Honey, Light, & Brunner, 2008; Marsh, 2012; Schildkamp, Poortman, & Handelzalts, 2016; Shakman, Wogan, Rodriguez, Boyce, & Shaver, 2020; Wayman, Wilkerson, Cho, Mandinach, & Supovitz, 2016). In recent years, school districts across the US are purchasing increasing amounts of data system technology to aid in this work, including instructional data warehouse (IDW) server systems to store the data, and importantly for data use in schools, data dashboard and data visualization systems intended to help organize and display the data across students, classrooms, and schools, with the goal to inform teacher and administrator decision making so that they are able to make more informed decisions on instructional interventions and instructional and organizational improvement (Ahn et al., 2019; CDSPP, 2014; Farley-Ripple, Jennings, & Jennings, 2021; Knoop-van Campen & Molenaar, 2020; Tanes, Arnold, King, & Remnet, 2011; Tyler, 2013).

Figure 1.1 provides this logic model of data use in schools, adapting the work of multiple authors (Bowers, 2021; Bowers & Krumm, in press; Mandinach et al., 2008; Mandinach & Schildkamp, 2021; Marsh, 2012; Schildkamp et al., 2017; Schildkamp et al., 2016). Much of the research on data use in education has focused within the dashed section of Figure 1.1, detailing how educators can engage in the collaborative work in evidence-based improvement cycles of turning data and visualizations into information, knowledge, and action through collaboratively and iteratively discussing the data as it pertains to the work of teachers in their classrooms, the inferences the teachers together draw from that data, and what the teachers together decide they should change in their practice, and how they will measure the effect of those changes over time. Less attention has been paid in the research to the issues of data capture and collection, database organization and use, and data visualization and dashboard construction (Bowers, 2021; Bowers & Krumm, in press; Krumm & Bowers, in press). This is problematic, as without informative and useful data visualizations and dashboards it is difficult to

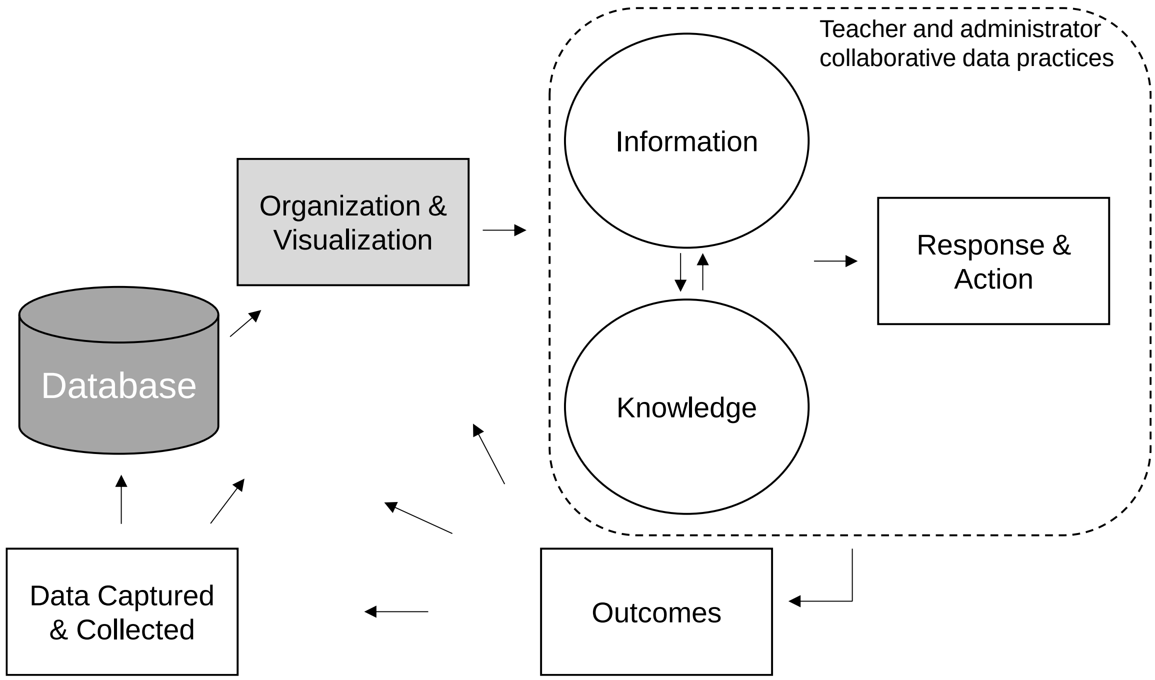

Figure 1.1: Logic model of data use in schools.

understand how teachers and administrators would then be able to put these analytics to use in their data discussions. Note also in Figure 1.1, that the multiple arrows from outcomes as well as data collection and capture represent the point that often, data and evidence skip the data collection and capture phase, are not represented in the database or data dashboards, and perhaps receive only minimal organization and summarizing (Vanlommel & Schildkamp, 2019).

Research on Data and Dashboard Usefulness in Schools

However, despite this rich set of research on data use practices in schools, the research to date has shown mixed or little to no impact of these data use, dashboard, and visualization recommendations on actual teacher practice. In a recent narrative review of 39 individual data use studies, including quantitative, qualitative, and mixed methods studies, the authors conclude that 15 of the studies found positive effects of data use, while the majority of studies found either mixed results (10 studies) or no relationship (14 studies) between data use and instructional improvement (Grabarek & Kallemeyn, 2020). In a different study focusing on the interaction of educators with the data system, examining one large school district with about 65,000 students, 670 teachers, and 73 schools, researchers coded each click in the data warehouse for if it was related to instruction (“instructional clicks”), finding no relationship with elementary or junior high math, or junior high reading over three years (Wayman, Shaw, & Cho, 2017). In a recent study examining the popular NWEA MAP interim assessment product, researchers examined clickstream logfile data of educators working in the data dashboard from across 20 schools in 5 districts, finding that “overall engagement with the system was fairly infrequent… In general, educators logged on to each report only a few times per year and utilized only a few of the reports available.” (p.110) (Farley-Ripple et al., 2021). Indeed, recent randomized controlled experimental research in the US focusing specifically on teacher data use (Gleason et al., 2019) as well as early warning systems and indicators for at risk students have found little to no effect on overall student progress (Faria et al., 2017; Mac Iver, Stein, Davis, Balfanz, & Fox, 2019).

Why Are Data Dashboards Not Used More Often by Educators?

Recent research suggests five main reasons for this lack of positive findings of data use and dashboards in schools. First, while data use is a topic that is espoused almost universally by educators across schooling systems in the 21st century, actual time, attention and discussions around instructional data on individual teacher practices and student outcomes continue to be rare (Dever & Lash, 2013; Meyers, Moon, Patrick, Brighton, & Hayes, in press) with common planning time often devoted instead to discussing student behavior issues or planning special events among the multiple and varied pressing issues that schools confront on a daily basis. Second, teachers continually note across the data use research that the data available in databases and dashboards focus mostly on standardized test scores, attendance, and demographics, which are the data reported for policy compliance (Bloom-Weltman & King, 2019), little of which they say is relevant to their daily practice in their classrooms (Brocato, Willis, & Dechert, 2014; Cosner, 2014; Jimerson & Wayman, 2015; Riehl, Earle, Nagarajan, Schwitzman, & Vernikoff, 2018). And so rather, third, teachers continually report that the data most relevant to their practice are the data that are closest to their daily work in the classroom, including formative assessments, in-class assignments and homework, and periodic interim assessments (Farley-Ripple et al., 2021; Jennings & Jennings, 2020; Reeves, Wei, & Hamilton, in press; Wilkerson, Klute, Peery, & Liu, 2021).

Fourth, another hypothesis is that little attention has been focused on the first step in the data use process of translating data from databases and data collection routines to actionable visualizations (Bowers, 2010; Bowers et al., 2019; Bowers & Krumm, in press; Krumm & Bowers, in press). While the research widely acknowledges a long history of the positive perception of data visualization by teachers to help enhance their teaching and student learning (Klerkx, Verbert, & Duval, 2014), for many schools today, data visualization takes place through the work of the principal, the data team, or the "data person", usually in Microsoft Excel, with a focus on descriptive bar charts, in which on one or two days a year these charts are provided to teachers as the extent of the data analysis (what I term "bar graph day") with some form of general discussion on the implications by teachers and administrators, and then the school returns to similar charts and discussion the following year (Bowers, Shoho, & Barnett, 2014; Meyers et al., in press; Selwyn, Pangrazio, & Cumbo, in press). While useful in describing and disaggregating data across groups and time in schools (Bernhardt, 2013), descriptive bar charts generated in an ad hoc manner by busy professionals, who have a staggering array of duties and calls for their attention on a daily basis, can only go so far in helping uncover instructional issues that teachers can act on (Bowers, 2017). One reason for this level of data analysis and visualization is the traditional lack of attention to data analytics, data science, and data visualization in school leadership preparation programs and training (Bowers, 2017; Bowers et al., 2019).

This is not to say that bar charts are the issue, as bar charts are well-known for their interpretability and the accuracy of inferences for comparisons in the research on data displays and cognition (Heer & Bostock, 2010; Munzner, 2014), and in a recent review of education dashboards across K-12 and higher education for both teachers and learners, the data visualization most often used was a bar chart (Schwendimann et al., 2017). Rather, as noted across the research on data use, this work is not a one-time or rare event, but rather effective data use practices include regular ongoing discussions by the teaching faculty, facilitated by school leaders, but ultimately owned and conducted, as the work of teachers, for the work of teachers, to inform their daily instructional challenges focusing on the content they are teaching and the results of assessments and inferences for their students (Gerzon, 2015; Hoogland et al., 2016; Jimerson et al., in press; Popham, 2010).

Fifth, recent innovations in data analytics and visualizations have begun to make their way into schools through the myriad sets of data dashboards connected to these database systems (Michaeli, Kroparo, & Hershkovitz, 2020). Yet, as also noted above, there is little evidence to date that teachers and administrators not only use these dashboards, but that they are effective in informing instructional improvement and the work of teachers and administrators in schools (Bowers & Krumm, in press; Farley-Ripple et al., 2021). In reading across this literature, it is striking that while the dashboards and visualizations are well-intentioned, the research from the data use side is quite one-sided, as the data visualizations and dashboards are either treated as the given tools that are already on-site or selected at some previous time before the research began. Alternatively from the dashboards side of the research, there is little justification or inclusion of teachers or administrators in the design or evaluation of the visualizations and dashboards themselves (Schwendimann et al., 2017). Lacking from much of this work is the inclusion of teachers and administrators in the co-design of these important visualizations and dashboards that are intended to help with their work in schools. Indeed, as noted in learning analytics, the research on data dashboards in education suggests that not only is the evidence of effectiveness of dashboards weak (Jivet, Scheffel, Specht, & Drachsler, 2018), but that "the value of teacher dashboards may depend on the degree to which they have been involved in co-designing them (Holstein, McLaren, & Aleven, 2017)" (p.74) (Echeverria et al., 2018).

Bringing Educators and Data Scientists Together to Build Actionable Data Visualizations

Co-design between educators and data scientists is an important requirement in data visualization, as the collaboration between researchers and educators in the design and implementation of dashboards hinges on the usefulness of the design to the actual work and practice of the educators and administrators (Bowers & Krumm, in press; Cober, Tan, Slotta, So, & Könings, 2015; Matuk, Gerard, Lim-Breitbart, & Linn, 2016; Roschelle & Penuel, 2006). Indeed, as stated over 40 years ago, this issue of the lack of the perspective of teachers and school administrators in the design of information management systems was captured well by Clemson (1978) in the journal *Educational Administration Quarterly* in referring to school administrators and their management of the school using data management, visualization, and data modeling systems to build models and inform decision making:

> Attempting explicitly to model an educational system is difficult because educational processes are both exceedingly complicated and very poorly understood. Most attempts at modeling are further hampered by the fact that invariably mathematical techniques and programming languages are used that have technical requirements that are so exacting that the manager is excluded from meaningful participation. Two serious consequences can result. The manager may not understand the model, and, therefore, even if it were a good model, [they are] unlikely to use it. Further, by excluding the manager from the

> model-building process, the model will not be tested against the manager's own store of experience with the situation. This is tantamount to saying that the model will not reflect the political realities that are crucially important to the manager. Therefore, in terms of the manager's needs, the model will not be a good model. (p.22) (Clemson, 1978).

And so it goes today, almost half a century later for data use and data dashboards in schools, as the school administrator, and indeed, the teachers and their potential collaborative data use practices have seemingly been left out of the conversation in the design and implementation of data dashboard systems. In one of the few reviews of dashboard systems to date which includes both data dashboards aimed at teacher data use as well as learning analytics and intelligent tutoring dashboards aimed at students, out of 55 research articles on education dashboards examined, only 15 (27%) provided information on evaluations of the dashboards in authentic settings in which the dashboard was shown to stakeholders and data gathered about their real use (Schwendimann et al., 2017).

The core issue at hand then, is that missing from the research to date are examples and exemplars of a) data visualizations and dashboard designs that are co-designed by educators and data analysts, b) visualizations that would take advantage of the data that exists within current education data systems and warehouses, c) are responsive to the research on analysis, visualization, human-computer interaction, and dashboard design, and d) center the perspectives and the work of educators as co-developers of the visualizations as the intended users. Thus, at the intersection of data use, evidence-based improvement cycles, and data visualization and dashboards, there is a deep need to bring together the expertise of both data visualization and dashboard design, and teacher, school and district administrator experience, in co-design processes which aim to identify 1) data that are actionable and useful to the daily work of teachers and administrators, 2) data that are available in the data warehouse, and 3) data visualization designs that address teacher and administrator problems of practice.

Building on this research, as the logic model provided in Figure 1.1 above describes the process of data use in schools across the data use research and practice literature, the dashed region is the area of focus for much of this literature, focusing on helping teachers and administrators build collaborative conversations around evidence and data, as the core of the work is ultimately human-centered and focused on building trust and positive relationships between the adults in a school as a learning organization. To date, much of the work on understanding positive data use practices in schools has understandably focused on these collaborative data practices represented in the dashed box of Figure 1. Much less attention has been devoted to how data are captured and collected, the extent to which some school data flows into databases (attendance, state test data, demographics) while much of the actual data generated daily in schools (such as classroom formative assessments and individual student-student and student-teacher interactions) are informally or ad hoc collected or not collected in a systematic way at all.

A Data First Task Wrangling Model to Iteratively Develop Data Visualization Tools

Yet, these issues in data use and data visualization are not unique to education. As noted in the broader data visualization in organizations research and summarized by Crisan and Munzner (2019):

> The visualization research literature assumes that experts have an understanding of these data and intend to derive actionable insights through exploratory visual analyses (EVA) (Battle & Heer, 2019). However, domain experts who need to integrate and analyze heterogeneous data are becoming increasingly overwhelmed by the complexity and heterogeneity of their data, in addition to its volume. (p.1) (Crisan & Munzner, 2019).

Thus, Munzner and colleagues have suggested the "four-layer model" (Meyer, Sedlmair, & Munzner, 2012; Meyer, Sedlmair, Quinan, & Munzner, 2015; Munzner, 2009) for visual information and dashboard design to inform organizational decision making in which each of the following are successively nested within the next of 1) domain characterization on the outside broadest layer, 2) data and task abstraction and design, 3) encoding visualization interaction technology (design and prototyping visualizations), and 4) algorithm design to automate the visualization nested within at the lowest layer. This framework provides an attractive means to separate and plan for the tasks of bringing together educators and data visualization designers and coders to help focus the work on the problems of practice in the organization, and represents the central framework that helped guide the design of the Data Collaborative Workshop discussed throughout this book. Importantly for educator data use, this line of work also considers the constraints around the possibilities of visualizations, as policy and data availability place constraints on what is possible, regardless of what the data users and data visualization designers and coders come up with (Crisan, Gardy, & Munzner, 2016).

Within this space of exploratory visual analytic processes of bringing together domain experts to create visualizations that address their problems of practice, these authors have built a "data first" design framework (Oppermann & Munzner, 2020), which starts with "data reconnaissance" and "task wrangling" (Crisan & Munzner, 2019). As summarized in Figure 1.2, historically, design methodologies focus first on defining the task then moving to data and visualization to address the issues of the task. Yet, as these authors argue, the amount of data within organizations and the ambiguity of the tasks and possibilities of what can be learned from and acted on from that data are core problems for domain experts at the start of the design process (Crisan & Munzner, 2019). The tasks, given the data, are not crisp. They are instead fuzzy. Thus, when domain experts only have a fuzzy conceptualization of the task and what data and visualizations might be possible have not yet been explored, then a core recommendation is to start instead by centering the domain experts and the data, beginning with what Crisan and Munzner (2019) term is "fog and friction" through which domain experts first explore the possibilities in the data (acquire), create visualizations to understand the scope and possibilities of the data (view), which leads to relating the visualizations and understanding of the data to a possible set of tasks defined by the domain experts (assess), and then the process motivates the domain experts to iteratively find new data to address the new questions uncovered through the process (pursue) as the domain experts gain clarity on the task (Crisan & Munzner, 2019). Thus, rather than a data organization and visualization process, this work is a task clarity process. As summarized in Figure 1.2, this process thus puts the domain experts (people) and the data at the center of the process with the goal of moving from fuzzy conceptions of the task to crisp conceptions of the task, and as a byproduct, visualizations and encodings are created that inform the task using the data that are at the center of domain experts' discussions.

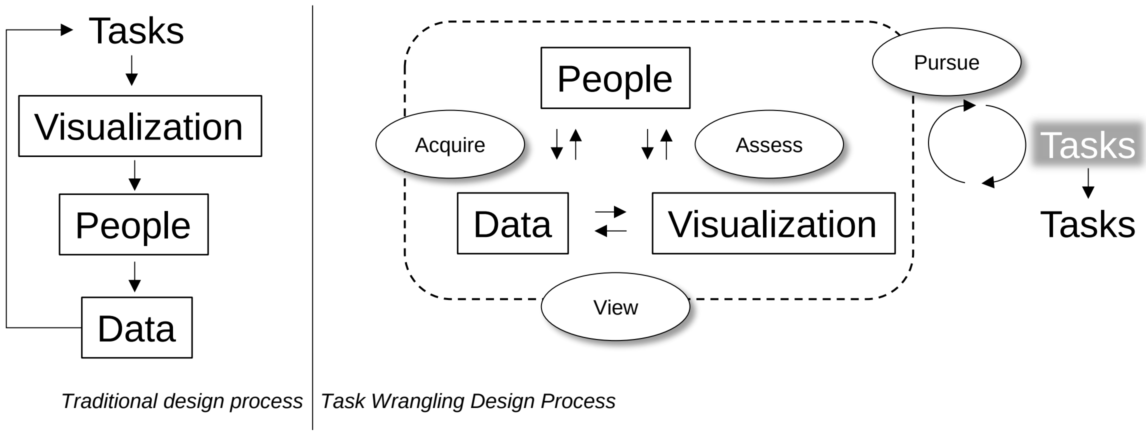

Figure 1.2: A simplified summary adapted from the Crisan and Munzner (2019) tasks focused model. The traditional visualization process model (left) starts with data scientists defining a task, creating a visualization (termed embeddings in Crisan and Munzner, 2019), piloting the visualization with domain experts for usability, and then accessing and applying the visualization to datasets, which then feeds back on informing future tasks. Conversely, the task wrangling design process (right) assumes that the visualization tasks are ill defined and so starts by centering the people and the data to build pilot visualizations to understand the data and visualizations and how they relate to domain experts' challenges through acquire, view, and assess. This leads to pursuing different forms of data to continue the process and in turn through iterative cycles the goal is for the process to help domain experts move from a fuzzy conceptualization of the visualization task to a crisper conceptualization.

A Data Collaborative Workshop Event

In the present project of the Data Collaborative Workshop, we drew on these "data first" principles to inform the design of the two day event, as by bringing together educators and data scientists for a co-design event, each as domain experts bringing a wealth of experience in their respective domains, our goal was to create datasprint groups that understandably start with a fuzzy conceptualization of the task, and so instead would begin with the data and domain experts exploring the possibilities, which through iterative rounds of discussions during the workshop, would advance and articulate task wrangling, building from fuzzy task conceptualizations to crisp, and generate visualizations given the data that is available within the current instructional data warehouse for the districts. Importantly, the collaborative workshop was designed to bring educators and data scientists together as equal partners and domain experts such that rather than the data scientists creating a visualization or dashboard and placing it in schools (with the same expected minimal impacts noted above in the current research), as a co-design process the goal was to center the work of educators and their data use needs and combine that knowledge with the data scientist's visualization and coding expertise to pilot new visualizations that may begin to address important issues that matter to teachers and administrators.

Education Leadership Data Analytics (ELDA)

Recently, this work that is at the center of the intersection of facilitating educators' use of data to inform evidence-based improvement cycles, combined with the work of data scientists to help organize and visualize the data, has been termed "Education Leadership Data Analytics" (ELDA) (Bowers et al., 2019). As noted in this work:

> Education Leadership Data Analytics (ELDA) practitioners work collaboratively with schooling system leaders and teachers to analyze, pattern, and visualize previously unknown patterns and information from the vast sets of data collected by schooling organizations, and then integrate findings in easy to understand language and digital tools into collaborative and community building evidence-based improvement cycles with stakeholders (p.8) (Bowers et al., 2019).

Thus, in designing the Data Collaborative Workshop, we conceptualized this work as Education Leadership Data Analytics (ELDA), working at the intersection of teacher and school leadership, evidence-based improvement cycles, and data science, in an effort to surface the challenges and successes of educators' data use through collaboratively building data visualizations using available data formats from their data warehouse, and partnering educators with education data scientists and education researchers.

Central Themes of the Book

Throughout the chapters in this edited volume, teachers, administrators, data scientists, and education researchers each speak to these multiple and overlapping aspects of the work of data use, data visualization in dashboards and instructional data warehouses, and how to apply this expertise to these issues of:

- Task wrangling and data use organization in schools
- Visualization tools and technologies
- Data constraints and availability
- Addressing the issues of educator daily data needs
- Making data dashboards useful and actionable
- Informing the broader conversation on data use and data dashboards
- Innovating with data visualizations to address educator data use needs.

Thus, this project and ultimately this book brings together these multiple perspectives throughout the chapters.

This book is the final phase of a National Science Foundation (NSF) funded collaboration (NSF #1560720) between the Nassau County Long Island Board of Cooperative Services (Nassau BOCES) and the 56 school districts which they serve, and Teachers College, Columbia University (TC), specifically my research group at TC (the Bowers Education Leadership Data Analytics Research Group). Nassau BOCES is the central data warehouse and professional development office for the 56 school districts of Nassau County Long Island in the state of New York, just to the east of New York City, serving about 200,000 students and 20,000 professional staff across a wide variety of district contexts. TC, located in New York City, is the oldest and largest graduate school of education in the United States, and has a long history of research and innovation in teaching, K-12 school administration and leadership, data analytics, and innovative collaborative design spaces, such as the Smith Learning Theater in which the Data Collaborative Workshop event was held in 2019. The NSF grant, titled *Building Community and Capacity for Data-Intensive Evidence-Based Decision Making in Schools and Districts* was awarded in 2016 and consisted of a three-phase collaborative project between Nassau BOCES and TC as detailed in Figure 1.3.

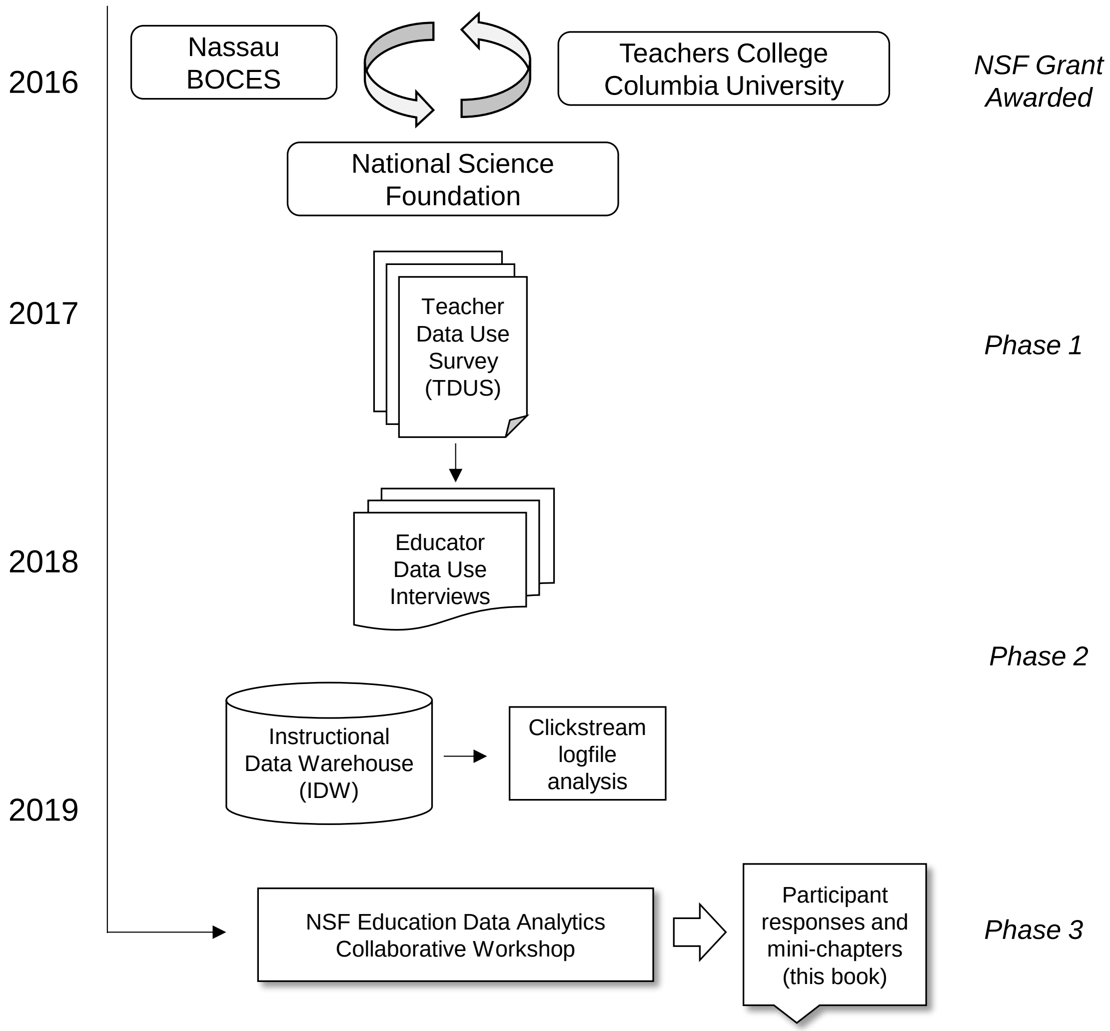

Figure 1.3: The three-phase NSF (#1560720) funded project *Building Community and Capacity for Data-Intensive Evidence-Based Decision Making in Schools.*

In Phase 1 of the collaborative project, we surveyed almost 5,000 educators across Nassau County to understand what they say about data use practices in their schools, using the Teacher Data Use Survey (TDUS) from the US Department of Education (Wayman et al., 2016), which we followed-up with 40 in-person qualitative interviews of educators on their perceptions and practices around data use. In Phase 2, we examined the patterns of educator clicks in the Instructional Data Warehouse (IDW) to gain a better understanding of not only when educators use the IDW dashboard system, but what seems to be of interest given the range of available data and visualizations available. At the time of writing of this book, the research journal articles on phases 1 and 2 are in process. We focus here in this book on Phase 3.

In Phase 3 of the project, as discussed in subsequent chapters of this book, in December of 2019 we brought together teachers, school and district administrators, and Nassau BOCES IDW and professional development staff, with data scientists and education researchers in the TC Smith Learning Theater over two days, matching participants into 11 separate datasprint teams. We drew on the research discussed above to design the event to provide a space for educators, data scientists, and education researchers to collaborate on the design and piloting of data visualizations that address the problems of practice articulated by the educators. The data scientists were provided the data file formats from the IDW before the event, and could code in real time in collaboration with the educators to iteratively design and display data visualizations. Throughout the event, participants heard from a variety of data use and data visualization researchers and industry experts, who were also participants on datasprint teams, and were provided a range of opportunities to network, share innovations, and surface and discuss issues that matter to their work in schools. In Chapter 2, I discuss the design of the Data Collaborative Workshop and the affordances provided through the Smith Learning Theater in detail. This type of collaborative opportunity rarely happens in the education data use and dashboard field, and our goal here in Phase 3 in this book was to provide the perspectives from across a wide range of the workshop participants, in an attempt to capture their insights, perspectives, and thoughts on how this work can inform data visualization, data dashboards, and ultimately data use and evidence-based improvement cycles in schools. After the conclusion of the event, we invited all participants to write a "mini-chapter" about their perspectives that were informed through the Data Collaborative Workshop, either individually or in teams, and we were thrilled to received 25 separate chapters. These chapters throughout this book, along with chapters from the event organizers including myself, represent the breadth of expertise represented at the workshop, from teachers, school and district administrators, Nassau BOCES staff, education researchers, and data scientists, including multiple data dashboard experts from both the educator perspective and the industry and research perspective.

Part I: Education Data Analytics Collaborative Workshop Organization and Studying the Event Itself

This book represents a unique opportunity to hear from the people doing this work of data visualization and education, in each of the different domains, from the classroom to the dashboard and multiple perspectives in between. This book is organized into three parts. In Part 1 we focus on the Data Collaborative Workshop event, in which through the pre-event survey, post-event survey, and the range of multi-modal data collected through the instrumented space of the Learning Theater, chapter authors work to capture summaries and analysis of the multiple perspectives from the attendees on data use in schools, the challenges and successes of data visualization, and how to inform data visualization and dashboard development in the future. Following this introduction chapter 1, and the overview, design, and orchestration of the workshop in chapter 2, then in chapter 3 Seulgi Kang provides a summary and discussion of the multiple job roles and perspectives of the attendees, their evaluation of the workshop, as well as a summary of participant perspectives on data visualization in dashboards and schools organized by job role. Ha Nguyen, Fabio Campos, and June Ahn in chapter 4 provide an analysis of the data collected during the workshop as an opportunity to explore a co-design participative event and how the perspectives of attendees inform the work of data visualization, especially as these authors are able to write from their perspective as national-level applied data visualization researchers. They find through an in-depth analysis of the data from the workshop that while there is a strong appetite for visualizing and putting into action types of data beyond the data usually represented in IDWs, efforts throughout the workshop gravitated through necessity towards the constraints of the data available within the IDW, thus focusing on test scores, test item analysis, attendance, behavior, and the like. Using correlated topic modeling automated text data mining techniques, Karin Gegenheimer in chapter 5 analyzes the long-form essay responses of participants from the pre-event and post-event surveys, focusing on clustering the responses of attendees around their perspectives on their challenges and successes of using data and evidence in schools, and how those perspectives may have changed or been informed through the workshop. She found that in general, educators focused on what to do with data, while researchers and data scientists focused on data quality and the unique opportunity to collaborate with practitioners, together underscoring the importance of co-design events that bring these two groups together around a shared purpose.

The Smith Learning Theater at TC is a large instrumented and technology-rich open event space that includes not only a variety of tools to facilitate collaborative participant interaction, such as a variety of marker boards, seating arrangement, tables, and partitions, but it also integrates an array of tools for projection of individual computer screens on most surfaces in the space (each team projected the data scientist's screen in real-time as they live coded), and includes individual location tracking (with consent) through the use of a chip on a lanyard for each participant. In chapter 6, led by Chad Coleman, the authors analyzed this novel location tracking data as evidence of not only where participants were in the Learning Theater space throughout the event, but also analyzed the data as a proxy representing the attention of individuals. These authors analyzed the moment-by-moment movement of individuals throughout the second day of the event, summarizing the physical coherence of teams over time within the space in an effort to understand how this data can be helpful in designing collaborative co-design events, and how this data suggests which teams had higher coherence based on this unique location data.

In the final chapter of Part 1, chapter 7, Richard Halverson, as the keynote speaker on the first day of the event, provides a look towards the future of data use in schools from a systems-level perspective. In today's education data systems, much of the data collected is designed to be reported up the system for policy use, and so it is unsurprising that data use dashboards and interventions have not been shown to be particularly effective. However, in looking to the future, Halverson envisions the growing use of personalized learning systems and data systems that more authentically engage teachers and administrators, and that the data throughout the system will flow in more deliberate and informative ways between learners and educators and educators and the system. This evolution of education data systems will then create school agency with data as regular data-driven work between students and teachers, and teachers and administrators takes place in ways that educators and learners alike value and find useful in their daily work in schools.

Part II: Data Collaborative Workshop Participant Datasprint Team Chapters

Part 2 of this book turns to the perspectives from the datasprint teams themselves. Across the eleven datasprint teams, authors represent each team's perspective, and for multiple datasprint teams, individual and collaborative groups of authors contributed more than one individual chapter from different and informative perspectives, including teachers, administrators, data strategists, data scientists, and education researchers. Each datasprint team was named with a symbol to make wayfinding in the Learning Theater simpler, including (mirroring the order of the chapters through this book, with many chapters from different individual perspectives from the same team): Cube, Arrow, Chevron, Circle, Cylinder, Diamond, Hexagon, Pentagon, Square, Star, and Triangle. How these datasprint teams were organized is described in Chapter 2. Throughout the event, we were purposeful in working to build the datasprint teams' identities as a team, and so throughout each chapter in Part 2, authors refer to their specific datasprint teams by symbol name, and the collaborative work that took place therein.

In the lead chapter for Part 2, chapter 8, Meador Pratt, as the central administrator at Nassau BOCES and collaborative partner on this multi-year NSF funded project, provides an in-depth discussion of the foundations of this project, the background for Nassau BOCES and their work with the IDW and their partner districts, the discussions and work to generate the visualization from his datasprint team during the workshop, and importantly, how the Nassau BOCES team then took their reflections from the project and the Data Collaborative Workshop and built processes to continue this work beyond Phase 3 of the grant. While Nassau BOCES has an iterative cycle of dashboard design with their district partners, their own data has shown that many educators throughout the system are unaware of the tools within the IDW that could help inform decision making. Pratt outlines a strong three group typology of data conversations from the perspective of the people who do this work daily in bridging between the IDW, visualization design, and educator data needs, while addressing issues of policy and data reporting required by local and state agencies: 1) Informative data conversations – showing what's available; 2) Inquiry data conversations – collaborating with teachers, administrators, and the IDW team; 3) Elevated data conversations – includes the data scientist and builds additional capacity towards what may be possible. Throughout the chapter, he provides a deep discussion of the decision structure for how to generate a useful visualization for teachers, given the domain expertise of the datasprint team, and exemplars on how to pilot the work generated from the Data Collaborative Workshop in actual data systems moving forward.

Building on these perspectives, in chapter 9 Wanda Toledo provides a detailed discussion of the work of data use and the datasprint team from her perspective as a school principal. Speaking to the design of the workshop and the work of the datasprint team, she notes that the work combined research and practice in ways that helped to generate pilot analyses and visualizations that speak directly to data use problems for educators. Toledo offers a clear set of questions that guide the attention of school leaders when they dig into data, as well as the central tensions of how to share this information with teachers to inform their work. Through this work, the data visualization centers the strengths of the school, while addressing the "why?" question and allowing educators to drill down into different aspects of the data to surface current challenges.

From his work as an education data scientist working in school districts nationally, in chapter 10 Nicholas D'Amico notes how traditionally in this work, data scientists lack the subject-level and school management expertise that is needed to drive the usefulness of data visualizations, and thus this work must be collaborative and team-centered. D'Amico articulates three main topics when it comes to doing the local and embedded work of ELDA in school districts, in that one must be aware of the multiple discrete and overlapping skills and traits needed for a successful group, which is different from the process of how to arrive at key questions and problems, and then the need for a defined process to design visualizations with specific metrics that inform educator work. These issues speak directly to the issues of task wrangling with data first strategies noted above. D'Amico notes specific recommendations for leading an iterative design process in school districts to do this work, which includes leveraging the work streams that are already present in the organization to build on current successes, skills, and workflows, using exemplars from outside the organization as a useful means to accelerate the progress of the team, and to be purposeful about creating different and engaging professional development and training addresses core issues for the project from multiple directions and lenses.

For the IDW and central dashboard for Nassau BOCES and its partner district, the BOCES at the time of this project used the IBM Cognos system as one of its main dashboard and data organization systems. As a product manager for IBM Cognos Analytics, in chapter 11 Mohammed Omar Rasheed Khan provides a chapter in which he discusses a perspective which has rarely been provided in the research on data use in schools, namely that of the data dashboard vendor and industry, as a domain expert and participant in the co-design Data Collaborative Workshop. Khan provides valuable insights into current technologies in data use and dashboard systems for organizations, and how they relate to work in schools. Throughout, he makes a compelling argument that through the increasing usefulness and accessibility of data exploration tools and technologies, these tools empower the non-technical user to iterate faster through creating their own unique dashboards and reports, and identify patterns and insights that have previously gone unnoticed. In the chapter, he then demonstrates an example of how this work looks in practice, providing example code in open source software, and reflections on how to generate actionable data visualizations using current digital tools and datasets in school districts.

Aaron Hawn, a data scientist and researcher in learning analytics, discusses in chapter 12 the work of collaborative dashboard and data use design through first starting with data usefulness and usability, the need to pull multiple data resources together to allow the user to see across different data types, how to take action with data as the next step, and the central importance of building a culture of data use around actionable data dashboards. Hawn provides a focus on the central issue that while users want all of the data in one place, different users (teachers, principals, superintendents) across different times (fall, spring, summer) will need many different dashboard solutions, recognizing that questions and data needs are dynamic over time in schools. Hawn walks the reader through the intriguing idea of a data dashboard calendar, tailoring and personalizing reports to time of year and job role, and then provides actionable and concrete ideas on user interface design and dashboard layout identified through the datasprint team conversations and Data Collaborative Workshop feedback from across the event.

In chapter 13, Burcu Pekcan, as a teacher and graduate research student, discusses the work of her datasprint team and the Data Collaborative Workshop from the perspective of useful and actionable teacher professional development. Pekcan centers the research on professional development and professional learning communities, and discusses how data use and data visualization collaboration, as experienced during the workshop, can inform this important teacher development work in schools. Key to this work is the domain expertise of teachers and how the collaborative work as professional development leverages the deep knowledge and experiences of teachers as equal collaborators, as through integrating the types of visualizations piloted during the workshop into teacher practice, student learning may be improved. Sunmin Lee, in the same datasprint team at the event, in chapter 14 discusses these facets of the work in her chapter through the lens of an education data scientist, noting that throughout the Data Collaborative Workshop, data scientists were asked to work in real-time in collaboration with educators and researchers, live coding, and receiving feedback and iterative development ideas in real-time. Traditionally, this is not how data scientists operate. Rather, the work usually entails rounds of gathering information on user needs, building visualizations, then testing these with users, providing independent amounts of time for each stage. Throughout her chapter, Lee provides a detailed description of this work as a data scientist in collaboration with educators, and the challenges and successes of learning from data together as domain experts in an iterative and collaborative process. Lee makes a compelling case for data science to be more tightly coupled with the work of educators in schools.

In chapter 15, Melissa O’Geary, a district director of data, assessment, and administrative services, and Laura Smith, who is a reading specialist in the same district, propose the “direct data dashboard (DDD)”. In their model, an ideal data dashboard provides an explorable and useable tool that is user-friendly to teachers and administrators, easily accessed, and used both to modify and inform real-time instructional changes by teachers, as well as long-term analysis for the organization and community. Providing their deep experiences as educators using data to inform instruction, the chapter outlines the needed components and facilitative tools that would help educators use data in their practice, especially given the practical realities of the everyday work of teaching and student learning. A central important contribution is the emphasis placed throughout the chapter on the experiences of teachers, and how their questions and daily practice can provide actionable directions for dashboard design and implementation. Concurrently, Louisa Rosenheck, as a researcher and data scientist, builds on these ideas in chapter 16, discussing in her chapter how the data collected in schools and displayed in dashboards often does not represent the data that educators are most interested in, and thus the deep, personal, and human-centric work of teaching and learning is not represented in the available data. Rosenheck notes the centrality of the co-design process for building actionable data dashboards, and discusses the central points of the need to diversify the different types of data available to teachers while concurrently building tools and analytics that are able to handle a broader set of data that teachers are interested in. This work thus builds capacity for data use with teachers, integrates data with personal relationships and the knowledge they generate, and empowers students and families through data and tools.

The datasprint team "Team Cylinder" coauthored chapter 17 as a team to reflect on their collaborative experience with data use, visualization, and the workshop, as educators, data strategists, data scientists, and researchers, including coauthors Elizabeth Adams, Amy Trojanowski, Jeffrey Davis, Fernando Agramonte, Andrew Krumm, Leslie Hazle Bussey, and AnnMarie Giarrizzo. Their chapter represents a deep dive into collaborative data visualization and co-design, representing an intriguing set of possibilities represented through their work. Throughout the chapter, the datasprint team walks the reader through the details of the process that the team followed to first understand their shared questions given the data and time available, then how they iterated through multiple visualizations and data summaries as they worked collaboratively towards understanding issues of student chronic absence and how it relates to student achievement. Through detailing and surfacing the issues with this collaborative work throughout the workshop, the team became much crisper and clearer on the question, task, and the possibilities for visualization and action in schools. A central component of the chapter is the benefit of the work of collaborative co-design visualization between educators, data scientists, and researchers, as the work not only pilots data analysis and visualizations, but just as importantly builds community and capacity for all involved.

Fred Cohen, as perhaps the most experienced educator and leader at the event, with an illustrious 50 plus year career in education including teaching, the principalship, and as a deputy superintendent, brings keen insights in chapter 18 to the challenges and successes of dashboard and data visualization co-design between educators and data scientists. Throughout his career, Cohen has helped pioneer and instill the usefulness of data and evidence in the work of teaching and leading across Nassau County districts and schools. Throughout the chapter, he provides three concrete "what if" scenarios, focusing first on the successes and benefits surfaced throughout the event, but then expanding on the challenges posed, through using specific data visualizations that were built and piloted during the Data Collaborative Workshop. In the first what if scenario, he imagines what might happen if the two-day workshop were in fact a long-running practice of constant collaboration between educators and data scientists, which could result in ever more interactive, detailed, and importantly, responsive data visualizations that meet the needs of educators. Second, Cohen reflects on the idea of "data currency" in that for data, such as graduation data, how "current" the data are is as important for its usefulness as what the data are. Third, Cohen highlights his frustration with the dual findings that multiple individual educators across the districts he works with are fabulous users of the IDW and dashboards, yet the data also show that few educators actually do use the dashboards. Cohen concludes by wondering what might be possible if the data were both more tailored to specific teacher questions, and were provided to them on a regular basis in truly accessible ways.

Yi Chen, as a data scientist participant, provides a deep set of perspectives in chapter 19 on his work as a data scientist within his datasprint team at the event, providing a glimpse into the co-design process from the data scientist and coding visualization perspective. Through his chapter Chen demonstrates through visualizations and included code in R, how the visualization for the datasprint team developed through a process of analyzing the trends in the data and combining this with educators' questions to be able to see how student achievement flows over time through grade levels, providing the ability to identify specific student trends over time that are informative for teacher practice. Through the interplay of data, collaborative co-design, code, and iterative visualizations, Chen details the depth of the process along with the successes and challenges throughout the multiple iterations to get to a final visualization that takes advantage of the power of the visualization software and the data scientist, through developing a visualization that addresses the questions and data use and design issues articulated by educators.

As a principal, Kerry Dunne in chapter 20 provides an in-depth look at the use of data in her school, and how throughout the work of educators in the organization, their focus on specific questions and data helps drive instructional improvement. Dunne provides the step-by-step process to first focus attention on questions and data that are available and actionable, and then the specifics on how the school iterates on these questions and data to get to next steps. The chapter is a fascinating look inside this difficult work, providing actionable details that are useful beyond the walls of one specific school. Importantly, Dunne walks the reader through specific innovations that could be possible through more informative data visualizations, such as the conversations motivated from the workshop, and then details step-by-step how a school could go about using this data for specific instructional interventions. From the principal's perspective, the chapter provides a rare and important look that brings students, teachers, data, and action together to address core questions that are individualized to student needs in specific subjects, relying on the data systems that can help inform this work.

While there is a need throughout the data use literature in education to further highlight the perspectives and voices of both educators and data scientists, Robert Feihel in chapter 21 provides the even rarer perspective of the IDW project manager in which he details his work of data collection, management, and operations. Throughout the chapter, Feihel provides the unique perspective of the difficult and detailed work of raw data collection, management, and organization throughout his work in the IDW. The theme of the chapter focuses on "properly representing" data, as often, given the broad diversity of options for visualization of data for use by educators, the visualization represents the data in some form, but is not useful to the organization. This is oftentimes due to the lack of acknowledging the data users' needs and their journey in the system. For example, reviewing a long list of possible data organization and visualization options within the IDW is not very helpful in addressing specific user data needs to help them take action with the data, as often there are paradoxically too many reports to choose from (too much) and not enough information to understand the details of how to generate the report and what it can do to answer useful organizational questions (too little). Throughout the chapter, Feihel then applies these concepts and issues to the work of the datasprint team from the Data Collaborative Workshop, detailing the specific actions and iterations of the team to collaboratively build useful visualizations. Importantly, Feihel provides the details of the sequence of how the team built and iterated on their visualizations, from the ideas generated during discussions at the workshop, hand drawn mock-ups, first iterations, and a final visualization. Throughout the chapter, Feihel provides a deep and compelling narrative that concludes from the perspective of the people who manage and organize the data system itself, that for data visualizations to be useful for educators, that the two central keys to success are simplicity and feedback.

In chapter 22, Josh McPherson, a school principal, dives deeply into the iterative work of his datasprint team during the Data Collaborative Workshop, noting that together, the team agreed that dusty data sitting in folders unused (electronic or otherwise), is an issue across schooling organizations. But what to do about it? Throughout his chapter, McPherson weaves together his deep experiences as a teacher and administrator in using data and evidence in his practice with the step-by-step iterative work of the datasprint team during the workshop. Often, educator data practitioners will use conditional formatting in Excel or Google Sheets to organize and examine data. Yet, through the collaborative datasprint teamwork, the team discussed and piloted visualizations, such as a tree map, to help them address their questions for turning the data into action. Importantly, the team piloted and created an interactive visualization that individualizes the data view that can be toggled by teachers, providing insight into the learning standards that they are most focused on with their students. An important innovation is the idea to link teachers together within the visualization from beyond the walls of a specific school, helping teachers find mentors and colleagues who have had success with students in similar communities around the same learning standards that they are currently teaching. In this way, the datasprint team not only piloted a visualization, but a recommendation and mentorship system which if implemented, could help connect teachers in real-time around their current instructional needs. Thus, throughout the chapter, McPherson details how through this work, data visualizations can help move teachers from passive participants in data visualization, to active contributors, moving the teacher to the center of the data use experience, providing actionable information as well as connections and networking to build capacity and relationships.

In chapter 23, Leslie Duffy, a district Coordinator of Computer Services, and Anthony Mignella, an Assistant Superintendent of Instruction, provide a detailed discussion of their work in their district in visualizing school and student data through their dashboards to make it relevant for educator practice. The chapter offers a window into the process of how districts can organize and summarize the many streams of data for specific users, here with a special emphasis on counselors. As one example, Duffy and Mignella highlight the district's "Performance Map" and early warning system in which counselors are able to visualize student course taking and pinpoint where students may be at-risk so that they can offer supports to help students graduate on time. In another example, they highlight the types of data that they build into dashboards and visual displays for school data use, which has helped deepen the data discussions throughout their schools between administrators and teachers. Throughout the chapter, Duffy and Mignella emphasize the importance of data being up-to-date, easy to access, and provide insights through the design of the visualization. Building on these perspectives, Elizabeth Monroe, who was a data scientist in the same team, team Star, details in chapter 24 the work of the datasprint team during the Data Collaborative Workshop from the data scientist's perspective, focusing on developing team rapport, focus, and impact to create meaningful work. Monroe details the specific steps taken by the team throughout the event, building from the initial icebreaker activities, to specifics in which datasprint team members were able to bring together multiple ideas around data and coding needs for stakeholders, specifically in autogenerating a letter template that schools could customize to help communicate with parents and students. Integral to the process was that Monroe not only shared her code with the team, but they began the work of learning the R coding language together through this implementation, as the data scientist helped the educators load the open source software on their computers and begin to customize the letter through the R code themselves. Monroe provides the final results and R code in the chapter, noting that through both live coding in the datasprint team, but also importantly establishing rapport early on in the process, the team together was able to build code collaboratively, learning from each other, as they customized the output given the user needs noted throughout the event.

Byron Ramirez, Programmer Analyst at Nassau BOCES, in chapter 25 walks the reader through a richly detailed description of the work of datasprint team Triangle. Ramirez provides a depth of detail for this type of co-design collaborative team work that is rarely found in the research, starting from the beginning and noting how the team aligned around a shared interest in science instruction. In combination with chapter 2 of this book volume, Ramirez's chapter provides the fine-grained details of each step of the two-day Data Collaborative Workshop, through the lens of team Triangle and their collaborative work to build a data visualization that addressed the issues discussed and built together over their time together. For those looking to replicate the experience in some way, this chapter provides a fantastic view into the work. To conclude the chapter, Ramirez takes on the issue of what is being asked for when the organization decides to design a dashboard. This is a central theme that authors throughout the book discuss, and here Ramirez draws out the theme to summarize how to bridge this gap from ideas and solutions to data dashboards that engage practitioners and help them in their work, in which the central recommendations include a strong role for iterative and continuous stakeholder engagement throughout in the design and implementation process.

Part III: Tools and Research for Data Analysis in Schooling Organizations

At the center of data use is data visualization. Tara Chiatovich, a data scientist, provides an introduction and excellent guide to data visualization for school data users using the powerful and accessible ggplot2 R statistical software package in chapter 26. Chiatovich's aim is to provide actionable examples to get school data users up and running quickly with ggplot2, so that anyone can start to visualize their data using one of the most popular and useful tools for data visualization in open source code. In her chapter, she provides a complete walkthrough and guide for how to get started, from installing and getting setup, to then examples with some of the most frequently used types of visualizations in schools, including bar charts, histograms, and scatterplots. Data examples come from the data used throughout the Data Collaborative Workshop event, providing useful background details for how many of the data scientists across the datasprint teams built and displayed the data visualizations from across the event. Importantly for this event, the chapter also represents a core tutorial for the data scientists, as Chiatovich presented much of the content from the chapter on the first evening of the workshop event as a tutorial to help all of the data analysts, data scientists, and researchers learn more about data visualization in R to help them generate ideas and code for the second day of the Data Collaborative Workshop. Chiatovich starts first with the minimal code to get up and running and then expands to more fancy code, walking the reader through each step to go from the first steps of data visualization of first making ugly but useful charts to start, and then moving to more beautiful charts. Throughout, she also provides her reflections on her work as a data scientist with school leaders on the types of data visualization that work, and importantly, the work flow for data visualization that can help move schools towards more effective data use. The chapter is an excellent resource for educators, school and district leaders, and data analysts on the foundations for data visualization with actionable code and recommendations from an expert data scientist.

In chapter 27, Tommaso Agasisti and Marta Cannistrà, as education researchers and data scientists, discuss the central issues currently in research and practice in data use and early warning systems (EWS) for applying learning analytics, education data mining, and machine learning techniques to understanding and positively intervening in the student journey through school to promote persistence. A core issue throughout the current research on EWS and at-risk prediction is that often many of the statistical models and machine learning algorithms see each year, event, and datapoint for students as independent, yet as Agasisti and Cannistrà discuss, this is not the case as the educational process is cumulative, and so more accurate education outcome prediction and EWS's must take this into account. Throughout the chapter they detail a new theoretical model, building on the past research and practice, focusing on the work of the data analyst and the usefulness and accuracy of the predictions that leverage the deep sets of data collected throughout the system, both the static data that are collected once or infrequently, and the dynamic data that is updated continually, each of which are built into current EWSs to help inform school practitioner decision making.

In the final chapter, Manuel González Canché examines the issue of randomized controlled experiments in schools and teacher assignment to treatment or control conditions using a complex systems network approach. He discusses the reality of these types of experiments in schools, and how often the composition of the groups in such experiments change over time. For example, participants may join the treatment group because teachers heard the treatment was being offered and they would like to join, or administrators assigning students to the treatment group outside of the experimental protocol because they think the students need more help, each of which results in the group inclusion not being random. González Canché discusses throughout the chapter that this issue can be addressed from the start of such experiments by using a complex systems network approach. This approach uses network analysis with students and teachers as the nodes, estimates peer effects to understand and visualize the non-random clustering of students and teachers within such experiments. Throughout, González Canché provides an example worked through with the full R code for the complex systems network approach, which represents an actionable guide for researchers and practitioners looking to address this important clustering issue in baseline comparisons for these types of school-based experiments.

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CHAPTER 2

Planning, Organizing, and Orchestrating the Education Data Collaborative Workshop

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Abstract

This chapter details the motivation, structure, and design of the two-day Education Data Analytics Collaborative Workshop held in the Smith Learning Theater at Teachers College, Columbia University in New York City, on December 5 and 6, 2019. This workshop brought together teachers, school and district administrators, district and county-level data analysts, education researchers, education data scientists, and education data dashboard developers. As the final phase of a multi-year National Science Foundation (NSF) funded (NSF #1560720 *Building Community and Capacity for Data-Intensive Evidence-Based Decision Making in Schools and Districts*) collaboration between the Nassau County Long Island New York Board of Cooperative Services (Nassau BOCES) and the 56 school districts which they serve, and Teachers College, Columbia University, the Education Data Analytics Collaborative Workshop was designed to bring educators and data scientists together to inform data use, data visualization, and data dashboard practice in schools in new and innovative ways by providing the rare opportunity for educators to work collaboratively in real time together with data scientists and data visualization experts to create data visualizations that address the needs and current problems of practice of teachers using the data

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that are available in current Instructional Data Warehouses (IDWs). This workshop was intentionally orchestrated around the recommendations of teacher co-design and iterative design-based collaborative research. The design of the workshop included novel uses of automated text analysis to cluster 77 participants into 11 individual “datasprint” teams based on pre-event survey long-form essay responses, partnering educators with data scientists and researchers based on a shared language of data use and data visualization. The workshop was structured so that over the two days each datasprint team would engage in multiple iterative rounds of collaboration to analyze and visualize mock data from the educators’ IDW to generate data visualizations that address issues of teacher and administrator data use practice. This chapter details the event planning, orchestration, workshop design, and data visualization final results. Specifics include datasprint team creation and member matching, introduction activities to generate conversations, quick-talk “cabana” speakers providing data use research ideas across teams in a condensed time format, team ideation clustering and convergence, a data visualization “expo” to expose participants to a large variety of visualization ideas, participatory location tracking in the event space, a “journey/traveler” protocol to provide cross-team interactions and exchange of ideas, the final data visualizations designed and generated from event, and a summary of the post-event satisfaction survey responses of workshop participants.

Purpose and Background

Data use, evidence-based practice, and organizational improvement cycles are core practices by teachers and administrators in today’s schooling systems, as schools collect a wide range of data across students, classrooms, and schools (Agasisti & Bowers, 2017; Boudett, City, & Murnane, 2013; Halverson, 2010; Krumm, Means, & Bienkowski, 2018; Mandinach & Schildkamp, 2021; Marsh, 2012). A large amount of this data is collected and organized through district Instructional Data Warehouses (IDWs) and visualized using data displays, visualizations, and dashboards to inform data driven decision making (Bowers, 2021b; Bowers & Krumm, in press). Data use research shows that teachers continually use data from their daily formative and summative practices in deep and productive ways (Gerzon, 2015). Yet, as noted in chapter 1 of this book volume (Bowers, 2021a), when focusing at the school-level for overall organizational improvement, while research on systematic school data use to date suggests a strong promise of data use for instructional improvement, much of the research demonstrates that the potential of data use in schools is as yet unmet (Grabarek & Kallemeyn, 2020). For example, this research has shown for Instructional Data Warehouses (IDWs), and data dashboards specifically, that despite a broad diversity of types of data and visualizations within district dashboards, teachers and administrators rarely use these resources to inform decision making conversations in schools (Bowers, 2021b; Farley-Ripple, Jennings, & Jennings, 2021; Wayman, Shaw, & Cho, 2017), as educators note that the data represented in the dashboards either are not timely or relevant enough for their daily practice, or that the visualizations and data do not address their problems of practice and data use needs in their schools (Brocato, Willis, & Dechert, 2014; Reeves, Wei, & Hamilton, in press; Riehl, Earle, Nagarajan, Schwitzman, & Vernikoff, 2018; Wachen, Harrison, & Cohen-Vogel, 2018; Wilkerson, Klute, Peery, & Liu, 2021). Concurrently, research that has focused on education data science, learning analytics, and education data dashboard and visualization design indicates that educators are rarely involved in the design or evaluation of the visualization and dashboard prior to the launch of the tool (Schwendimann et al., 2017).

Thus, together, this literature points to four main issues in education data use and data visualization of 1) that teachers and administrators rarely make use of the full potential of data visualization and dashboard systems, yet 2) teachers and administrators note that dashboard systems usually either do not have the data they are looking for, or do not organize and display the information they need in an accessible and timely format, while concurrently 3) data visualization and dashboard specialists rarely take into account the data needs of educators or collaboratively design visualizations with teachers and administrators as equal partners before marketing and deploying the data product to schools, and so 4) it is then unsurprising that the research on data visualization and educator dashboard use beyond specific exemplar cases has to date shown little relationship on average with school instructional improvement. Thus, there is presently a deep need in school data use research, theory, practice, and policy to bring educators and data scientists together around these issues. For example, teachers and administrators partnering in successful and useful collaborative design with data scientists and data visualization researchers to co-design these digital tools have the potential to inform the research and design of data visualization to make these tools be more effective and useful for the daily work of educators (see Chapter 1 this book, Bowers).

The purpose of the Education Data Analytics Collaborative Workshop was to bring together teachers, school and district administrators, district data warehouse and professional development experts, data scientists, and education researchers to collaboratively design, iterate, and build novel data visualizations together during a two-day workshop. Held on December 5 and 6 of 2019 in the Smith Learning Theater at Teachers College, Columbia University, the Education Data Analytics Collaborative Workshop represented the final phase of a multi-year National Science Foundation (NSF #1560720) funded collaboration between the Nassau County Board of Cooperative Services (Nassau BOCES) Long Island New York, and the 56 school districts which they serve, and the Education Leadership Data Analytics (ELDA) research group at Teachers College, Columbia University (TC). In this chapter I detail the design and orchestration of the Education Data Analytics Collaborative Workshop. Subsequent chapters in this book provide details from the data collected throughout the workshop and from the pre- and post-event surveys, as well as the individual and team discussions of the work of the datasprint teams from throughout the event. This chapter is organized into three main sections:

1) The intention to create a collaborative co-design opportunity to bring teachers and administrators together with data scientists and researchers as partners to build data visualizations together that address educator practice.
2) The planning, design, and orchestration of the datasprint teams and the workshop to include structured opportunities for collaboration across all participants.
3) The final data visualizations from the datasprint teams and summaries from the post-event satisfaction survey.

A Collaborative Co-design Workshop

The design for the Education Data Analytics Collaborative Workshop was developed in collaboration with Nassau BOCES and informed through a combination of both the previous experiences of the Education Leadership Data Analytics (ELDA) research group at TC and the research on design-based and co-design iterative collaborative professional development opportunities in five main ways. First, the Education Data Analytics Collaborative Workshop was the final phase of a long-term NSF funded collaboration between the data analysts, researchers, professional development coordinators, and administrators in Nassau BOCES and TC. The overall collaboration and grant funded project are discussed further in this book from both the TC (Chapter 1, Bowers) and Nassau BOCES perspectives (Chapter 8, Pratt). As a research-practice partnership (Coburn & Penuel, 2016;

Farley-Ripple, May, Karpyn, Tilley, & McDonough, 2018) this work included many meetings over multiple years between the key personnel in each organization to build on each other's needs and ideas, especially for the workshop as the final phase of the grant funded project. These collaborative conversations formed the primary foundation of the work and the articulated needs of Nassau BOCES and the districts.

Second, the Education Data Analytics Collaborative Workshop built on what the TC researchers had learned from an event hosted a year earlier, the 2018 Education Leadership Data Analytics (ELDA) Summit (Bowers, Bang, Pan, & Graves, 2019). The ELDA Summit, held at Teachers College, Columbia University in June of 2018, was an open invitation event in which over 120 participants attended a variety of sessions, including a pre-event research project poster session, keynote talks, and an interactive afternoon in the Smith Learning Theater at TC in which multiple "quick-talk" speakers gave ten minute talks on data use, visualization, data science, data ethics, and data management, and attendees participated in design-based collaborative groups in which they discussed the central issues at the intersection of education leadership, evidence-based improvement cycles, and data science. Participant responses to these activities culminated in a white paper report published in 2019 (Bowers et al., 2019) in which Education Leadership Data Analytics was defined as follows:

> Education Leadership Data Analytics (ELDA) practitioners work collaboratively with schooling system leaders and teachers to analyze, pattern, and visualize previously unknown patterns and information from the vast sets of data collected by schooling organizations, and then integrate findings in easy to understand language and digital tools into collaborative and community building evidence-based improvement cycles with stakeholders (p.8) (Bowers et al., 2019)

This definition builds on the research on data science in education, and the potential that recent innovations across the big data, data science, machine learning, and learning analytics fields have for informing educator and administrator decision making and evidence-based instructional improvement (Agasisti & Bowers, 2017; Bienkowski, Feng, & Means, 2012; Bowers, 2017, 2021a; Fischer et al., 2020; Krumm & Bowers, in press; Krumm et al., 2018; Piety, Hickey, & Bishop, 2014; Piety & Pea, 2018). Yet, despite the potential of ELDA, participants also noted significant challenges, in which chief among these was the need for the central role of the voice and experiences of educators in the design and implementation of this data analytic work in schools. Indeed, participants noted that the vast majority of attendees at the ELDA 2018 Summit were researchers, not practicing K-12 educators or administrators. Thus, one goal for the subsequent 2019 Education Data Analytics Collaborative Workshop was to ensure that the majority of participants were teachers and school and district administrators, centering the voices and expertise of educators in the work of data use, data analysis, and data visualization in schools.

Third, given the research on data visualization and design noted above and discussed throughout Chapter 1 in this book (Bowers), especially for data dashboard use by teachers and administrators, we recognized that current data visualization practice for school data dashboards is problematically focused on a step-by-step set of assumptions. Summarized well in Crisan and Munzner (2019) from their work on data landscapes and task wrangling from human-computer interaction, data visualization, and design-based research (Crisan, Gardy, & Munzner, 2016; Crisan & Munzner, 2019; Meyer, Sedlmair, & Munzner, 2012; Meyer, Sedlmair, Quinan, & Munzner, 2015; Oppermann & Munzner, 2020) this work takes a "data first" design perspective that is collaborative, participatory, and centers the work of data visualization around the seeming paradox of not focusing on the visualization as the primary outcome, but rather understanding the task that can be informed through working to collaboratively organize and visualize the data. In this process, data visualizations and digital tools emerge as secondary products from the iterative cycles of this task wrangling work, in which in each collaborative iterative cycle the task moves from a fuzzy conceptualization to crisp, and data visualizations and tools become more defined and eventually automated into dashboard-style systems to address the now more crisply defined task.

Here I summarize this research into two models: 1) visualization-as-outcome, and 2) task-clarity-as-outcome. Building from this growing set of research across the data science, education data use, and data visualization literatures, I posit here that one reason why education data dashboards and visualization use in schools have perhaps been shown to date to be mostly unrelated to school instructional improvement is that data visualization traditionally in education uses the visualization-as-outcome model, which I summarize as:

1. A dashboard or visualization is requested from management, or a request is submitted from a specific individual school, district, administrator, or teacher, oftentimes the power users.
2. The data analyst identifies what data are available.

3. The data analyst decides on a visualization strategy and builds the code and visualization.
4. The visualization is then implemented in the IDW and dashboard system as another à la carte option among the many already available.
5. Educators are potentially notified.
6. Data are rarely collected on the extent to which the new visualization is used.
7. Repeat

This visualization-as-outcome model thus is designed to produce a data visualization, dashboard, data organization, or summary, as the outcome. Importantly, this process assumes the task as given and known. Yet, as noted above, the research suggests that often the issue at hand is that the tasks themselves are unclear and fuzzy (Crisan & Munzner, 2019), and rather the visualization is secondary to the work of gaining clarity on the task: the task-clarity-as-outcome model. Thus, in comparison to the visualization-as-outcome model, the task-clarity-as-outcome model can be summarized as:

1. Bring educators and data analysts together as collaborative partners to iteratively discuss current teacher and administrator problems of practice.
2. Write down and organize the conclusions of the discussions and collaboratively decide on the priority of the issues noted that relate directly to educator practice, including the voices of educators and data analysts as equal partners.
3. Iteratively discuss what data are needed to address these issues given data availability, data constraints, and the current data formats in the database, centering the perspective of both the educators and data analysts.
4. Iteratively and collaboratively design, build, and code visualizations to address the issues identified.
5. Repeat.

Thus, in the task-clarity-as-outcome model, the tasks that educators and data analysts are confronted with become the issues that are iteratively and collaboratively discussed. The data visualizations and code are secondary. In effect, in a task-clarity-as-outcome model, the data visualizations are iterative, intermediate, temporary, and drafts early in the process. Gaining clarity on the task is the outcome. Usable visualizations are secondary to the process, as through the discussions of the issues, tasks, and then the work to attempt to visualize the data available given the discussions between the practitioners and data analysts, the tasks gain clarity as iterative rounds of visualizations are created. From the perspective of Crisan and Munzner (2019), the final code and deployment of the visualization into a dashboard system come after an iterative process such as this, as the visualization only fits the task once the there is alignment between task clarity, the data available, the needs of the end-users, and the data visualization and dashboard system. Thus, our design of the Education Data Analytics Collaborative Workshop drew on these ideas of the task-clarity-as-outcome model in which rather than start with the data and ask how can we visualize it, and then ask how teachers could use this visualization for specific tasks, the intention of the design of the workshop was to focus datasprint teams on the question of what is the task that educators identify as a current problem of practice in their work and what visualization will help us understand the task and what we need to do as an organization to address the identified problem of practice.

The fourth design component of the Education Data Analytics Collaborative Workshop that informed our planning was a focus on intentional co-design processes throughout the workshop. As noted from the research in learning analytics on the lack of evidence of the effectiveness of data dashboards (Holstein, McLaren, & Aleven, 2017), “the value of teacher dashboards may depend on the degree to which they [teachers] have been involved in co-designing them” (p.74) (Echeverria et al., 2018). We drew on the research on co-design in education (Brandt, 2006; Matuk, Gerard, Lim-Breitbart, & Linn, 2016; Muller & Kuhn, 1993; Roschelle, Penuel, & Shechtman, 2006) to inform our planning and orchestration of the workshop. The literature on co-design with teachers as participatory designers notes the following as important considerations:

> From the literature, we can derive two conditions that support teachers as participatory designers: providing scaffolds to support teachers throughout the design process and emphasizing contextual knowledge. Brandt (2006) contends that in order to succeed, the participatory design process must be carefully orchestrated. This means that the process needs to be highly-facilitated such that teachers are presented with a clear set of objectives, activities, and milestones, with their role being clearly specified and supported (Roschelle et al., 2006). Muller and Kuhn (1993) also underscore the need for scaffolds—putting in place activities that befit specific contexts and needs, such as contextual inquiry for design, and collaborative prototyping and evaluation. (p.207) (Cober, Tan, Slotta, So, & Könings, 2015)

For the planning and orchestration of the workshop, as detailed below, we drew on these recommendations for co-design to: 1) center educators throughout the workshop as experts emphasizing their contextual knowledge, 2) provide scaffolding and a highly-facilitated process, and 3) infuse the event throughout with clear objectives and activities that continued to center teacher and administrator expertise and contextual knowledge throughout the iterative and collaborative prototyping of new visualizations.

This scaffolding and facilitation also extended to the data scientists and researcher participants in the workshop. We asked the data scientists to do quite a bit of work, from examining, collating, and organizing the data, to participating in the co-design discussions and activities throughout the workshop, and to be the data visualization and coding expert in the datasprint team. This required data scientists to live code from their laptops on projected screens for their datasprint team and everyone in the Learning Theater to see throughout the event. Additionally, the education researchers invited to participate and speak during the event, who were also members of datasprint teams, brought a wealth of knowledge on data use and data visualization in schools. Their expertise was also a needed resource for each of the datasprint teams, as well as across the teams for all participants at the event. To provide additional scaffolding and facilitation for the data scientists and researchers, as noted below, at the end of Day 1 of the workshop, we included an end-of-day Collaborative Coding Workshop, in which multiple data scientists provided tutorials on different ways to code and display visualizations, providing data scientists and researchers across the datasprint teams with ideas and actionable code for them to use immediately on Day 2, as well as provide networking and professional development for the data scientists and researcher attendees.

And fifth, a final design goal was to build into the event intentional cross-team collaboration and information sharing. Often, when placed into a working team environment for an extended workshop such as this one, a participant can feel isolated to just their assigned team, and cut off from the larger conversation from across the event. Additionally, given the wealth of expertise across the attendees we worked to structure the design and pacing of the workshop to hopefully maximize the amount of interactions across groups, the invited researchers, and data visualization experts, while at the same time providing time for the datasprint teams to work to discuss real-world problems of practice in schools with data, and then build visualizations and code to address those issues. As will be detailed below, multiple aspects of the Learning Theater itself enabled the work of the datasprint teams as well as cross-team collaboration and information sharing.

The Smith Learning Theater at Teachers College, Columbia University

The Education Data Analytics Collaborative Workshop was held at the Smith Learning Theater at Teachers College, Columbia University. The Learning Theater is a 6,000 square foot multimodal event space, which includes a wide range of collaboration, display, and data tools. For the Education Data Analytics Collaborative Workshop, the design of the space first included the eleven datasprint team locations. Each datasprint team was named with a geometric symbol including Cube, Arrow, Chevron, Circle, Cylinder, Diamond, Hexagon, Pentagon, Square, Star, and Triangle. Each team had a central set of movable tables, chairs, whiteboard, and supplies such as markers, sticky notes, paper, and the like. Importantly, each team also had a portable projector to display any team member's laptop onto the whiteboard. The Learning Theater also includes large projection displays along all of the outer walls as well as a full suite of high-resolution studio-quality camera equipment and personnel. To provide an opportunity for teams to see into the work of other teams throughout the event, the Learning Theater staff worked throughout the event using a roving camera crew to display and highlight the work of individual teams onto the large projection screens. Thus, all datasprint teams could look up to see what at least one other team was working on at any one time, with the intention this would allow team members to bring in ideas from other teams in real time. The Learning Theater also includes many large-format digital screens, which were used in each of the below described "cabana" and "expo" activities to provide individual presenters their own screen to plug into to display a presentation or visualization from their computer to a small group. And finally, the Learning Theater also includes participatory real-time location tracking through a "Quuppa" system. The Quuppa chips are small RFID devices (about the size of a nametag or badge) clipped to lanyards, in which each participant's location in the Learning Theater is recorded every few seconds, and projected (as dots on a map of the space) providing a novel set of data on attendee location, attention, and movement throughout an event. Importantly for Learning Theater events, for all participants consent for data collection, filming, and the use of the location tracking system is obtained before attendees enter the event space. For a more detailed discussion and an analysis of this data collected during the workshop, please see the chapter in this book by Coleman et al. (chapter 6).

Education Data Analytics Collaborative Workshop Event Planning

Initial Meetings and Participant Recruitment

Given the many different participants and intentional structure and orchestration of the co-design and collaborative aspects of the event, there were multiple stages required for the pre-event, event, and post-event planning structure and sequence. Figure 2.1 provides an overview of the sequence and timing of events that we followed to prepare for the workshop in December of 2019. Building on the long-term collaboration between Nassau BOCES and TC, discussions on the workshop and specifics for pre-event planning in collaboration with the Learning Theater staff began in July and August of 2019. Additionally, in July and August, we launched national-level application and recruitment for multiple data scientists and data visualization experts in education to attend the event. The goal of national-level recruitment was to provide an opportunity for a wider range of education data scientists and researchers to apply to attend and participate in the event outside the planning team's immediate network. Then towards the end of summer and early fall, Nassau BOCES worked to recruit teachers and administrators from specific districts, requesting district superintendents to attend the event themselves (or appoint a representative), and to nominate a principal and a teacher from the district to attend. In addition, the planning team individually invited multiple national-level education data use and visualization researchers. We also invited a representative from the IBM Cognos team to participate, as the IBM Cognos platform was the foundational IDW and dashboard platform used by Nassau BOCES at the time. These efforts around participant recruitment yield 77 total participants, over 40 of which (more than half) were teachers or school or district administrators (for more information, see Chapter 3, Kang and Bowers).

Pre-event Survey and Datasprint Team Construction

As the date for the workshop neared, we wanted to group participants into datasprint teams based on how similar their perceptions of their own challenges and successes were around data use and data visualization in the K-12 schooling organizations they work with, for educators, data scientists, and researchers. Our aim was to create teams with six to seven members in which two of the members were data scientists or researchers, ensuring that each team had a member who had experience visualizing data through coding in the R or Python open source statistical software programs. To learn more about our participants, as shown in Figure 2.1, throughout October and November, we provided an online pre-event survey to first gather information

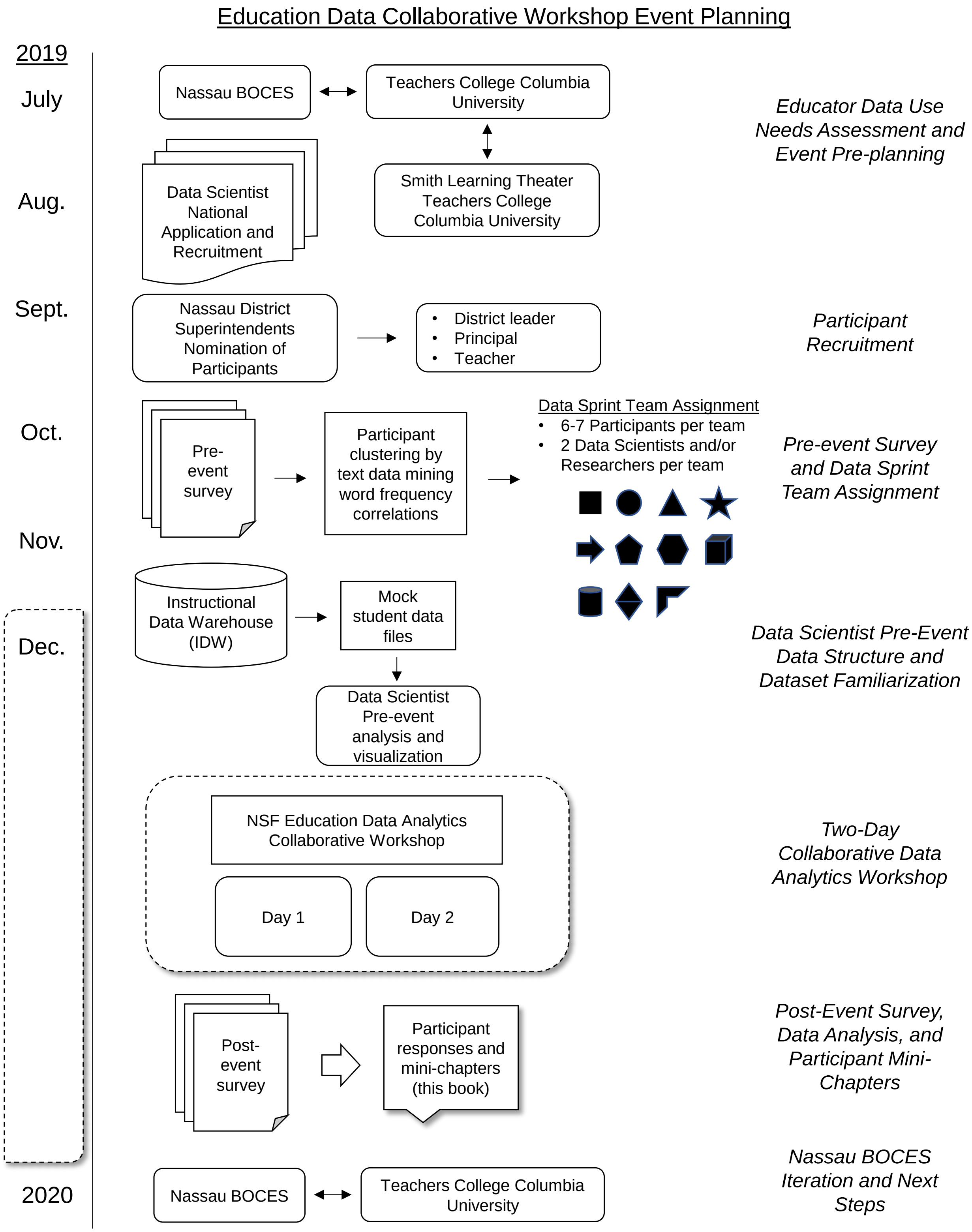


Figure 2.1: Timing and sequence for event planning for the Education Data Analytics Collaborative Workshop.

for name badges, current job roles, and information for catering preferences. Importantly, we also wanted to learn about participants' perceptions on data use and data visualization. To do so we included the following three open-ended long-form essay questions in the pre-event survey, adapting data use and data system questions from the previous research noted above, of which the first is adapted directly from Brocato et al. (2014):

- What components of a longitudinal data system are needed to best meet the needs of superintendents, principals, and teacher leaders?
- What challenges and successes have you experienced using data and evidence in your practices in schools/districts?
- Thinking about data and evidence that are available in your current systems, how could the data visualization and evidence be improved? How would these improvements help you?

To match participants into datasprint teams, we used text data mining for the matching process based on the similarity and word frequency correlations across participant responses to these three questions on the pre-event survey. We relied on our previous research in education leadership, school finance, and learning analytics for the models (Bowers & Chen, 2015; Slater, Baker, Almeda, Bowers, & Heffernan, 2017; Wang, Bowers, & Fikis, 2017). We first concatenated each participant's responses to the open-ended pre-event survey questions to generate one "document" per participant. Text data mining, specifically correlated topic modeling (CTM) used here, is a data mining technique which takes as input a sparse words by document matrix, and generates as the output a topics by documents and topics by words matrix. Importantly for our use here, a correlated topic model is a probability model, so rather than classify documents into a specific latent topic, each document is given a probability. This method has been shown previously to work well to empirically create collaborative online discussion board groups based on participant word correlation frequency patterns (Bowers, Pekcan, & Pan, 2021). Following these recommendations, we used these probabilities to map participants into a two-dimensional space using multidimensional scaling to identify similar clusters of word correlation frequencies. These clusters of participant response similarity were then used to create the datasprint teams, assigning each participant to one unique datasprint team based on each individual's shared common language with others in the team from the survey.

Creating a Shared Data File for the Workshop

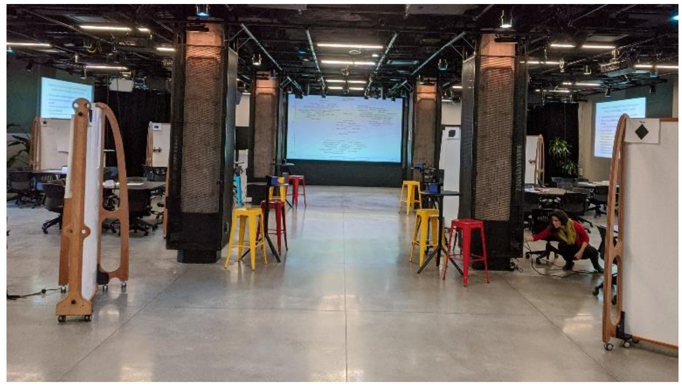
In anticipating the work of the datasprint groups, we wanted to provide the teams with a consistent set of data that 1) included a broad variety of data that is available in the IDW, and 2) that the data file formats match the current IDW so that code generated on them during the workshop could potentially be used by the districts and Nassau BOCES. To generate this dataset, the Nassau BOCES staff worked throughout the months preceding the workshop to create a fake mock dataset that included realistic IDW data in the file formats that match the IDW data structures. The types of data in the mock dataset included for example multiple years of linked student attendance, standardized test scores, and how the scores relate to district and state benchmarks. This mock dataset was then sent to the data scientists a few days before the event to give them an opportunity before the event to examine the structure of the data and types of data available for the workshop.

The Workshop and Post-Event Follow-ups

We held the Education Data Analytics Collaborative Workshop over two days, which I describe in detail in the below sections. As summarized in Figure 2.1, after the workshop, we followed up with a post-event survey, asking participants to provide feedback on their satisfaction with multiple aspects of the event, as well as returning to the three long-form essay questions from the pre-event survey. Importantly, we also asked participants if they would be willing to write a chapter for this present edited book, and we received 25 chapters from 33 authors/co-authors, representing educators, Nassau BOCES data administrators, data scientists, and researchers (see Chapter 1 Bowers, and Chapter 3 Kang and Bowers, this book). During the chapter writing process, we also offered authors the opportunity to analyze the de-identified data from the pre-event and post-event surveys, which resulted in multiple authors analyzing the data in their chapters in this book, including among others: Kang and Bowers (chapter 3); Nguyen, Campos and Ahn (chapter 4); and Gegenheimer (chapter 5). Following the Education Data Analytics Collaborative Workshop, while the grant funded project was concluding, Nassau BOCES and TC continued to discuss the outcomes from the workshop, and as detailed in chapter 8 by Meador Pratt, Nassau BOCES has continued to advance their data visualization and IDW systems given the discussions and outcomes from across the project and especially from the workshop.

The Education Data Analytics Collaborative Workshop Structure and Orchestration

Figure 2.2 details the structure and pacing of the Education Data Analytics Collaborative Workshop for day 1 and day 2. The workshop opened on the morning of day 1 with participants registering at check-in with their



name badge including the symbol for their upcoming datasprint team. As attendees then entered the Learning Theater, they were asked to find their name on the large central display. The display contained the two-dimensional plot of the multi-dimensional scaling of the correlated text mining results (discussed above), with each participant's name on the plot (rather than a dot). In this way, each participant saw their name in relation to all other attendees plotted into a two-dimensional rectangle, which we mapped to the rectangle of the Learning Theater space itself. We split the figure into multiple "countries" by drawing dashed lines between the clusters, and we asked participants to find their name on the plot which corresponded to an area in the Learning Theater, then gather in that area and discuss with people near them issues of data visualization and data use in their work. Thus, where each person was standing related directly to the text mining results, such that the other people nearby already shared a common language about data and data visualization due to the clustering from the word correlation frequency algorithm mapping. Even if an attendee did not know anyone at the event, the goal with this process was to ensure that the people around them already had a shared common language, which would hopefully kickstart conversations. The intention with this starting structure was to center the educators in the space as the experts, while providing an icebreaker activity and networking opportunity for participants to meet each other and begin discussing data visualization right from the start. Participants were then asked to look at their name badge and then go to their datasprint team area in the Learning Theater, and we then proceeded with introductions and initial discussions within teams returning them to the questions from the pre-event survey. Throughout the morning we emphasized three main goals of the two-day collaborative workshop of:

1. Build capacity and knowledge around the data and data visualizations that teachers and administrators need to help inform instructional improvement.
2. Network with educators, data scientists, and education researchers to inform practice, tools, and research.

3. Create analysis, visualizations, tools, and conversations that help all of us improve data use and data visualization to address your needs in schools.

The lunch speaker was Professor Richard Halverson from the University of Wisconsin-Madison who provided a talk that discussed not only the current research and evidence on data use and data systems, but a look to the future and where data systems may be going next (see chapter 7 this book, Halverson).

The afternoon of day 1 then transitioned to what we termed "cabana quick talks". As we had invited eight national-level education researchers to speak to their research on data use and data visualization, we wanted to provide them the space to give a 10-minute talk with 5 minutes for questions. However, to hear from each speaker with questions and transitions would not only use a large amount of the time for day 1, but would mean that everyone in the workshop would be mostly passively listening for two hours, rather than discussing, collaborating, and networking which is recommended given the co-design literature discussed above. To create an active and engaging session, on the ends of the Learning Theater we set up eight small "cabanas" (four on one end of the space, four on the opposite end) for 8 to 10 people to stand or sit, with a large screen for each presenter to display a presentation. Each cabana was labeled with a nature symbol: moon, sun, mountain, cloud, flower, wave, tree, lighting. The cabana quick-talk speakers were asked to temporarily leave their datasprint team area and prepare their cabana space during the lunch speaker. Each datasprint team table then had a stack of cards, each with one of the symbols printed on it. The purpose of the cabana quick talks was presented as:

> Cabana Quick-Talk Purpose: To learn more about different applications of data use and data visualizations in order to inform instructional improvement and capacity building in schools. The central question: How do we make data visualizations compelling to help build collaboration between and evidence use by teachers and administrators?

We asked each datasprint team member to pick a cabana symbol card at random and then attend that quick talk. Team members then returned to their datasprint teams. Once back to their datasprint teams, participants were asked to write their thoughts about what they noticed and wondered from the quick talks on individual sticky notes, and then go around the table and discuss one of their notes each. We then repeated this activity a second time with

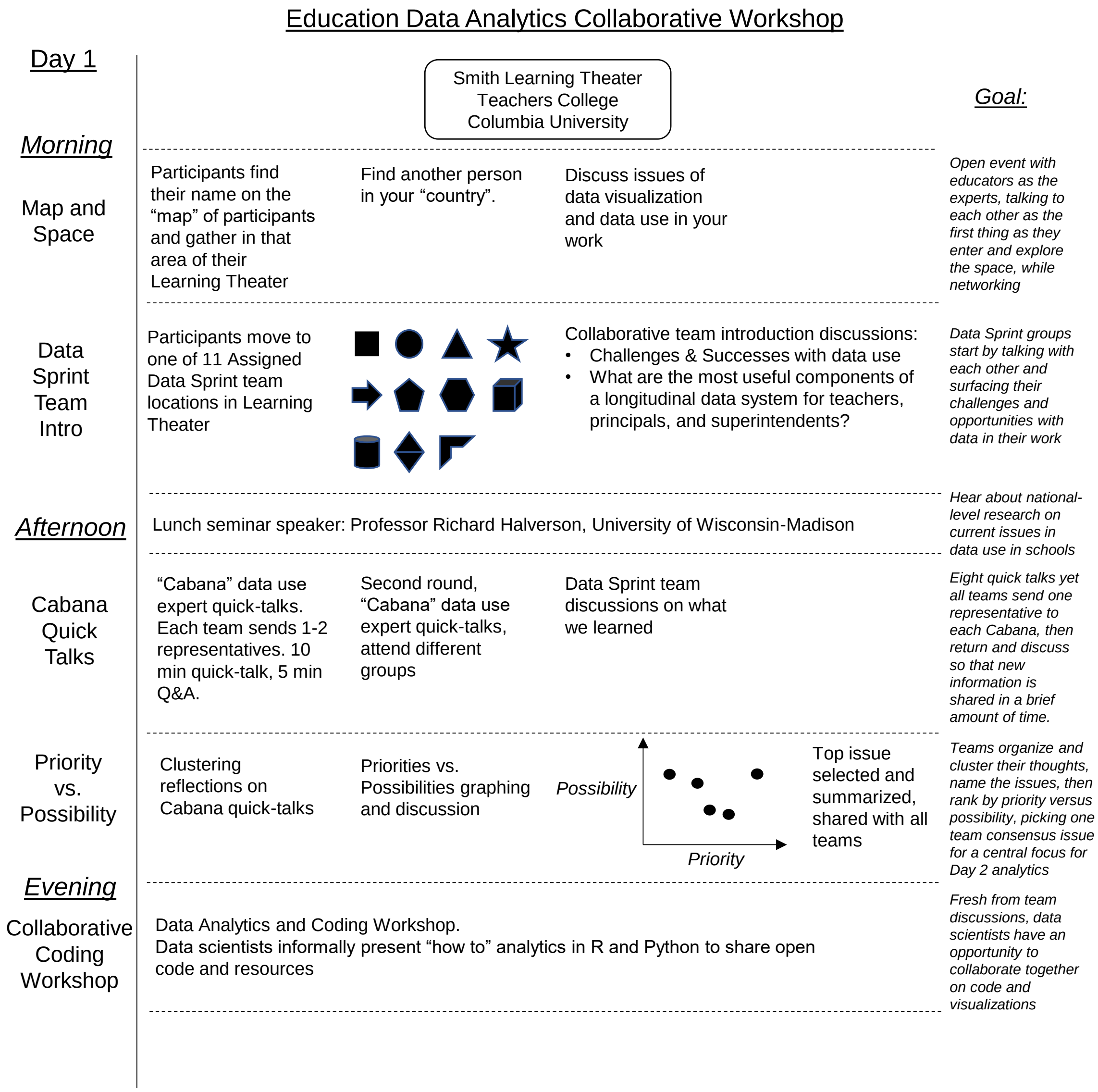
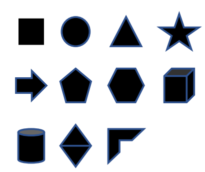


Figure 2.2: Day 1 and Day 2 Workshop and Orchestration (continued on following page)

Day 2	Education Data Analytics Collaborative Workshop			*Goal:*
Morning Quuppa devices	Each attendee receives location tracking "Quuppa chip" on a lanyard on sign in	Anonymous dot "map" of participant locations displayed continuously in Learning Theater on screen throughout the day	Data used to understand participant attention and flow throughout the day	*Capture participant location as a proxy of attention while publicly displaying what is being recorded so participants can see their data.*
Data Vis Expo	Data Visualization and Dashboard Expo: Eight invited Expo presenters in education data visualization and dashboards provided large screen and room for 10 attendees in "expo" format in the Learning Theater	Attendees encouraged to explore and discuss each visualization as they please with Expo presenters	Networking for Expo presenters and participants. Expo stations include the Nassau BOCES data visualization and dashboard that the educators have access to, as well as IBM Cognos among many others which is the system for the BOCES.	*Provide opportunities for participants to engage with and explore current innovations in data visualization as exemplars to build on for their Data Sprint teams.*
Data file structure & content	Nassau BOCES presentation on the data and data files available for analysis and visualization	Data file format matches the current data system for the BOCES	Mock data files include a range of available data types for analysis, including state test scores, attendance and demographics, linked to state standards and benchmarks.	*Teams hear from data managers for the county so as to ground their ideas for the Data Sprint team on what data are actually available today in what format.*
Who What When Where	Who, What, When Where: Data Sprint Teams are asked to focus their discussion on these questions:	Data Visualization plan should focus on two of the four of: • Who do you need to focus on to address your question? • What (variables, demographics, scores) do you need to focus on? • When (what timeframe) should this question address? • Where do you need to focus on to address the question?		*Provide an opportunity for teams to discuss specifics for the data visualization design given the data available and their central focus question.*

Afternoon
Team Data Sprint
	Data Sprint Working Session in the 11 assigned Data Sprint Teams:
	• Purpose: Data scientists and educators work iteratively in a structured format to draft and build visualizations with data that addresses the central focus questions of each team.
	• Each team should start by drawing out their visualizations on the blank sheets of paper provided.
	• Keep in mind the core questions:
	  • How do these visualizations help practice?
	  • How do we help make this data more useful for practice?
				*Using the previous discussions, ideas, and drawing, data scientists live code and work with educators to create data visualizations to address the Data Sprint team focus question.*

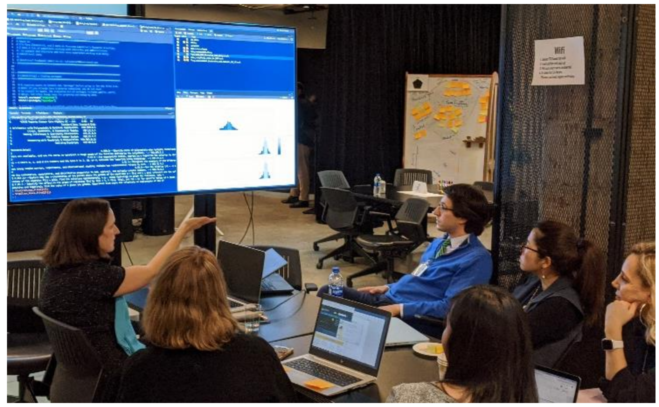
	Working Lunch			
Journey Travelers	Journey/Travelers: While each Data Sprint team continues to work, one educator at a time from each team reports to "Basecamp" to "Journey" to another Data Sprint team.	At Basecamp, each Traveler receives a "backpack" with a clipboard, notepad, sticky notes, and pens, then selects one other Data Sprint team to travel to and learn about their visualization and process.	Travelers return to Basecamp after 10 mins., write summary notes and post to the Basecamp "Journey-Wall". Repeat with different Travelers four times.	*Provide opportunity for teams to receive feedback from other teams during the design and coding process, and cross-pollenate ideas between teams, as well as additional networking.*
Team Galleries	Share-out of Data Visualization: Each team shares their central question and their data visualization solution.	Gallery walk: Each visualization is displayed on separate displays throughout the Learning Theater. Participants review each visualization.	Final Tally: Participants remove their Quuppa location tracking device and leave it on the table in front of the visualization that "you feel would be most useful for teacher and administrator practice".	*All participants have an opportunity to see each visualization product. Then as a rough metric, the final tally of tracking devices provides a sense which were the most popular.*

Figure 2.2: Day 1 and Day 2 Workshop and Orchestration (continued from previous page)

everyone attending a different cabana quick talk. Through this process, rather than two hours of speakers with a passive audience, in one hour, at least two people from each datasprint team heard from each quick-talk speaker, and all teams had a representative attend all of the quick-talks, plus the cabana quick talk speakers themselves were members of individual datasprint teams. Participants were active, moving about the Learning Theater space (an important consideration as this was the activity right after lunch), and importantly, they were provided time (although brief) to individually digest what they heard, begin to think about applications and understandings, and then voice those thoughts in collaboration with their datasprint team, beginning the co-design process.

Following the cabana quick talks and a break, datasprint teams were then asked to cluster and discuss their ideas on their sticky notes, working to organize the thoughts and ideas from the team into larger clusters on each team's individual whiteboard. Teams were asked to create names for the different clusters, identifying the central issues, questions, and ideas around issues of data visualization and data use in schools that the datasprint team together were discussing. Teams were then asked to rank these clusters in two dimensions, priority and possibility, from 1 (low) to 5 (high) and plot them on their whiteboard. Priority meaning what ideas are the most urgent, versus possibility meaning which ideas are the most tractable and do-able. Teams were then asked to select their top issue from the priority

versus possibility rankings, and list these in a shared online resource, in which all teams could review. Throughout the chapters in this book, authors from the workshop provide pictures of this important whiteboard work, which is a useful representation of the iterative ideation and co-design process within each team, rarely captured and discussed by participants in the research and practice literature in education data use and visualization.



Day 1 then concluded with the data analytics coding workshop, in which the educators could attend if they choose to, and the data scientists and education researchers were provided an opportunity to share ideas around coding and visualization, especially using the mock dataset, as a means to provide professional development, networking, and preparation for the data visualization coding required for day 2.

For day 2 of the Education Data Analytics Collaborative Workshop, participants entered the Learning Theater and received a Quuppa location tracking device on a lanyard. We projected a map of the Learning Theater throughout the entire day with each participant as a dot for where their Quuppa chip was, to provide a level of transparency on what location data was being tracked throughout the data. Please see chapter 6 of this book by Coleman et al. for a detailed analysis of the location tracking data throughout the event. Day 2 of the workshop then opened with the "data visualization expo" in which participants entered the space to find that each of the cabana quick-talk locations from the previous day now had presentations from the data scientists and education researcher visualization experts on large format displays demonstrating a wide range of specific individual data dashboards and visualizations. For example, the Nassau BOCES team presented the data visualizations and dashboard that were currently available across their districts, while at a different location, a representative from IBM Cognos presented the upcoming new iterations of the system which was used by Nassau BOCES (for further discussion see Chapter 8, Pratt, and Chapter 11, Khan). The data dashboard representations extended beyond IBM Cognos as well, with data visualization expo presentations from a wide range of examples and perspectives, many of which are discussed throughout the chapters in this book. We termed this part of the workshop as an "expo" as we did not ask the presenters to stick to a talk with slides, but rather to display an interactive dashboard or visualization, and we asked participants to tour the Learning Theater to experience each of the different visualizations and ask any questions they had, as well as network with the expo presenters and others from the previous day. The intention of the data visualization expo was to start day 2 building on the work of the previous day through providing a semi-structured activity that gave participants a strong sense of agency in what they wanted to engage in, many examples of current innovations in data dashboard visualizations in education to prime datasprint team ideas for the rest of the day, and an opportunity for the expo presenters, who were also datasprint team members, to demonstrate the potential of the visualizations and their work that they had been describing from the previous day's activities in their teams.

Day 2 of the workshop then proceeded with a presentation by Jeff Davis, a senior manager at Nassau BOCES and the central contact for the workshop on the mock dataset from the IDW for use throughout the event. This presentation detailed the specifics of what data were available in the dataset and the data file formats, providing attendees the specifics on data availability and data structure to help facilitate the datasprint team discussions around possibilities and coding for their data visualizations that they would be working towards in the afternoon session. After a break we then asked the datasprint teams to engage in a discussion in which they returned to their work from the previous day which we had left up as they had left it over night from day 1 on the whiteboards in their datasprint team space. We asked them to take into consideration the data format and availability that had just been presented for what was available in the mock datafiles, and that they should discuss the following to start to get specific for their planned data visualization given the possibility and priority question identified on day 1, discussing the following four questions:

1. Who do you need to focus on to address your question?
2. What (variables, demographics, scores) do you need to focus on?
3. When (what timeframe) should this question address?
4. Where do you need to focus on to address the question?

These sets of questions were intended to help the datasprint teams become much more specific in their discussions and plans for iterating on a possible data visualization.

Day 2 of the workshop then transitioned to a working lunch and the afternoon coding and visualization session, in which teams were provided the following prompts to help guide their work to generate visualizations and code:

- Purpose: Data scientists and educators work iteratively in a structured format to draft and build visualizations with data that addresses the central focus questions of each team.
- Each team should start by drawing out their visualizations on the blank sheets of paper provided.
- Keep in mind the core questions:
    - How do these visualizations help practice?
    - How do we help make this data more useful for practice?

As noted above, one issue with workshops such as this in which teams are created and asked to work together over an extended time is the potential for isolation within the team. Our goal in the workshop was to have the datasprint teams work collaboratively both within and across the teams. Additionally, we knew that the afternoon session would be quite intensive for the data scientists as they were live coding and analyzing the datasets, and so we wanted to provide an opportunity for additional cross-team discussions, networking, and idea generation, as well as provide feedback to each datasprint team as they worked on their visualizations. This was the intention then of the afternoon "Journey/Travelers" protocol. In 20-minute rounds we asked one datasprint team member from each of the eleven teams, who was not a data scientist, to "report to basecamp". The basecamp was set up to one side of the Learning Theater, with a "backpack" of journeying supplies that included a clipboard, note cards and sticky notes, and pens. We asked each person who reported to basecamp to select a datasprint team that was not their own, and "journey" to that team. We also asked each datasprint team to appoint a facilitator who would meet and discuss with the journeyer. Discussions at the datasprint teams were to take 10 minutes, and we gave the following prompts for journeyers to ask to start the discussion:

- Can you tell me about how you have gone from your priority statement to the work you are doing now?
- What data elements have been important for your discussion?
- How do you see the visualization you are working on helpful for teacher or administrator practice?

After these discussions we then asked the journeyers to return to basecamp, and summarize their thoughts on three large sticky notes, keeping in mind the question "Based on your work with data in schools, in what ways does this team's visualizations inform practice?". We then placed these notes on a very large set of whiteboards, clustering the notes by datasprint team symbol. We then repeated the process multiple times. In this way, datasprint teams were visited by multiple other participants, increasing the networking and collaboration across teams, and the information sharing possible, and at the same time building a series of reflections on each team's ongoing work.

The Education Data Analytics Collaborative Workshop concluded with datasprint teams each sharing out their visualization. Each team had a few minutes to present their visualization, and the camera crew in the Learning Theater helped to capture and display each visualization and speaker, and display the information for all participants to see and hear. Participants were then provided time for a gallery walk to review each of the visualizations, as each team was asked to display the visualization onto the eleven different datasprint team whiteboards such that attendees could walk around and view the different solutions. We then asked each attendee to remove their Quuppa chip and place it at the datasprint team location in response to the question for which visualization "you feel would be most useful for teacher and administrator practice". This final process thus provided an opportunity for all attendees to see the work across all of the datasprint teams as well as affirm the most popular presentations.

Education Data Analytics Collaborative Workshop Outcomes

In this section I provide a selection of the outcomes from the Education Data Analytics Collaborative Workshop. In the chapters in the rest of Part I of this book as well as throughout the book, the authors analyze and discuss both the data generated from the workshop as well as specifics around the visualizations created within each of their datasprint teams. Figure 2.3 provides the final summary visualizations for each of the eleven datasprint teams, with visualizations in the upper part of the figure perceived generally as more popular by participants. An issue during the end of the workshop was that given the limited amount of time available for the presentations (just a few minutes) participant perceptions of each visualization may have depended largely on the presentation itself, rather than the specifics of the visualization, as in the final gallery walk, while participants could look at the displayed visualization, there was little time for additional questions or interactivity as we ended the workshop.

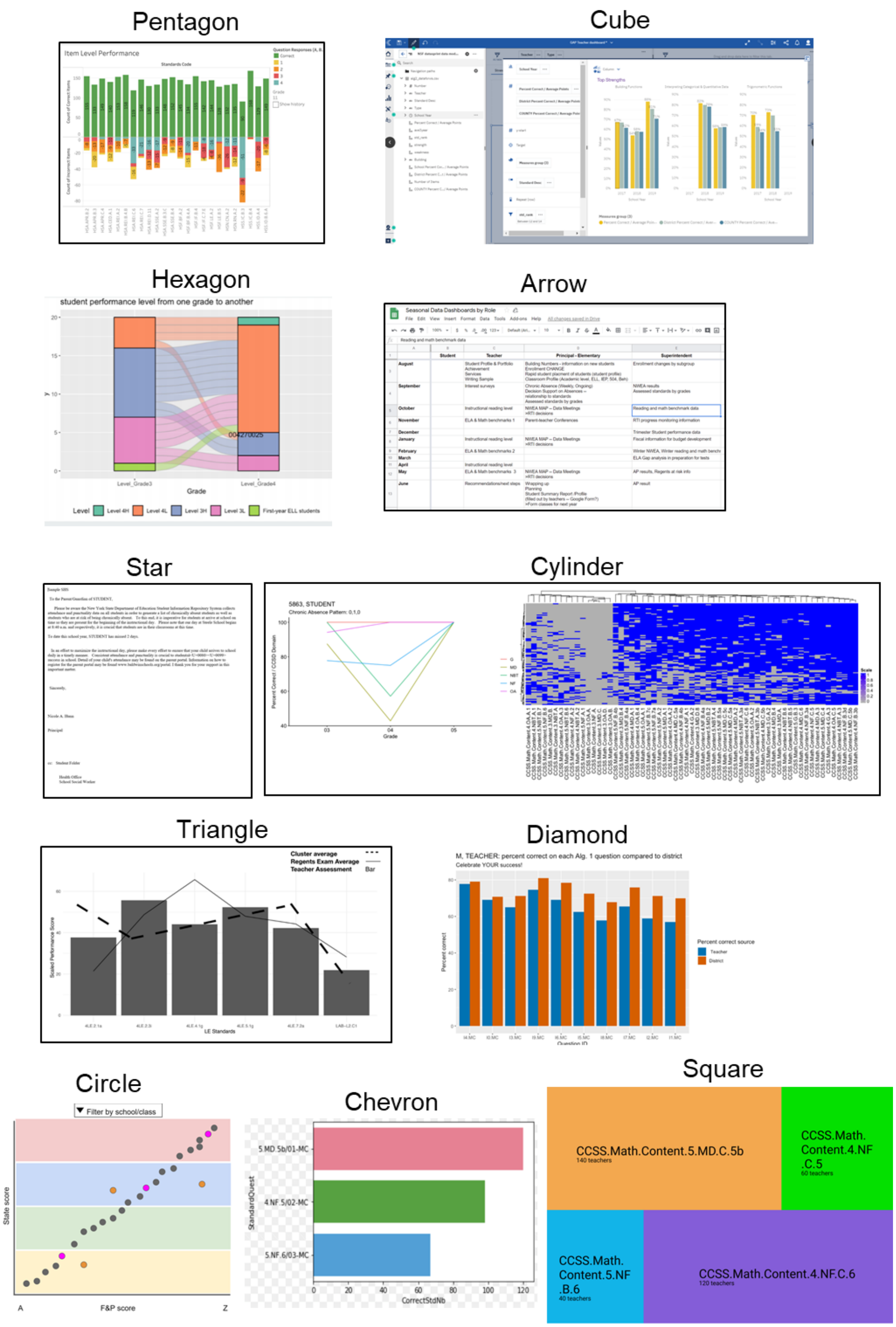


Figure 2.3: Final presented data visualizations from each Education Data Analytics Collaborative Workshop datasprint team. Visualizations in the upper part of the figure were generally perceived as more popular.

Bowers, 2021

Throughout this book, chapter authors discuss each of these visualizations in Figure 2.3 in the following chapters:

Pentagon:	Chapters 8, 18, 21
Cube:	Chapters 4, 8, 9, 10, 11
Hexagon:	Chapter 19
Arrow:	Chapter 12
Star:	Chapters 23, 24
Cylinder:	Chapter 17
Triangle:	Chapter 25
Diamond:	Chapter 18
Circle:	Chapters 8, 15
Chevron:	Chapters 13, 14
Square:	Chapters 4, 22

In Figure 2.4, I summarize the average responses to the post-event satisfaction survey. Overall, (Figure 2.4 top) participant satisfaction was on average above expectations across the different parts of each of the day 1 and 2 activities with the day 1 keynote lunch seminar and day 2 activities as the highest rated. Given the intention to center the work and voices of educators throughout the event, the middle section of Figure 2.4 shows that the educator attendees rated the event on average somewhat higher than the data scientist and researcher attendees, although none of the differences were statistically significantly different. To examine the extent that the event informed participant ideas in these domains as well as extended their networks, the bottom panel of Figure 2.4 shows that participants on average agreed that they identified at least one new idea to use in their work and met at least one other person who they may follow-up with after the event.

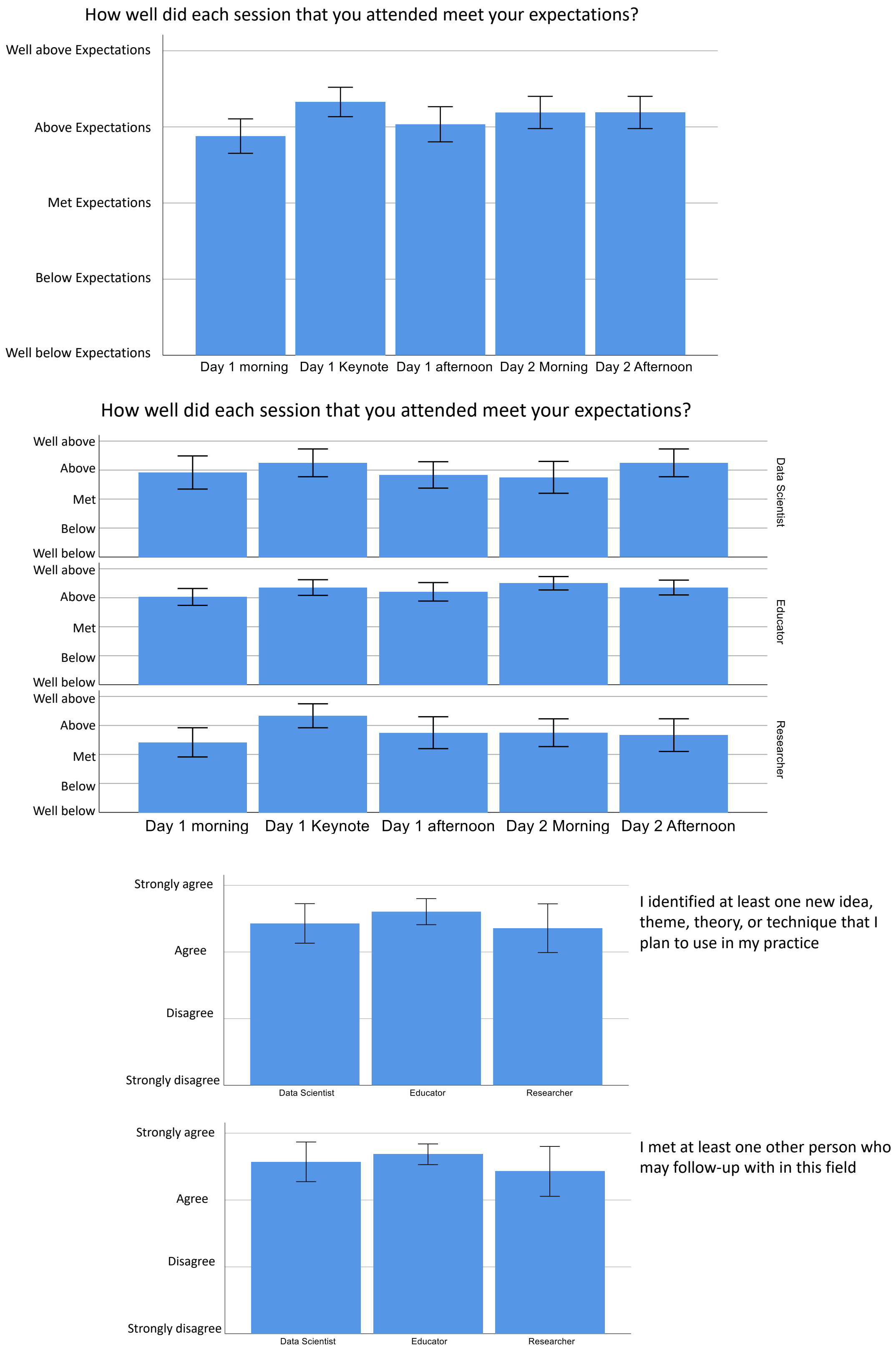


Figure 2.4: Summary averages of participant post-event satisfaction.

Final Reflections:

As the principal investigator on this grant project, I was very enthusiastic about this final phase of the project and the Education Data Analytics Collaborative Workshop. The workshop provided a rare opportunity to bring together educators, administrators, data scientists, and researchers, and get them talking about the data visualization and dashboard work that is important to the daily practice of teachers and school and district leaders. From the post-event survey, as well as the response to the opportunity for workshop participants to contribute chapters to this book, I believe the workshop was a success. Yet, as detailed by the many authors in the following evocative chapters, there is much exciting work to be done in the effort to create data visualizations and data dashboards that address the needs of teachers and administrators. Working to build opportunities to bring together educators, data scientists, and researchers has great potential to deeply inform the work of each group, as we build capacity and experience in data visualization that can inform evidence-based improvement cycles and instructional improvement in schools. I look forward to future research continuing to capture the perspectives of each of these important groups of professionals, and further refine and improve data visualization research in education across schools and communities.

Returning to the above discussion of the task-clarity-as-outcome model in which the data visualizations generated from an iterative co-design process are secondary to the work of moving organizational tasks from fuzzy to crisp, gaining clarity throughout the process, the chapters throughout this book from the participants represent an attempt to capture this task-clarity-as-outcome model work. The visualizations generated from the datasprint teams are useful outcomes themselves, especially as multiple subsequent chapters here from participants discuss the detailed ways in which the visualizations and analyses can be used next in their practice. Additionally, together the chapters throughout this book from the many participants provide an exploration of the task of data use in schools, from the perspectives of the main stakeholders in the process, including educators, data scientists, researchers, and the central data management staff, here from Nassau BOCES as well as IBM Cognos. Taken together, the chapters throughout this book provide a deep description of practitioners working to gain clarity around the task of visualizing and using data in schools from the data that currently is available in IDWs. While I argue that it is too early in the domain to come to definitive conclusions about these tasks, the rich discussion of those tasks from multiple perspectives throughout the chapters in this book and how they relate directly to the practical issues of doing data visualization and data use work in schooling organizations open an exciting and new window into this task clarity process on the journey towards more effective and informative data use in education.

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CHAPTER 3

NSF Education Data Analytics Collaborative Workshop: How Educators and Data Scientists Meet and Create Data Visualizations

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Workshop Overview

On December 5 and 6, 2019, the National Science Foundation (NSF) Education Data Analytics Collaborative Workshop was held at Teachers College, Columbia University in New York City. Approximately 80 participants from New York and beyond gathered for a two-day workshop. This workshop was a part of the final phase of the collaborative NSF funded research project (NSF #1560720) "Building Community and Capacity for Data-Intensive Evidence-Based Decision Making in Schools and Districts", a collaborative partnership on data use and evidence-based improvement cycles in collaboration with Nassau County Long Island BOCES (Board of Cooperative Education Services) (Nassau BOCES) and their 56 school districts in Nassau County Long Island, New York.

The workshop was the final third phase of the three-phase collaborative NSF project. In phase 1, about 5,000 surveys were collected on educator data use practices across the districts, as well as 40 in-person interviews with educators, working to understand what educators say they need in their data use practices in schools. In phase 2, researchers analyzed hundreds of thousands of rows of clickstream logfile data of educator clicks in BOCES Instructional Data Warehouse (IDW) to understand what data is accessed and when. In this final phase 3 of the project, we aimed to achieve three goals through a collaborative workshop: (a) to bring Nassau County leaders and educators together with data scientists, to build collaborative conversations, workflows, visualizations, and pilot code; (b) to train Nassau County's educators around data use using the current data system available to them; and (c) to publish open-accessed R code as well as educator perceptions of this intersection of data use and education data science to inform future work around data dashboards, data visualization, data use, and evidence-based improvement cycles for instructional improvement in schools.

The ELDA Summit 2018 and NSF Education Data Analytics Collaborative Workshop

As a final phase of the NSF grant, this collaborative workshop built on the Education Leadership Data Analytics (ELDA) Summit 2018, an initial workshop conducted in 2018 to expand the discussion on Education Leadership Data Analytics (ELDA) (Bowers et al., 2019). As the capstone event of the NSF grant collaborative project, the 2019 NSF Education Data Analytics Collaborative Workshop combined together the aspects from the 2018 meeting and new learnings and collaborative opportunities around the goal of enhancing evidence-based decision making in schools. Thus, it is important to understand what aspects the ELDA Summit 2018 brought into the NSF grant project.

The ELDA Summit 2018 gathered 120 researchers and practitioners at Teachers College, Columbia University in New York City on June 7 and 8 of 2018. The summit succeeded in bringing experts from three fields – education leadership, data and evidence use in schools, and data analytics and data science, where the importance of evidence-based decision making in schools is on the rise (Bowers et al., 2019).

To sum up the main takeaways from the 2018 summit, the attendees of that meeting agreed on a strong academic training system specifically for education data practitioners, a firm network to connect three domains of ELDA – 1) Education Leadership, 2) Data Science and Data Analytics, and 3) Evidence-Based Improvement Cycles, as well as on issues with data privacy. However, the central issue that surfaced from the ELDA Summit 2018 was the need for a greater role of the voices of teachers and administrators along with building stronger partnerships between practitioners (educators and administrators) and researchers (data scientists and education researchers) in order to support the use of data analytics and data dashboards within schools (Bowers et al. 2019).

This call for centering the voices of practitioners became one of the main goals for the 2019 meeting and reconfirmed ELDA's aim to bring practitioners and researchers together for the final phase of the NSF project. Thus, building on the work from 2018, the 2019 NSF collaborative workshop was built around a two-day event, focusing mainly on facilitating interactions between practitioners and researchers in each "datasprint team" in which data scientists were partnered with 5-6 educators over the two days.

To build robust participation, we first recruited education data scientists by posting a call in summer of 2019 for education data scientists to apply to participate, which yielded about 30 data scientist and education researcher participants. To invite education practitioners to the workshop, Nassau BOCES sent an invitation to specific districts in the county, requesting that each school district superintendent recommend one teacher, one building administrator, and one district administrator to participate.

Organization of the Workshop

In a pre-event survey sent to nominated attendees a few weeks before the event, we collected short essay-style answers to questions that could help the ELDA team build datasprint teams according to the similar interests or perspectives of participants. The questions were:

- What challenges and successes have you experienced using data and evidence in your practices in schools/districts?
- What components of a longitudinal data system are needed to best meet the needs of superintendents, principals, and teacher leaders? This question was drawn from previous surveys on data use from these three different educator roles by Brocato, Willis, and Detchert (2014).
- In thinking about data and evidence that are available in your current systems, how could the data visualization and evidence be improved? How would these improvements help you?

Datasprint Team Member Analysis: How We Designed Teams

Once we received the responses from the participants on the pre-event survey, we were able to estimate the final count of participants and create 11 teams with an average of 7 participants, including for each datasprint team: 3-5 practitioners (educators and administrators) and 3-4 researchers (data scientists and education researchers). Figure 3.1 details these distributions for each team.

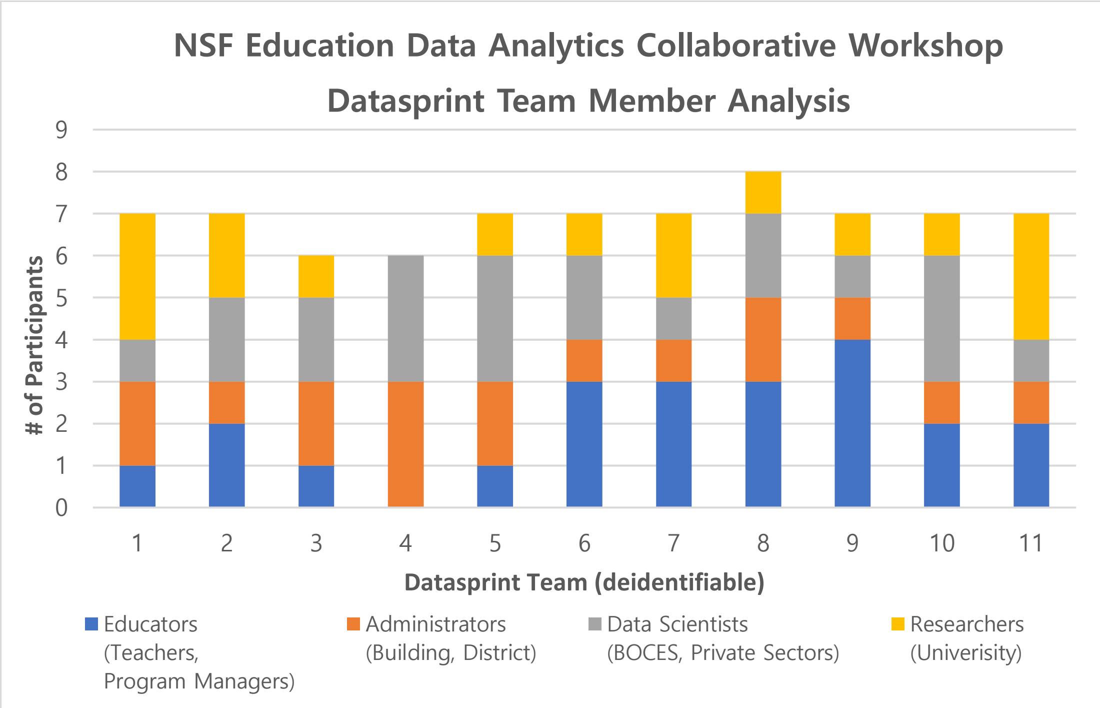


Figure 3.1. *Education Data Analytics Collaborative Workshop Datasprint Team Member Analysis; Mean (Educators= 2.00) (Administrators = 1.55) (Data Scientists = 1.91) (Researchers = 1.45)*

For the team member analysis in the Figure 3.1, we used four categories: educators, administrators, data scientists, and researchers. The category for each participant was assigned based on the participant's response on the job title question in the pre-event survey. *Educators* are those who are working in schools and/or working with students, such as teachers, data coordinators, assessment directors, subject directors and technology directors. *Administrators* include either building administrators or district administrators, such as assistant principals, principals, assistant superintendents, and superintendents. *Data Scientists* are those who have data analytic skills and work in Nassau BOCES, higher education institutions, or the private sector; this category includes occupations like statisticians, data developers, data scientists, and project managers. Lastly, *Researchers* are education researchers whose main institutional affiliations are universities. This category mostly consists of professors, Ph.D. students, researchers, or graduate students. Note that there is certainly a gray area between data scientists and researchers since the assignment to the category was solely based on each participant's response to their job titles and employers. However, we believe that this does not interrupt our main analysis to demonstrate that there was a fairly equal proportion of practitioners (about 40 educators and administrators) and researchers (about 40 data scientists and education researchers).

After the workshop event, in a post-event survey, we also asked participants to identify themselves in two different ways; we asked them to select which applies to themselves among the three options – educator, data scientist, and researcher (see Figure 3.2) , and also, we asked them to select all that applies to identify themselves from more detailed descriptions of their usual positions (see Figure 3.3). Both Figure 3.2 and 3.3 demonstrate that a majority of the participants were educators (including teachers and administrators), which is attributable to the strong partnership and central role of Nassau BOCES and administrators and teachers from across Nassau County throughout the NSF collaborative grant.

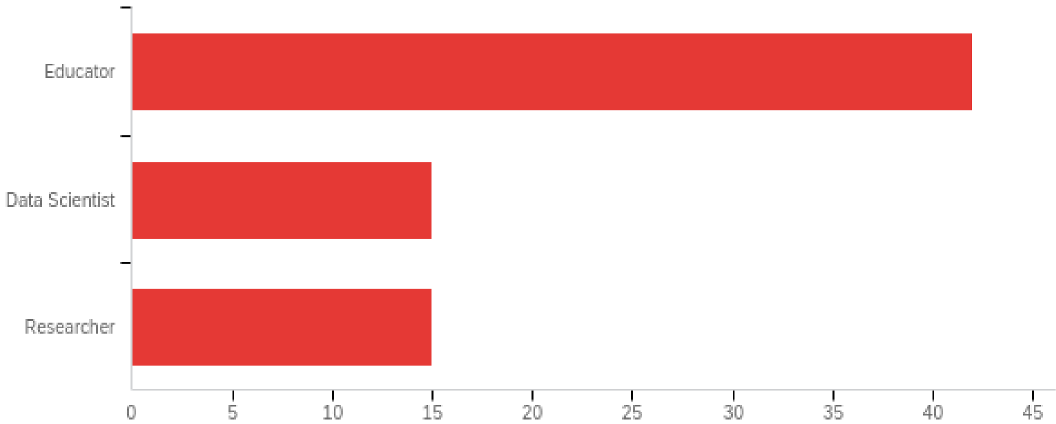


Figure 3.2. *Education Data Analytics Collaborative Workshop Post-event Survey self-identifier data analysis; Question: I attended the workshop as a… Select one.*

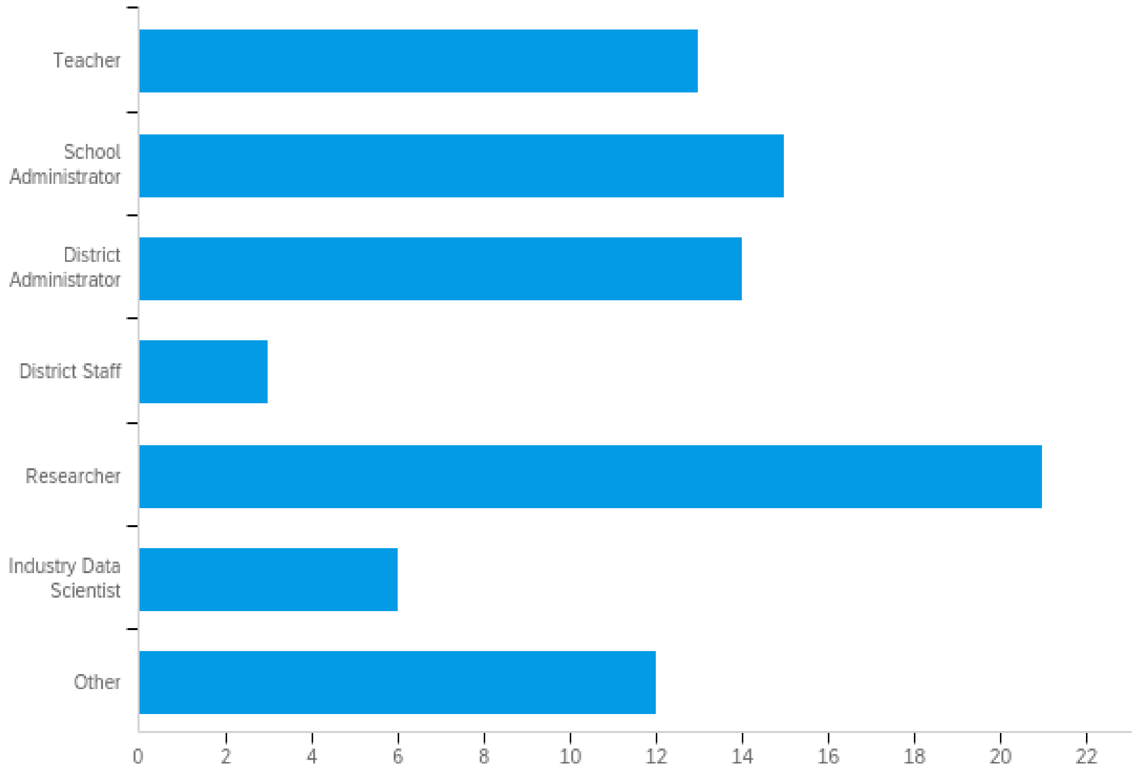


Figure 3.3. *Education Data Analytics Collaborative Workshop Post-event Survey self-identifier data analysis; Question: "I am a .... Select all that apply".*

Was the Workshop a Success?

The 2019 NSF Education Data Analytics Collaborative Workshop was particularly successful in engaging all participants during the two-day workshop. On the first day of the event, the final count of participants was 77. Since more than half of participants were practitioners from Nassau County, Long Island New York, most of them had to take a train to commute each of the two days of the event. Despite the point that this required one train trip and one subway trip to be present both days, the final count for the second day was slightly more than day one. Moreover, the response rate on the post-event survey for feedback and further research opportunities was 95%. Furthermore, 58% of post-event survey participants noted that they were interested in contributing to the present publication with a mini-chapter, of which 33 in total contributed across the range of co-authored chapters, providing their reflections on the outcomes of their datasprint teams and the visualizations (see Table 3.1).

Table 3.1. *Education Data Analytics Collaborative Workshop Participation Analysis.*

Type	Pre-event		Event		Post-event	
	Invited	Completed Informed Consent	Participated 12/5 (Day 1)	Participated 12/6 (Day 2)	Completed Post-event Survey	Joined Next Step
Count	115	86	77	78	74	33
Percentage (#/total)		74.8% (86/115)	89.5% (77/86)	90.7% (78/86)	95.5% (74/77.5*)	44.6% (33/74)

*: the number is a mean number of the first- and second-day participants.

Findings from the Workshop

In this section, we present recurring features that the participants mentioned in the post-event survey about their experiences during the workshop.

The Best Sessions that Meet Participants' Needs

We asked the participants the question "*How well does each session that you attended meet your expectations?*" to understand whether each session meets the expectations of the participants. There were in total five sessions, divided by the first day and the second day, as well as by morning and afternoon, with a special keynote lunch with Professor Richard Halverson from the University of Wisconsin - Madison on the first day.

Overall, the participants showed a high satisfaction by rating the entire workshop an average of 4.23 out of 5 on a five-point Likert scale of 1 = very dissatisfied to 5 = very satisfied. Among the five sessions, however, the participants were most satisfied with the Day 1 Keynote Lunch presentation by Richard Halverson. This was an hour-long session during the lunch on the first day, a presentation successfully engaging both practitioners and researchers.

The Day 2 Afternoon session ranked as the next most satisfying session. This session includes a "Basecamp Journey" during the datasprint team collaborations. On the second day, the afternoon session was devoted to analyzing the dataset and building a data visualization according to each team's priority and possibility call. While the data scientists and education researchers were working on creating visualizations, educators and administrators had opportunities to “journey” around the event to visit with and learn from other teams and provide their thoughts and written feedback so that other teams could receive feedback from outside of their team and compare to what other datasprint teams were generating. This ability to “journey” briefly between datasprint teams to check-in with other teams and share ideas helped to create deeper cross-team conversations.

During the journey activity, one educator or administrator from each datasprint team first checked in at “Basecamp” to pick up a “backpack” that consisted of a clipboard, sticky notes, pens, and paper, they received instructions for their 10 minutes, and then selected from each team randomly to pick a “destination” among the ten other different teams. We then asked the educators/administrators who remained in their datasprint teams to welcome travelers and share the team’s working process – how, why, and what they are visualizing. There were 3 minutes for explanation and 2 minutes for a short question and answer. After traveling to the other team, travelers returned back to the “Basecamp” and were asked to provide written statements about either questions or opinions regarding the team they visited. Each traveler did this at least two or three rounds to different teams. We aimed to have three travelers visit three different teams, so that one datasprint team collectively saw what nine other different datasprint teams were doing. We planned this activity for about 45 minutes, but it took slightly more than an hour to wrap up this activity. In another section of the post-event survey, we did spot some feedback that the participants would prefer to have more time in certain sessions and have more conversations outside their own datasprint team. However, participants still appreciated the second day’s afternoon session, and this offers an important implication on how the workshop succeeded in involving all participants who had different levels of knowledge and expertise in data science.

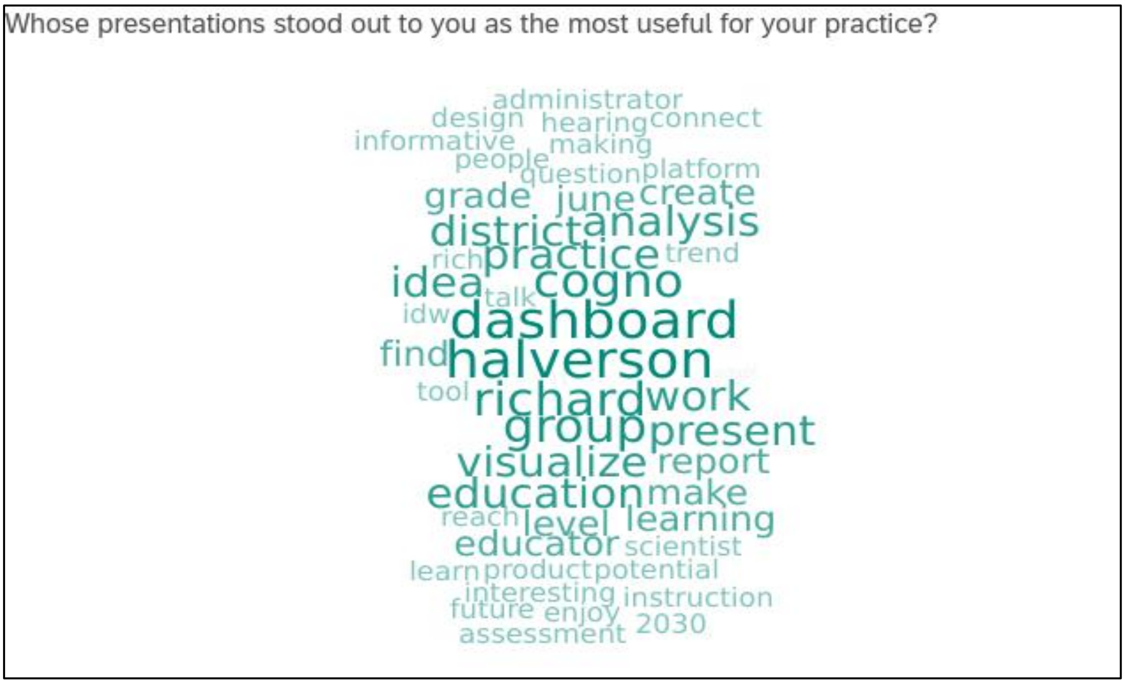
The Best Presentations that Stood out to Participants as the Most Useful

Including Halverson’s keynote speech on the Day 1, the workshop offered a great group of leading data scientists and education researchers to join and share their upfront works in data visualizations. The participants were able to be exposed to their works during what we termed the “Cabana” session in Day 1 and “Expos” session in the Day 2.

We used the word “Cabana” for helping participants visualize how the multi mini-presentation session on Day 1 would be structured. Our goal with the Cabanas session was to provide an opportunity for participants to hear from the invited national data experts in brief “quick talks” of 10 minutes for a presentation on their research and work, and 5 minutes question and answer. However, with eight quick-talks having all speakers talk for 10 minutes to the entire set of participants would have taken a large amount of the limited time. Yet, we wanted each datasprint team to hear from each of the data experts so that each team could incorporate the wide variety of perspectives on data use in schools from our invited speakers. Thus, the Cabanas. Each quick-talk speaker was provided a space around the event space to host about 8-10 people (seated or standing) and a large monitor so that they could present slides. We labeled each Cabana with nature symbols, such as tree, mountain, wave, sun, moon, etc. These symbols were printed on pieces of paper about the size of playing cards and at each datasprint team table, we asked each person to pick up a nature symbol. As there were eight symbols and about eight people at each of the 11 datasprint team tables, this made for groups of about 10 to attend each Cabana quick-talk. We asked attendees to gather at their selected nature symbol, and then commenced with the quick-talks at each Cabana, and then repeated with a different selection of symbols by the participants, mixing up the Cabana attendee groups. Datasprint teams were then provided time to discuss what they heard, noticed, wondered, and learned from the Cabanas to inform their conversations on useful data visualizations for education decision making.

At the start of Day 2, the workshop started with the "Expo". Different from the Cabanas in which the quick-talks speakers were mostly education researchers speaking to their findings on data use in schools, the Expo provided space for about 10 data visualization demos and presentations, and attendees on the second morning entered the event space and were able to walk freely from one kiosk to the next. Presenters were provided a large monitor to present their data visualizations, and presenters ranged from education researchers who provided data visualizations and dashboards, to the Nassau BOCES administration and their IDW dashboard, as well IBM's Cognos dashboard (the dashboard system used by Nassau County) among multiple others. Importantly, just as with the Cabana quick-talks, the Expo presenters were all attendees and members of datasprint groups themselves. The Expo session thus provided additional opportunities for interaction between the presenters and the participants since there was no "presentation time" set for the Expo session, but rather an hour-long timeline roughly.

Through the post-event survey's question "*For the presentations that you heard or participated in, what stood out to you as the most useful for your practice?*", we were also able to find which presentations during the two-day workshop that the participants found the most useful for their practice. We created a word cloud via Qualtrics to find the most common word in the short-essay answers. In order to answer the question with more precision, we excluded generic words to answer the question, such as the word 'data', 'student', 'teacher', and 'school'. Also, we exclude the words that the question itself includes, such as the word 'useful' and 'presentation'. This rule for exclusion in the word cloud is continued throughout this chapter.



**: this word cloud excluded the words: data, teacher, student, school, useful, and presentation.*

Figure 3.4. *Education Data Analytics Collaborative Workshop Post-event Survey Presentation Analysis; A word cloud created by Qualtrics*.*

There was no consensus among the participants' opinions since the workshop included broad diversity of different types of stakeholders, whose views are very distinctive from each other. Throughout the individual answers to this question on the post-event survey, each presenter's name was represented and participants were quite excited about the work they discussed. By analyzing the word cloud in Figure 3.4, three presentations appear to stand out to the participants: 1) Halverson's Connected Learning Model and Education for 2030; 2) IBM's newest version of Cognos Analytics Dashboard; and 3) participants' interest in the Nassau BOCES Instructional Data Warehouse (IDW). These interests highlight areas for future work in bringing together data scientists and education practitioners around data visualization, data science, and ELDA. Participant responses that captured these perspectives across multiple responses included:

> *What was most useful to me was the message that establishing trust is a critical factor in encouraging people to use and interpret data successfully. – Teacher participant*

> *One of the most useful things for my practice was overall realization that data usage appears to be emphasized at the district and building levels. However, teacher-level data interfaces, although they are prevalent, continue to be underutilized. Student-level dashboards appear to be non-existent. – School administrator participant*

> *We have really come so far in in getting data and making it useful and easy to use in our practice. Sharing what we use in our district and realizing that another person at my table created the same type of data spreadsheet helped me realize that we have similar interests. I also loved learning about all of the new data formats that have been generated by data scientists. – School administrator participant*

> *Most impactful was Rich's point about including learners in the conversation and use of data. This is very important to me in my work, but often comes up as an afterthought, and I find educators/administrators often discount it mostly because it can be hard to imagine how we should go about it. Somehow coming from Rich, or the way he presented it, this idea really took hold among the group! I heard people talking about it and connecting it to their datasprint projects throughout the rest of the time and that was very exciting. – Researcher participant*

> *The complexity involved with aggregating the data to gain the requested insights stood out the most. Everyone agreed that the data was actionable in one way or another, getting to what the action is was difficult without joining multiple data sources. – Data scientist participant*

> *The importance of working with stakeholders in developing, adapting, and improving visualizations. We need more spaces like this to support collaborative design. I also felt that it illustrated the complexity of creating effective data visualizations using available data. – Data Scientist participant*

The Most Applicable Data Visualizations the Participants Found

In the post-event survey, we asked the following question to find out how participants reacted to the exposure to various new data visualization methods and conversations: "*For the two-day event, please describe the data visualizations that you found most applicable to your context and role,* *and why.*” With short-essay type answers, we again created a word cloud for a visualization. Note that we exclude some generic words (‘data’, ‘teacher’, ‘student’), as well as the words that the question itself includes (‘visualize’, ‘applicable’, and ‘found’).

**: this word cloud excluded the words: data, teacher, student, visualize, applicable, and found.*

Figure 3.5. *Education Data Analytics Collaborative Workshop Post-event Survey Data Visualization Analysis; A word cloud created by Qualtrics*.*

Figure 3.5 is a word cloud that describes the most frequent words in the participants’ responses, and we found that the word “standard” appeared the most and was frequently combined with words such as “group”, “test”, and “year”.

These words imply three data visualizations that the participants found useful: (a) grouped standards for/by teachers – item analysis visualizations (b) multi-year GAP standard report and (c) non-standardized test data visualizations. A central finding from the answer to this question is that the most applicable data visualizations that participants found useful were not complex, but rather visualized the needed information in a simple and straightforward manner around the standards.

Participant responses that captured these perspectives across multiple responses included:

> *As a reading specialist, the visualization comparing reading level data with state testing data clearly shows teachers breakdowns in student learning and areas that they could focus on for student*

improvement. – Teacher participant

I found the visualizations that had specific information related to student data the most applicable. In my role, I want to know where my students' strengths are what I can teach them next to grow. I liked seeing the specific standards and itemized analysis visualizations. – Teacher participant

As a high school science teacher, I found the visualization our data sprint team made to be the most applicable. It takes the wrong answer analysis data that BOCES already has and presents it in an efficient and useful way for teachers and administrators to use. – Teacher participant

We discussed visualizations that would help teachers make immediate changes to classroom instruction – School administrator participant

Data visualizations are critical in the work that we do to ensure that we are positively impacting teaching and learning. Actually, data visualizations that link to more in depth data so that we can drill down from a wide view to individual student is truly impactful and useful. This allows for true discussions focused around teaching and learning based on concrete evidence. – District administrator participant

The data visualizations that are most applicable to my context and role are, in all honesty, all of the data visualizations. I am currently in the processes of trying to create a dashboard that will encapsulate a lot of the ideas from the NSF conference we just attended. – Researcher participant

Simple is the best. Although I know many types of visualizations as a data scientist, I found that during the workshop that teachers/administrators prefer to have a simple visualization (e.g. bar chart) so that they can interpret immediately. – Data scientist participant

Even though I have been using heatmaps at my work for almost two years, I still find that heatmap is the most useful visualization, especially at the data exploration analysis stage. Because it provides you an overall full picture of the data that you are interested in. In Heatmaps, you can inspect the correlation between *the rows as well as the columns. – Data scientist participant*

The Most Important Components of a Longitudinal Data System

The Post-event survey continued with the open-ended question, "*What components of a longitudinal data system are needed to best meet the needs of superintendents, principals, and teacher leaders*". This question was drawn from a previous survey study by Brocato, Willis, and Dechert (2014). As a reflection on the two-day event, this question effectively sums up the needs of practitioners and the perceptions of researchers on educator data needs, based on the collaborative conversations they had within their datasprint teams during the two day workshop. We also created a word cloud of the most frequent words from the responses, excluding words that are either generic or appeared in the question itself.

**: this word cloud excluded the words: data, teacher, student, system, longitudinal, and information.*

Figure 3.6. *Education Data Analytics Collaborative Workshop Post-event Survey Longitudinal Data Components Analysis; A word cloud created by Qualtrics*.*

Figure 3.6 depicts the needs of practitioners looking for information in their longitudinal data systems. The most common words the participants responded with were "attendance", "assessment", and "demography". It once again re-emphasizes that education practitioners have a range of data needs across a wide variety of data types. Overall, there was a frequent call for longitudinal student data in nearly all aspects, not just standardized test scores, which is easy to access, visualize, and use to take action. Additionally, another frequent call from the participants was the need for implementing a constant scale of assessment test scores. If the test scores are only applicable and interpretable in one school or district at certain time only, it becomes difficult to then use that dataset beyond that single context. Participant responses that captured these perspectives across multiple responses included:

> *Tracking student attendance, academic performance, teacher performance, comparing student demographics, and ensuring that all students are on track to meet given requirements – Teacher participant*

> *From what I heard over the course of the two-day conference, Nassau BOCES has all of the data that we need, it is just a matter of better visualizing it and put it to better use. A common theme on Day 2 was absenteeism. It seems that, longitudinally, all stakeholders would be better served if they have attendance numbers juxtaposed against student assessment scores. – Teacher participant*

> *An easily accessed longer term picture would help greatly. Not just results. Teacher comments, attendance, behavior issues would be some types of information that would be helpful. – Teacher participant*

> *Student historical data, assessment historical data, one stop shopping. Communal yet confidential access – School administrator participant*

> *Ease of access, ability to customize, drawing data from multiple sources – School administrator participant*

> *Reports need to be easy to access. The reports need to be meaningful to instruction AND actionable. Data visualizations are crucial to teachers' understanding of and implementation of data into their instructional practices. – School administrator participant*

> *Showing the crosswalks from New York State within the system so that all stakeholders can see where the standard is coming from and where it is going – District administrator participant*

> *An additional focus that emerged was the need to integrate other non-outcome measures (instructional quality or practices) plus formative rather than summative data (results from teacher created*

assessments for example). This would help with the data relevance need. – District administrator participant

My main takeaway from what educators were saying, is that more immediately, the different data repositories just need to work together!! – Researcher participant

The data system should paint a full picture of each student - achievement, absences, tardiness, supports and interventions, parental engagement… All elements of a child's being, performance, and needs should be tracked longitudinally to help give educators a full picture of who the child is and what the child needs to succeed. – Researcher participant

During the workshop, I learned that there were some gaps in having a consolidated data collection system from the school level (i.e. school information system) which can be stored efficiently in IDW. Many schools were struggling with getting data in order to populate indicators. – Data scientist participant

Conclusion

The NSF Education Data Analytics Collaborative Workshop provided useful insights on collaboration around data visualization for evidence-based improvement cycles. The Education Leadership Data Analytics (ELDA) team hopes this chapter brings readers insights on how we organized actual workshop to bring both practitioners and researchers together. Also, we hope that readers will recognize how to utilize the different types of workshop activities and the pre- and post-event surveys to understand how participants and the outcomes are affected by the organization of the workshop.

This final phase of the NSF funded research project (NSF #1560720) "Building Community and Capacity for Data-Intensive Evidence-Based Decision Making in Schools and Districts" was successfully completed with the generous support from the National Science Foundation, Teachers College, Columbia University and Smith Learning Theater at Teachers College, Columbia University. We also want to express our gratitude again to the staff from Nassau BOCES and the educators from Nassau County Long Island New York, who passionately participated in the workshop and expanded the conversations about education leadership data analytics. Lastly, we thank every data scientist and education researcher, including our own ELDA team members, who showed so much affection to the

success of this project and gladly shared their expertise during the two-day workshop.

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CHAPTER 4

Expanding the Design Space of Data and Action in Education: What Co-designing with Educators Reveal about Current Possibilities and Limitations

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What might happen if we invite educators, researchers, and data scientists to co-design data visualizations together? Educators possess certain mental models or values of the goals and applications of data visualizations. These mental models have direct implications for data collection, analyses, and design (Friedman et al., 2008). For example, educators or designers who value accountability may focus their designs and interpretations on standard data found in student information systems, such as grades and attendance. Conversely, mental models that emphasize local contexts may guide the designers towards other data sources, such as formative assessments and student experiences (Ahn et al., 2019; Farrell & Marsh, 2016b). Surveying the mental models that educators associate with data and visualizations is integral to designing data systems.

In the following chapter, we explore how the ideas that educators, data scientists, and visualization designers may hold, greatly inform the types of data visualizations that are ultimately designed for education data. We illustrate this process by documenting a co-design event that included different stakeholders in a K-12 school system: administrators, educators, data scientists, and researchers. The co-design experience took place in a National Science Foundation (NSF) sponsored workshop, where participants formed design teams to create scalable data visualizations that may drive school improvement. As participants in the workshop, we had the unique opportunity to observe how different education stakeholders perceived data, what they valued in educational data visualizations, and how varied propositions towards data related to the co-designed artifacts. We were able to use data such as participant surveys and design artifacts from the workshop to inform our analyses.

Our analyses of the NSF workshop were theoretically informed by two bodies of work: data-driven decision-making (DDDM) and human-centered design (HCD). The DDDM literature provides insights into how educators perceive and use multiple types of data to guide different instructional decisions (Means et al., 2011). The HCD field highlights the need to explore users' values in collaborative design practices (Friedman et al., 2008; Norman, 2014). We then describe the co-design process at the NSF workshop, from which we glean insights about how mental models of data may relate to the design focus in the prototypes of the participating teams.

We found that most of the participants in the workshop mentioned the use of standardized test scores or student demographics as their default models of what education data could be. However, educators also recognized the importance of formative data sources, such as classroom-based exit tickets or surveys of student engagement, in deriving instructional decisions. We highlight the distinction between standardized-administrative, and formative-implementation data because these data types have different implications for decision-making. For example, prior research has established that use of formative, implementation data relates to substantial, meaningful shifts in instruction, whereas standardized and administrative data typically motivate educators to reteach content, without adjustment of instructional delivery (Farrell & Marsh, 2016b).

In this chapter, we term the two data genres as: SAD (Standardized, Administrative Decision-making) and FIT (Formative, Implementation, and Teaching). Interestingly, although educators in the design workshop mentioned valuing FIT data substantially, we observed that most of the design teams defaulted to SAD data in terms of their final design ideas for education data visualizations. This finding illuminates a key tension, where education stakeholders might envision wider uses for educational data but naturally move back towards using existing mental models of standardized or administrative data only in their data systems.

To illustrate how this tension can play out in practice, we documented two teams from the workshop and compared their design approaches and artifacts. One team's prototype represented an emphasis on SAD data, whereas the other uniquely focused on FIT data. We found that the goal-oriented design notes in the latter team reflected the values of multiple stakeholders and may have pushed their designs beyond default notions of SAD data. This finding illustrates that the designers should consider the diverse stakeholders and their mental models of data use when developing data visualizations. Articulating the underlying needs of educators helps designers to target specific action for instructional improvement.

Theoretical Framework

Data Types: Beyond Standardized Data (It's Not Just Assessment!)

Educators incorporate multiple data types into instructional decision-making (Wayman & Stringfield, 2006). The historical focus on accountability emphasizes the use of standardized assessment, attendance, or demographics data, which "sum up" students' performance over substantive periods of time (e.g., quarter, semester, academic year). We term these summative, standardized data forms as Standardized and Administrative Decision-making (SAD). SAD data that psychometricians have carefully designed and validated are appropriate for evaluating learning in a summative manner (Stiggins, 2004). Thus, SAD data are common in the evaluation and grouping of students, teachers, and schools by demographics or proficiency levels (Marsh et al., 2006).

However, SAD data are far from enough to inform instructional decisions (Farrell & Marsh, 2016a; Farrell & Marsh, 2016b; Shapiro & Wardrip, 2019; Stiggins, 2004; Wardrip & Herman, 2018). Educators also report frequent use of formative data, such as iterative classroom assessments and student surveys (Datnow & Park, 2018; Farrell & Marsh, 2016b). We name these formative data Formative, Implementation and Teaching (FIT). Educators typically leverage FIT data to ground instructional decisions in more comprehensive and timely understanding of student learning (Farrell & Marsh, 2016b; Wardrip & Herman, 2018). For example, Wardrip and Herman (2018) observe that teacher groups who engage in year-long data discussions call on both student test performance and data on student behaviors, social relationships, engagement, and emotion. While teachers may start a data discussion by citing students' academic assessment, they regularly draw on formative data sources to contextualize the learning outcomes and decide on instructional decisions. Wardrip and Herman's (2018) work illustrates that reliance on only SAD data may not fully inform educators' decision-making.

What Actions do Data Provoke?

Educators' responses to data vary: educators can change *what* they are teaching, by tracking student progress to reteach content, "teach to the test", or adjust a curriculum sequence (Datnow et al., 2012; Marsh et al., 2006). Educators can also change *how* they are teaching, by shifting pedagogical strategies (Farrell & Marsh, 2016b). The latter outcome (i.e., reflections on instruction and changing "how", not just "what" to teach) is a common goal in data-driven decision-making, but researchers observe that teachers typically do not change any instructional practices at all after looking at data (Farrell & Marsh, 2016a).

We highlight the distinction between SAD and FIT data because they embody different perceptions of data use, which subsequently influence how educators interpret and employ data for instructional decisions (Bertrand & Marsh, 2015; Datnow et al., 2012). Educators may associate SAD data with assessment *of* learning, and FIT data with assessment *for* learning. While assessment of learning emphasizes accountability, ranking, or certifying purposes, assessment for learning focuses on informing the next instructional moves that an educator might make (Black et al., 2004). School practices become assessment for learning “when the evidence is actually used to adapt the teaching work to meet learning needs" (Black et al., 2004; p. 10).

The extant literature highlights the implications of SAD and FIT data for educators’ sensemaking and use of data for evaluating or informing instruction. Understanding the factors that may influence educators’ perceptions of SAD versus FIT data types is an important facet in designing data systems, particularly in selecting which data to process and how to visualize different data streams. We provide an overview of several key factors in the next section.

What Factors Shape Perceptions of Data Use?

Data Format. An explanation for why different types of data may induce different responses is that the data format shapes teachers’ interpretations, and subsequently, their instructional responses. A first facet is the ways in which the data are designed and collected: whether locally at the school and classroom levels, with quicker turn-around time (i.e., FIT data), or externally at the state levels, over large periods of time (i.e., SAD data; Farrell & Marsh, 2016b). Educators may gravitate towards local FIT data forms when they want insights about immediate student learning. Conversely, educators may turn to SAD data when they need predictive indicators of future performance on standardized tests (Young & Kim, 2010).

A second facet is the level of data aggregation for analyses: individual students, classrooms, grades, or schools. SAD data forms often aggregate student learning outcomes by demographics and proficiency levels. This student grouping likely motivates educators to replicate those classifications in practice (Farrell & Marsh, 2016b). Meanwhile, FIT data may provide more in-depth insights about individual students’ knowledge and reasoning, prompting teachers to adjust instruction for individual students (Black et al., 2004).

Stakeholders. Different stakeholders in the K-12 education system (i.e., district personnel, principals, teachers) have varied focus for data types and use (Ikemoto & Marsh, 2007; Kerr et al., 2006). To illustrate, Anderson et al. (2010) observe that district and school administrators tend to cite SAD data forms such as standardized tests, attendance, graduation rates, as SAD data forms allow administrators to make decisions about targeting and resource allocation. Meanwhile, teachers may perceive SAD assessments as lacking validity or alignment with instructional visions, in turn relying on FIT data forms such as evidence of student work (Coburn & Talbert, 2006; Coburn & Turner, 2012; Kerr et al., 2006).

Work Routines. The social, institutional, and political contexts for data practices are also central to understanding how educators adopt data for meaningful action (Coburn & Turner, 2011; Farrell & Marsh, 2016a; Kerr et al., 2006; Wardrip & Herman, 2018). Interactions with other educators who possess different visions for data use may lead to alternative decisions of which data to focus on, with varied implications for data-driven action (Coburn & Turner, 2012). In schools that value high-stakes standards, teachers who focus on raising accountability, most often engage with SAD data from a specific student population (Wardrip & Herman, 2018). However, presentations of data in ways that invite sensemaking, as opposed to dictating certain types of interpretations or imposing a feeling that the educators were being monitored, may yield productive discourse about classroom processes (Ahn et al., 2019).

In sum, several factors may influence the mental models we associate with data and uses for data: data types (e.g., SAD versus FIT), framing of the data (e.g., for learning or of learning), stakeholders (e.g., district personnel, school administrators, or teacher), and the contexts in which data practices are situated. **What happens if multiple mental models of data use interact, as in the case of our collaborative data workshop?**

Collaborative Design of Data Visualizations

To gain insights into the relation between mental models and co-designed data visualizations for education, we turn to the literature on human-centered design, particularly the notions of "value sensitive design" (Friedman et al., 2008) and "mental models" (Norman, 1983, 2014).

Users bring inherent values of how a design should work when interacting with the interface. Values such as cooperation, privacy, and participation must be accounted for in design to anticipate users' interaction (Friedman et al., 2008). Co-designing with users thus provides the opportunity to glean information about users' values and find better ways to design tools and systems that are sensitive to these values.

Designers and users also develop different mental models, or beliefs about the design and its use (Norman, 2014). Designers create a roadmap between the action the design may induce, the mode of interactions, and the design format. Meanwhile, users base their predictions about how the designs would operate in practice on their mental models and plan their interaction with the designs accordingly. A challenge for designers is to incorporate users' mental models into developing interfaces: "novice" designers rely only on surface-level features, while "expert" designers articulate the underlying design needs of the users and expand their design thinking to solve those core needs. For example, in creating data visualizations for K-12 systems, instead of focusing only on visualization types, designers should clearly define the range of decisions educators will make based on the visualizations, and then decide on the appropriate data format, visualization forms, and modes of data analysis and manipulation.

The data collaborative workshop that we participated in presented an opportunity to document how educators engaged in the co-design process of data visualizations. Throughout the workshop, educators voiced their ideas about how to foster data-driven decision-making and prototyped different designs. We analyzed what data types educators naturally gravitated towards, the levels at which they chose to visualize the data, the target audience for the designs, and the designs' intended outcomes. This analysis helped us imply the values and mental models that educators brought to the design task. Capturing the values that educators embraced and the interactions they expected for different types of data and designs illuminated promising directions for data visualizations to incorporate educators' workflow. The following questions guide our analyses:

RQ1. To what extent are educators aware of and value different data types?

RQ2. To what extent does this positioning relate to the prototypes that were created across teams?

Method

Study Setting & Participants

Our analysis drew from a unique, two-day collaborative workshop (NSF Grant 1560720). The goal of the workshop was to develop prototype data visualizations with educators and gather ideas for how data could be more usefully designed to inform their practice. The workshop included a range of activities for educators to discuss their current approach to data practices, what they deemed as lacking in current data warehouses, and their priorities and concerns in applying analytics to educational data. These discussions led to co-design sessions that spanned both days of the workshop (approximately 6 hours in total). Throughout the workshop, participants worked in teams of six or seven to develop prototypes in code, data visualizations from statistical software, or visual mockups that reflected their priorities and concerns in applying data to education decision-making. Each team had representatives from different stakeholders in a K-12 school system: administrators, educators, data scientists, and researchers.

The workshop organizers invited 75 participants (12 district administrators, 10 school administrators, 18 teachers and coaches, 21 data scientists, and 14 researchers). About 50.0% of the participants were female, 70.7% identified as white, 16.0% Asian, 9.3% Hispanic or Latinx, 2.7% Black or African American, and 1.3% Native Hawaiian or other Pacific Islander.

Data Sources

Pre-event survey. Prior to the workshop, participants had the opportunity to fill in an electronic survey on their attitudes towards and applications of data use and data visualization in educational contexts. The survey items captured the current practices educators had with data and their desired interactions with education data systems. In particular, the survey included three questions:

1. What challenges and successes have you experienced using data and evidence in your practices in schools/districts?
2. What components of a longitudinal data system are needed to best meet the needs of superintendents, principals, and teacher leaders?

3. In thinking about data and evidence that are available in your systems, how could the data visualization and evidence be improved? How would these improvements help you?

Design Artifacts. Throughout the workshop, participants worked in teams to develop their prototypes on paper and with digital tools (e.g., statistics software, analytics platforms, or visual wireframing software). The teams produced post-it notes and design artifacts on whiteboards throughout their design sessions, as well as final code and mockups. We analyzed these design artifacts to understand the guiding questions and design approaches to the prototypes.

Analytical Strategy

RQ1. Examining the types of data educators interact with and the action they intend to make with data helps us to infer the values educators associate with data routines. Consequently, we engaged in an open coding process of the pre-workshop survey responses to generate descriptive codes for the data types that educators were most familiar with and their ideas for how to use data. We created the codes at this stage directly from the responses. For example, a response such as "Our current challenge revolves around effective intervention and progress monitoring … I need longitudinal sub-skill tracking." resulted in one code for data type (i.e., "sub-skill tracking") and one code for action intent (i.e., "progress monitoring"). After the initial coding phase, we found that codes grouped into two clusters: SAD data consist of standardized assessment, demographics, attendance, and FIT data encompass formative assessment, behavioral data, and student survey.

To gain insights into what educators planned to use data for, we also refined action intent into subcodes (Table 4.1 provides exemplary answers). *General Improvement* refers to instances where educators mentioned use of data for improvement, without specifying the use cases. *Progress Monitoring* alludes to tracking student progress or learning outcomes during the year or across grade levels. *Comparison* was applied when educators gauged their students' performance against other classes, schools, or districts. *Grouping* refers to the clustering of students by performance or demographics. *Instructional Shift* is when educators explicitly stated the use of data to adjust their teaching practices. Finally, *No Action* is when there was no explicit action intent associated with the data.

To examine the extent to which values for data use may differ by educational stakeholders, we compared the results per professional role (e.g., teachers/coaches, school administrators, district leaders). We also calculated the code co-occurrences of data types and intended action, per professional role. We provide these statistics as well as examples from the responses to illustrate the nuances in educators' perceptions of data use across roles.

Table 4.1

Coding Scheme for Action Intent

Code	Definition	Example
General Improvement	Intent towards improvement; no specific use case	"Helping teachers and learners to think about how data can support their practices."
Progress Monitoring	Tracking progress	"Using various reports from our IDW and our own internal data reports we have increased our 4-year graduation rate from 90% to 97%."
Comparison	Compare across classes, schools, districts, states	"It's also important to have the ability for teachers to compare their data with other teachers in the same school, then same district, then same county, then same state, then nationwide."
Grouping	Cluster students by performance or demographics	"... demographic data within districts to see how each population is performing."
Instructional Shift	Explicit data use for practices	"While teaching Regents Chemistry, I was able to use low performance data on specific questions to guide my instruction the following years."
No Action	No explicit action intent	"Challenges are to align multiple data sources."

RQ2. To explore the persistence of educators' mental models, we coded for which *data types* the teams chose to visualize (i.e., SAD or FIT), and the *intended action* that the teams associated with their designs (e.g., progress monitoring, grouping, instructional shift). In addition, we examined the consistency of teams' design mental models, that is, the coherence between data types, intended action, and the target user groups and design features (Norman, 2014). Thus, we included a code for *aggregation level* (i.e., the level at which users can interact with the data in the visualizations, such

as student, classroom, school, or district level) and a code for *intended stakeholders* (i.e., potential users of the designs, such as administrators, principals, teachers, or students). Together, codes for data types, intended action, aggregation level, and intended stakeholders in the final prototypes helped us explore how educators' diverse values and mental models related to their final designed prototypes.

We performed descriptive analyses of code occurrences in each dimension: data types, data aggregation level, intended stakeholders, and action intent. We discuss the main themes that emerged across teams to illuminate the types of data, action, and stakeholders involved in the team prototypes.

The final prototypes reveal insights about the values that educators place on certain data, but do not shed light on the design process. To illustrate how teams constructed their design models and arrived at their final prototypes, we elaborate on two cases. The first case represents the majority of the designs, with a focus on SAD data. The second case is the only team that employed data beyond SAD, with a unique, explicit call for instructional shifts.

Analyses draw from teams' post-it notes and white board discussions at two phases of the design processes: *wondering* (when the teams set out to talk about their priorities/ concerns in data and data visualizations) and the *final prototypes* (reflection about what should be prioritized in the visualizations they developed). We selected these additional data sources because they were written by individual team members reflecting on data use and visualizations. The notes provide deeper insights into team members' mental models. Similar to the analyses of team prototypes, we coded the post-it and whiteboard notes for data types, data aggregation level, stakeholders, and intended actions. We compared the four dimensions between the notes and the final prototypes to explore how mental models of data practices among team members prior to and during collaborative design may be related to the design process.

Findings

What might happen if we bring together educators across a K-12 education system to create data visualizations? Overall, we found that educators recognized the importance of FIT data when brainstorming future data systems, but defaulted to SAD data when it came to design ideas.

These findings suggest that educators may have different mental models for the types of data that generate instructional improvement versus the data types to visualize. This implication is important for design-researchers because designs that do not match with educators' values may not promote meaningful adoption. We unpack these findings and describe an illustrative case where educators' values and designs were coherently linked to make a potential impact on education practice.

RQ1. Data Types and Intended Action

Finding 1. Most educators readily mentioned use of data for decision-making and frequently cited use of SAD assessment. We found that educators across the board valued data for improvement (Figure 4.1; panel A). All district administrators, 80.0% of the school administrators, and 94.4% of teachers and instructional coaches mentioned an intent to use data for improving instruction.

The most common action intent were general intent for instructional improvement (14 occurrences), instructional shift (11 occurrences), and progress monitoring (10 occurrences; see Table 4.2). A response was counted as expressing general intent if the participant mentioned some use of data, with a general description for "meeting student needs" or "informing instruction" and no concrete action. Instances of progress monitoring included tracking cohort growth and comparisons over time of assessment results. Finally, codes for instructional shift captured instances where educators use data to guide teaching practices. Examples include "use low performance data on specific questions to guide my instruction the following years." or "modify instruction in small group settings based on student needs".

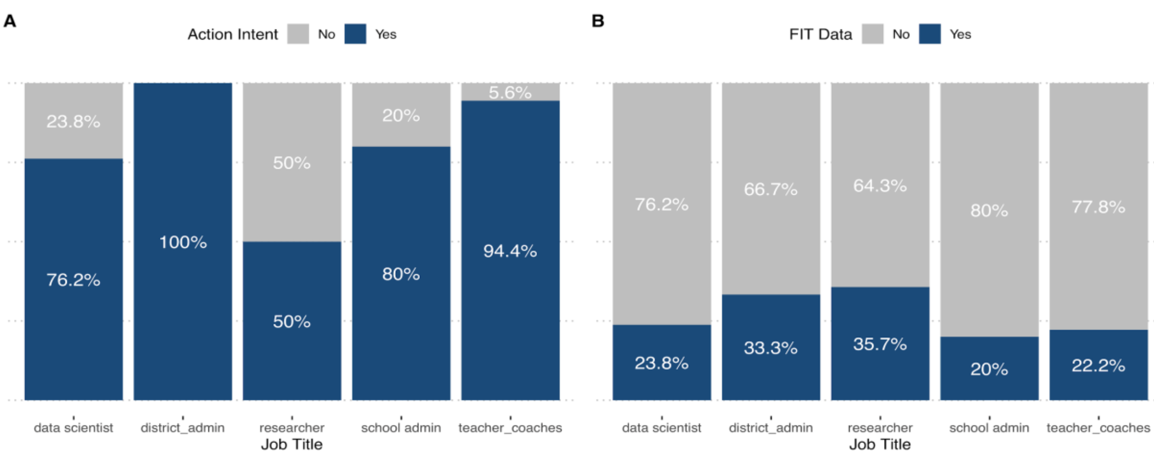
Table 4.2

Action Intent by Professional Roles

	District administrator (n = 12)	School administrator (n = 10)	Teacher/coaches (n = 18)	Total (n = 40)
General Intent	6	6	2	14
Instructional Shift	1	0	10	11
Progress Monitoring	2	1	7	10
No Action	3	3	0	6
Comparison	3	0	0	3
Grouping	0	1	2	3

Figure 4.1

Action Intent and Data Types by Professional Roles



We noted that FIT data only appeared in a small proportion of the survey responses (33.30% for district administrators, 20.00% for school administrators, and 22.20% for teachers and instructional coaches (Figure 4.1; panel B). The most frequent FIT data types mentioned were formative assessments (overall, 16 occurrences), followed by surveys of student attitudes, social emotion, and future plans (2 occurrences). Table 4.3 presents summary statistics for data types.

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Table 4.3

Data Types Mentioned by Professional Roles

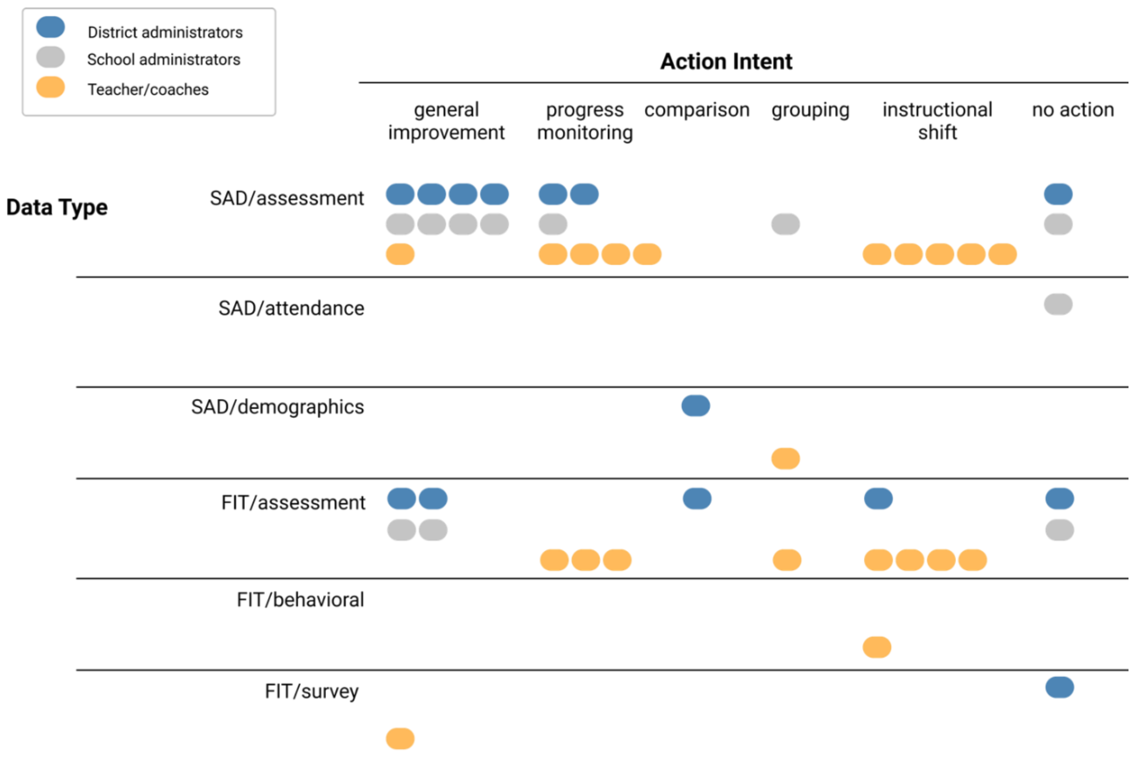
	District admin (n = 12)	School admin (n = 10)	Teacher/coaches (n = 18)	Total (n = 40)
SAD/assessment	8	7	10	25
SAD/demographics	1	0	1	2
SAD/attendance	0	1	0	1
FIT/assessment	5	3	8	16
FIT/survey	1	0	1	2
FIT/behavioral	0	0	1	1

Finding 2. Different data types may relate to different action intent. We analyzed the co-occurrences of data types and action intent by professional roles. We found differences in the associations between data types and action intent. Figure 2 illustrates these differences by visualizing the code co-occurrences by roles (blue: district administrators; gray: school administrators; yellow: teachers and instructional coaches).

In general, the co-occurrence for SAD assessments and general improvement intent was the most prevalent relation that emerged for district and school administrators. For example, a district superintendent mentioned "using comparative data information to drive school instruction" when reflecting on her current data practices. There were six occurrences when educators mentioned data use but did not associate use with any action intent, as seen in the answers by district and school administrators. For example, the participants mentioned different data types (e.g., state standards, third-party assessments), but did not link these data to any use towards decision-making.

Figure 4.2

Data Types and Subtypes, by Action Intent and Professional Roles



Meanwhile, teachers and coaches frequently mentioned SAD and FIT assessment data for progress monitoring and instructional adjustments. The two data types (SAD and FIT) often appeared in the same response, suggesting that educators relied on both types in decision-making. For example, a literacy coach mentioned the use of school documentation of students' reading and writing behaviors, together with district reading assessment and school assessment, to analyze student performance:

> We are working on using the data collected versus just getting a "score." When looking across our data from year to year, we can focus on specific students and also see how different grade levels perform. This year, we are focusing on looking across multiple assessments to see how they correlate and how to manage all the different assessment information.

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In this response, the coach referred to triangulating different data sources (i.e., "looking across assessments") to compare performance data across grade levels and track specific students' performance over time. Later in her response, the coach mentioned that looking across assessments allowed her school to examine the success of different literacy interventions and adjust instruction accordingly.

We also noted that several coaches and teachers tied data to specific use cases of instructional adjustment. Take the following response from a Chemistry teacher as an example.

> Successes: Each year we look at our GAP report and see how the students scored on each of the 85 questions on the Regents Exam. I look at the questions the students answered most incorrectly and I alter how I teach that topic (or those topics) the following year.
> Challenges: Personally, what I should be doing is using more data during the course of the school year. Use evidence from tests/quizzes on what topics need more time and which ones can be quickened.

The teacher cited the use of SAD assessments to identify gaps and adjust instruction (i.e., "alter how I teach that topic"). He also recognized the use of FIT data, such as tests and quizzes during the school year, to derive insights for instruction. However, the teacher admitted challenges in incorporating FIT data into his current workflow.

In sum, the pre-survey responses illuminated two key findings. Although SAD data were prevalent in educators' responses, educators also cited FIT data – most frequently formative assessment – as another source to glean insights about student learning progress and instructional improvement. We also noted variation in the action intent associated with data types across professional roles. Teachers and coaches were more likely to report using data to monitor progress of learning interventions and adjust instruction, whereas school and district leaders more frequently referred to data use for general improvement, without concrete use cases.

RQ2. What Mental Models were Prevalent in the Data Visualization Prototypes?

We analyzed the prototypes (code, mockups, presentations) of all teams to infer their mental models around data use. In particular, we examined the data types, the levels of data analyses, the stakeholders that the prototypes were geared towards, and the action intent that were part of each prototype (Figure 4.3). These elements provide insights into the data format and desired outcomes for data-driven action in each team.

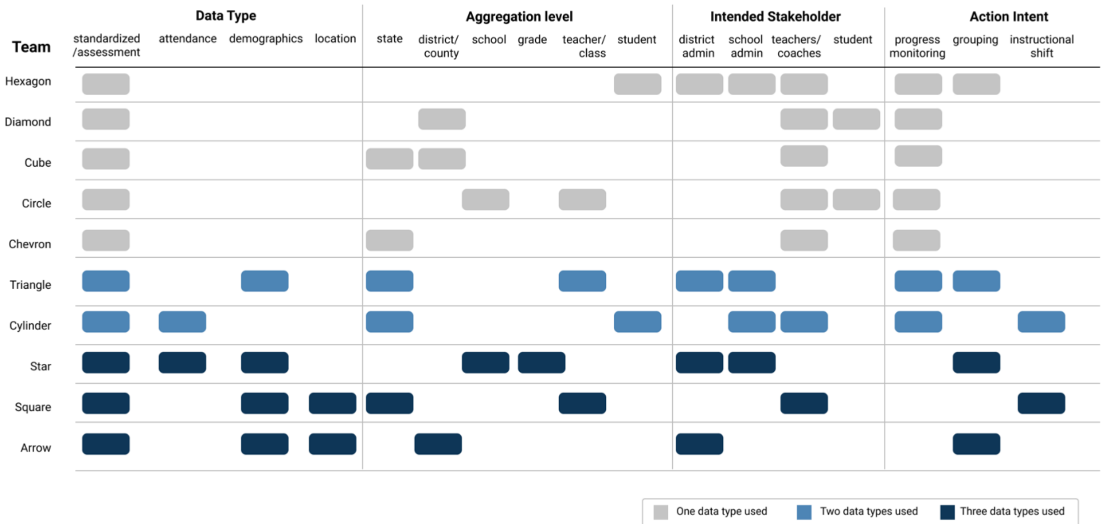
Finding 3. SAD assessment was the predominant data type in all prototypes. We found that the prototypes in all teams used standardized state performance. Other forms of SAD data such as attendance, demographics, and location (e.g., geomap) were complementary to the standardized assessment data. Design teams most often aggregated their data at the state level to visualize whether student performance met accountability standards.

Finding 4. Action intent for the prototypes tended to be limited. Team notes indicated that most of the prototypes were geared towards teachers and instructional coaches. However, few prototypes had explicit implications for instructional adjustments. The most common action intent that users derived from the data visualization prototypes were progress monitoring (e.g., "examine growth over the years" or "compare student performance against state standards") and grouping (e.g., "increase enrolment of student subgroups").

We found that only two teams developed prototypes with stated action intent for teachers, as indicated in the teams' notes. Team Cylinder (pseudonym) explicitly stated a goal for teachers to compare students' performance against state standards to "support planning or personalize learning". Another exception was Team Square. Team Square's dashboard identified teachers who performed well according to state standards and included information about teacher contact, class demographics and location in the same interface (Figure 4.4). Teachers could use the dashboard to identify other educators with similar work contexts and share experiences and resources, with the goal to improve instruction.

Figure 4.3

Prototypes by Team

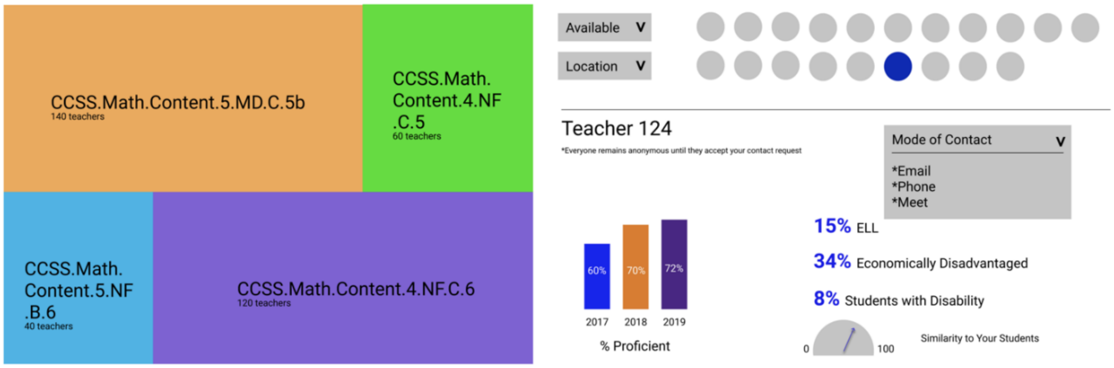


Note. Codes: data type used, level of data aggregation, intended stakeholder, and intended action.

Illustrative cases: Alignment of mental models and design. We examined the design processes in two teams to explore educators' mental models that may have related to their collaborative designs. The first team, Team Cube, was selected because their prototype reflected the majority of the designs, with a focus on SAD assessment and progress monitoring (Figure 5). Team Cube consisted of a Professor in Education, two district leaders, a school leader, and two statisticians. The second team, Team Square, was selected because their design represented a unique, explicit call for instructional improvement (Figure 4.4). The team consisted of a Professor in Education & Design, two teachers, and a district leader. We highlighted two discussion sessions in the team notes: initial questions about data practices and final goals for the prototypes, to illuminate how educators' values became present in the design process.

Figure 4.4

Team Square's Prototype



Note. The goal of the dashboard is for teachers to share instructional insights and resources. The left panel shows state-level Math standards. The right panel includes the contact information of a teacher who shows instructional improvement over time (i.e., increasing percentage of students who performed at or above proficient in state testing) and shares similar work contexts (i.e., student demographics).

Initial discussion on data practices. The notes in Team Cube mostly centered around data use by different stakeholders -- administrators, teachers, and students. Team members posed questions about how to integrate FIT data sources, namely a school climate survey and student exit tickets, in valid and meaningful ways to improve practices. Whiteboard notes reveal that the team discussion later shifted to data access and customization, particularly the ability to aggregate and disaggregate data for comparison across educational systems (e.g., state, district, school, class).

The practical application of data also emerged in Team Square's notes, with a similar focus on data access and data sources. However, a difference from Team Cube was several post-it notes that focused on fostering a collaborative culture around data use for reflection and sharing of practices. For example, at least two team members wondered about the impact of psychological safety (i.e., the feeling that one's ideas are welcome) on data sharing and the impact of collaborative settings and team composition on psychological safety. We also observed more attention to specific implementation practices in Team Square. For example, within data use, there were specific suggestions for comparing individual students with similar demographics across schools, performance levels, and standards, in ways that could inform instruction versus just comparing or monitoring.

To sum up, we found that although the two teams shared the premise around facilitating data use across education systems, the team discussions diverged. Team Cube's notes highlighted a specific feature (i.e., data customization) for comparison across school settings, while team Square's notes focused on a goal (i.e., finding ways to foster collaborative data use for teachers).

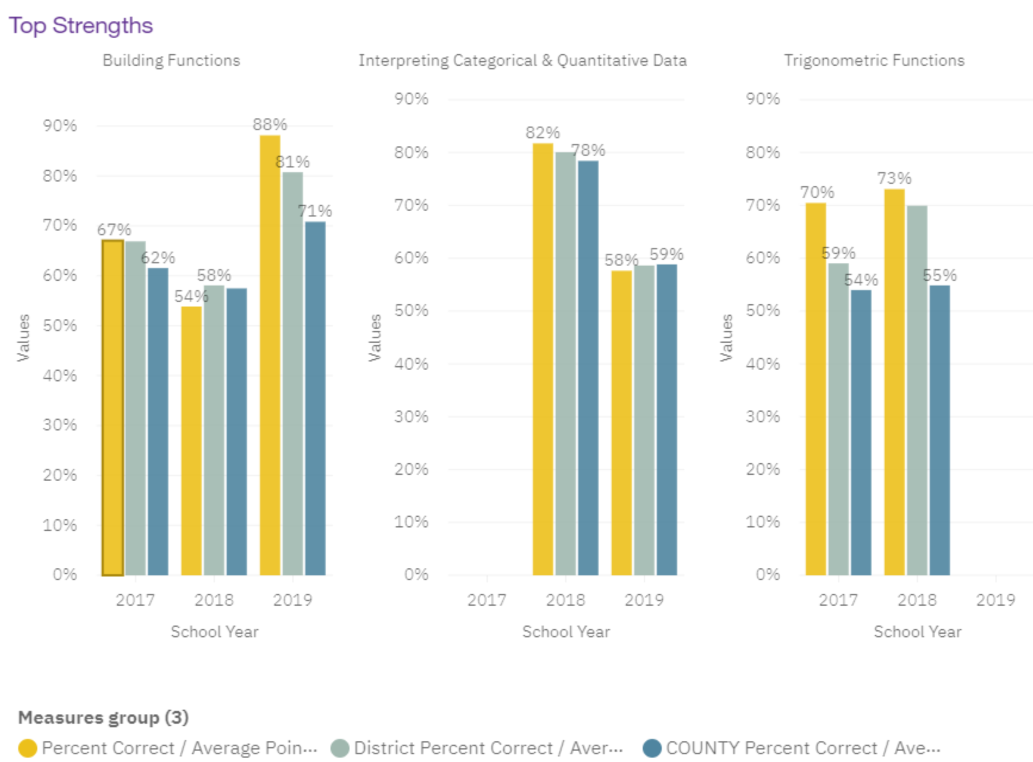
Prototype goals. The final prototypes reflected the focal features in team discussion: comparison versus collaboration. Team Cube noted the question that guided their design in the team's final notes: "To what extent can we identify specific areas of instructional strengths and needs?". The team identified three goals for their design: (1) ease of use; (2) relevance of data; and (3) pathway to instructional intervention. To answer their guiding question, the team visualized student standardized test performance from one grade level and highlighted the three strongest and weakest areas for growth (Figure 4.5). The design also incorporated aggregating data by levels, such as making comparisons across school, district, and county. As noted in our prior analyses, this focus on making comparisons across the system was a central point in Team Cube's discussion leading to the prototype.

Meanwhile, Team Square identified their design's aim as: "sharing of data promotes professional growth and collaboration" for "teacher empowerment". The design question was: "How can we share state assessments and standards-based scores to help teachers connect and share best practices with each other?" The final design (Figure 4.4) was consistent with these goals. Similar to Team Cube, Team Square's prototype employed student assessment in alignment with state standards. However, Team Square's design also included teacher information and classroom demographics, such that practitioners could identify and reach out to those with similar teaching contexts in order to share instructional insights that might work across similar situations that teachers faced.

Even though both Team Cube and Team Square employed student state test scores, the final designs differed in data types, design features, and the design's action intent. Only Team Square incorporated additional data sources, namely student demographics and teacher information, into their design. Whereas Team Cube's design was centered around data customization, Team Square's prototype focused on teacher networking. We conjectured that the different focal points in team conversations might have shifted their designs towards different directions: one that focused on comparison and progress monitoring/tracking, and one that added a layer of communication and collaboration. Finally, for action intent, we observed that Team Square appeared to have a more concrete goal for teacher empowerment between the initial discussion and final prototype. Although Team Cube aimed for their prototype to serve as a pathway to instructional intervention, the team's notes and designs did not explicitly state ways in which educators may achieve this vision.

Figure 4.5

Team Cube's Prototype



Note. The purpose of the visualization is to identify specific areas of instructional strengths and needs. The visualization presents a longitudinal, aggregate view of the school's performance in different content areas in state standardized testing. The side-by-side bars allow for comparison of performance across school, district, and county level.

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Discussion

Understanding the mental models that educators hold and the interactions they expect for different data forms and designs illuminates new directions for data visualizations for school improvement. Our analyses of educators' perceptions about data use and their co-designed artifacts gave us a window into the values and mental models educators brought to the design task. We found that the majority of educators readily mentioned use of data for decision-making and frequently cited use of SAD assessment in current practices. We observed that educators most often cited use of SAD data for general improvement intent (without concrete applications), progress monitoring, and grouping students by demographics and performance. Conversely, educators most often associated concrete implications for instructional shifts with FIT data. These patterns align with prior research on data-driven decision-making that standardized information may not be the most useful for devising tangible plans for instructional improvement (Farrell & Marsh, 2016b).

We also observed variation in the association between data types and intended action by professional roles. District and school administrators appeared to associate SAD data use with no action, or with general intent for school improvement and no concrete action. Meanwhile, teachers and coaches were more likely to cite specific examples of using SAD and FIT assessment data for instructional adjustments. This finding suggests that data systems that only focus on one data type may overlook the expertise and practices that educators in different roles bring into instructional decision-making. In particular, data systems that focus on accountability and standardized, administrative data forms may not be as relevant for instructional coaches and teachers in school improvement efforts.

Our findings have implications for the design of dashboards and data systems for educators in different professional roles. Results illuminate the need to (re)consider the types of data that may be valued and considered worth collecting, processing, and visualizing in data systems for educators across the K-12 system. In addition to considering levels of aggregation and customization, representations should include data sources and annotations that resonate with educators' practices. Educators are more likely to employ data for instruction when they see data as relevant and contextually grounded, as opposed to feeling that data are externally imposed for accountability (Coburn & Turner, 2011; Farrell & Marsh, 2016b).

In analyzing the teams' final prototypes, we observed parallels between educators' preconceptions of data practices and the prototypes they created. In particular, we found a strong focus on assessment data for monitoring/ tracking progress and grouping students. Analyses of the team notes indicated that educators were not necessarily unaware of the need to incorporate into their designs additional, FIT data sources such as students' behaviors and school engagement. Yet, none of the prototypes leveraged these data sources. Instead, all designs drew from SAD assessment data, and a few leveraged other SAD data forms such as demographics and attendance. We note that the types of questions we could ask from these visualizations of standardized assessments by groups or standards tend to be limited.

We also want to note that the design teams in this chapter worked under the constraint of data access and time. However, our illustrative case of Team Square suggests that other types of visualizations and actions are possible. What distinguishes Team Square from other teams appears to be a coherent link between their initial values for data use, desired outcomes, and final prototypes. The team's design used student demographics data not for evaluation and monitoring, but for networking and professional development. Team Square's illustrative case suggests an interesting conjecture, that prompting participants to take a step back and articulate how their designs serve data-driven, targeted educational practices may help to surface other purposes for data visualizations beyond progress monitoring or comparing students. In addition, if we want to shift participants' mental models for incorporating FIT data forms into data systems, we could also ask them to articulate a finer link between data and action, for example, shifting from "I use student exit tickets to adjust instruction" to "This exit ticket helps me determine whether students understand a new task".

Conclusion

This chapter contributes to our understanding of how educators value and act on data. Co-designing with diverse stakeholders can help us reveal the types of mental models that educators, researchers, and data scientists bring to educational data. Our experience in an NSF-sponsored, co-design workshop offered windows into how we can expand our imagination for what data systems to design and use for instructional improvement. Articulating how designs serve data-driven educational practices may help to uncover new ideas for data visualizations beyond Standardized and Administrative Decision-making (SAD) paradigms.

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CHAPTER 5

Challenges and Successes in Education Leadership Data Analytics Collaboration: A Text Analysis of Participant Perspectives

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An Introduction to Education Leadership Data Analytics

Since the Institute of Education Sciences was founded in 2002, educators, practitioners, and policymakers have increasingly come to the understanding that research should play a stronger role in education reform and improvement. Collaboration between education practitioners and researchers is essential to improve educational outcomes. To achieve collaborative systems that are meaningful and effective, researchers must focus on problems that are immediately relevant to practitioners, and practitioners must be able to access and interpret research. Research is often out of sync with the needs of educators, as the research process moves slowly, and the nature of data collection and analysis necessarily implies that research occurs retroactively. Similarly, researchers are not always interested in the same questions that plague educators, creating a disconnect between the evidence that is available and the evidence that teachers, school leaders, and district administrators need.

Research practice partnerships (RPP) seek to bridge the divide between research and practice. RPPs are "long-term, mutualistic collaborations between practitioners and researchers that are intentionally organized to investigate problems of practice and solutions for improving district outcomes" (Coburn & Penuel, 2016). The idea behind RPPs is that researchers and practitioners work together to understand and analyze problems that are specifically relevant to the district or state that the RPP serves. Coburn & Penuel (2016) identify three types of RPPs: (1) research alliances, which typically include partnerships between research organizations and districts or state education agencies; (2) design research, focused on curriculum and instructional materials; and (3) networked improvement communities, which concentrate on policy implementation and scaling up.

An emerging area within research practice partnerships is education leadership data analytics (ELDA). Bowers and colleagues (2019) define ELDA as the "intersection of education leadership, the use of evidence-based improvement cycles in schools to promote instructional improvement, and education data science." The idea is very much in line with the research practice partnership vision: researchers and data scientists work collaboratively with schools and districts to explore and analyze relevant data (which is often collected and housed by the schools and districts themselves), and then create written reports or digital interfaces that are easily accessible and interpretable to practitioners. Through ongoing collaboration, ELDA provides a structure to support data use and evidence-based improvement cycles in schools.

Research practice partnerships like ELDA that specifically focus on data use in schools are certainly relevant, given the increasing use of data in all aspects of K-12 schooling. Accountability reforms such as No Child Left Behind and Race to the Top created space for and normalized the broad use of data and data driven instruction in K-12 schools. Schools and districts collect data on a wide variety of outcomes – student test scores, disciplinary measures, attendance – and rely on these data to make important decisions about school processes (Coburn & Turner, 2011; Farley-Ripple & Buttram, 2015; Marsh & Farrell, 2015; Spillane, 2012). School leaders use student-level data to assign students to classes, and classes to teachers. Within classes, teachers use student-level data to create seating charts, to decide which students will receive individualized instruction in small-group settings, and to pair students for group work. As a former teacher, data-driven decision making characterized every aspect of my practice. Analyzing students' exit tickets was a daily routine, as I would use those data to inform the next day's lesson. When I was lesson planning, I would look at data from the previous year to help identify common student misconceptions and potential strategies to address them. Using data as part of my instructional practice was so routine that it is hard for me to imagine what it would have been like to teach any other way.

The use of data in schools opens the education field to emerging partnerships between practitioners, researchers, and data scientists to work together to create systems and structures that support effective data-driven instruction and, more broadly, evidence-based improvement cycles. There is still more work to be done in this area. In a report summarizing the first ELDA summit in 2018, Bowers et al. (2019) concluded that ELDA researchers and practitioners need more opportunities for joint capacity building. In a post-event survey, participants ranked capacity building, conceptualized as "developing and fostering effective and ethical partnerships between researchers and practitioners in order to use data to drive quality education" as the biggest priority for future work in ELDA. Capacity building received a score of 4.09 on the priority scale, where responses were scored on a 1-5 likert-type scale in which one is lowest priority and five is highest priority. The need for more capacity building was also reflected in participants' responses to the following reflection question: *Given the sessions you attended at the ELDA summit as well as your own experiences, to you, what are the central ideas, issues, and challenges in the domain of ELDA?* where the most common responses revolved around "developing, growing, refining, and incentivizing feedback loops between researchers and practitioners in the use of data analytics for instructional improvement" (Bowers et al., 2019).

However, in the same post-event survey following the 2018 ELDA summit, participants noted concerns with the challenges of sustained collaboration among researchers and practitioners: they ranked capacity building as a 3.35 for possibility (again ranked on a 1-5 likert-type scale, where one is least possible and five is most possible), much lower than its score of 4.09 on the priority scale (Bowers et al., 2019). Taken together, the 2018 event realized a strong demand for collaborative work in ELDA, while simultaneously acknowledging that bridging the fields of education leadership, education data science, and evidence-based improvement cycles remains a challenge.

The 2019 Education Data Analytics Collaborative Workshop

The 2019 National Science Foundation Education Data Analytics Collaborative Workshop seemingly answered this call by offering a two-day datasprint workshop in which ELDA researchers, practitioners, and data scientists would work together in teams to (a) understand and prioritize educators' data use needs, and (b) address these needs by building visualizations and data dashboards, which could then be used in schools and districts. This workshop provided a unique opportunity for ELDA capacity building – the collaborative work experience that practitioners and researchers need.

I attended the 2019 workshop as a data scientist. Though many participants had attended the 2018 summit a year prior, this event was my first collaborative ELDA event. When I first learned of the workshop, I was immediately interested. The event would bring together educators and researchers (in academia and in industry) and would focus on collaborative learning and relationship building. It seemed like a unique opportunity to learn from and work alongside professionals outside of my immediate network, and importantly, to hear from teachers and school leaders about their data needs.

During the two-day datasprint workshop, participants were grouped into teams, and each team was tasked with identifying a data priority in schools and building a prototype to address the selected priority. Importantly, each team included at least one practitioner, researcher, and data scientist. The workshop's organization and purpose necessitated the expertise of each participant's role, which created an engaging and productive environment in which participants were able to both learn and teach.

In my team, I observed that practitioners, researchers, and data scientists each approached the datasprint work in distinctly different ways. For instance, practitioners, which included teachers, school leaders, and district administrators, were most often focused on solving immediate problems – data availability and data accessibility. Researchers tended to think about how best to understand a given issue or problem, and the data scientists were often concerned with the feasibility of a potential solution. These patterns are not surprising, given the unique purpose of each participant's work. Yet it was interesting to observe how our individual thought processes contributed, and sometimes inhibited, our team's success. Even in a space specifically designed for ELDA collaboration, collaboration is challenging. The constraints and work processes that practitioners, researchers, and data scientists face in their own work do not necessarily align, which led participants to approach tasks from different lens and with different aims.

I began to think more about what makes collaboration successful. What can we learn from this two-day workshop about successful collaboration? In what ways does it help us identify areas for improvement? To better understand how practitioners, researchers, and data scientists approach ELDA collaboration differently, I analyzed participants' open-ended pre- and post-survey responses. Specifically, I used the deidentified open-ended survey response data to classify participants' responses to the following pre- and post-event survey questions:

(1) Pre-event: *What challenges and successes have you experienced using data and evidence in your practices in schools/districts?*
(2) Post-event: *What challenges and successes have you experienced using data and evidence in your practices in schools/districts and how does the experience of the two-day event inform this?*

Correlated Topic Modeling using Deidentified Survey Data

Responses to the pre- and post-event surveys were linked to participants' background information, including their professional title, which I used to construct participant role as practitioner, researcher, or data scientist. I note that the event participants are certainly not representative of all practitioners, all educators, or all data scientists, and I do not generalize beyond those participants who attended the 2019 event and responded to the pre- and post-surveys. The purpose of this exercise is simply to better understand the different perspectives of ELDA practitioners, researchers, and data scientists, and examine the extent to which an event like the NSF Education Data Analytics Collaborative Workshop can provide a space for structured and sustained partnership in the field.

I used correlated topic modeling, a natural language processing (NLP) technique, to uncover the latent topic structure of the survey responses, by participant role. Machine learning methods like NLP present promising applications in education-related research, as they allow for the systematic processing of qualitative data at a scale and speed that was previously impossible. Because the nature of qualitative methods emphasizes human processing, a typical qualitative analysis – while rich in nuance and depth – often lacks generalizability. It is simply impracticable to hand-code a sample size large enough to be representative of a distinct population. Data scientists in machine learning, however, have focused on the automation of these human processes such that they are almost infinitely scalable and consistent. Once an algorithm is created and trained, it is able to efficiently code information from complex raw data, and to scale up is only a matter of increased computer processing time. In addition, the automated nature of algorithmic processing ensures that results are absent of research subjectivity or human bias.

Because I am interested in differences between responses by participant role, I ran separate topic models for the pre- and post-survey questions for each type of participant: practitioner, researcher, and data scientist. In other words, I defined my corpora by survey question and participant role. I therefore constructed six separate corpora (two survey questions by three participant roles) and used these corpora as the basis for my topic models.

I used Latent Dirichlet Allocation (LDA), a type of unsupervised correlated topic model that empirically identifies unobservable groups, or topics, in text data (Blei, Ng, & Jordan, 2003; Bowers & Pan, 2019). The intuition here is that any given text document, such as an open-ended survey response, is composed of a set of topics. Though the topics are unobservable (i.e., one would need to read the document to identify them), they can be empirically identified from the combination of words in the document. LDA follows the "bag of words" framework, which supposes that a text document is made up of a bag of words, and that the presence of a given word, or given set of words, in the document can be attributed to a latent topic in the document's structure. Importantly, LDA allows topics to be correlated with one another, such that multiple topics can share the same words. For example, the combination of words "data," "analysis," and "use" could be attributed to a topic on collaborative data use in schools *and* data fairness and ethical considerations – though the presence of the same set of words would not contribute to separate topic identification. In short, LDA analysis identifies the topics that generate the unique combination of words in text documents.

LDA returns the estimated topic groupings, high frequency words associated with each topic, and the probabilities of each document (in this case, survey response) being associated with the identified topics. I used this information to label and conceptualize the topics, first using the high frequency words to generate a "first pass" topic label, then reading through the open-ended survey response to validate or modify the topic labels. To ensure the accuracy of my topic labels, I read survey responses until the topics were "saturated," i.e., until additional survey responses provided no more information about the already defined topics.

Results

Table 5.1 shows the topic structures of participants' open-ended responses in the pre-event survey, by participant role. There are noticeable differences in the topics across practitioners, researchers, and data scientists. Practitioners' responses underscore their focus on *what to do* with data. Practitioners described successes with data driven instruction and using data to ensure all students' needs are met, while noting various challenges related to the technical aspects of data use in schools. For instance, practitioners described a lack of comfort with data, as many educators are inadequately prepared to review and analyze data. As one principal described, “Many teachers do not have a fundamental understanding of the data and how to use it. As a principal, I am very limited with the amount of time I have to provide training and give teachers time to review data.” Not only did practitioners cite challenges with data literacy, but they also expressed facing serious time constraints when it comes to reviewing and analyzing data, and having important data conversations, whether those are between teachers and instructional coaches, or schoolwide meetings focused on progress monitoring and goal setting.

Table 5.1. Pre-survey topics and associated high frequency words, by participant role

Question: What challenges and successes have you experienced using data and evidence in your practices in schools/districts?

	Topic	Word Stems
PRACTITIONER	Data driven instruction and using data to ensure all students' needs are met.	Ensure, Meet, Provide, Effect, Level, Identify, Princip, Measure, Drive
	Making decisions about how to use data: data collection, setting time aside to review data, triangulating data from multiple sources, students who opt-out.	Decision, Struggle, Collect, Read, Source, Improv, Question, Topic, Test
RESEARCHER	Lack of consistency in data collection and analysis across schools and districts. Limited opportunities for conversations around evidence-informed practice.	Evaluate, Educ, Practice, Type, System, Analysis, Visual, Help, Collect
DATA SCIENTIST	Reliability and credibility of data to represent reality, and ethical considerations, including bias in data. Helping data users (educators) learn how to correctly interpret data to minimize these concerns.	Learn, Base, Educ, Familiar, Interpret, Class, Experience, Coupl, Organize
	Access to useful and high-quality data. Focus on district partnerships where districts can voice data needs and data scientists can access data.	District, Report, Visual, Indic, IDW, Improv, Govern, Transform

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In contrast, researchers' responses centered on data quality and opportunity for collaboration with practitioners. Data quality was a main concern for researchers, as many described facing data inconsistencies (i.e., consistent identifiers and measures) across schools and districts, which makes it difficult for analysts to make useful comparisons across schools within districts, or across districts and states. One graduate student suggested that "we need a centralized or standardized data collecting system throughout districts or even further." Researchers also expressed a want for more opportunities to share their work with educators and to help practitioners "think about how data can support their practices."

Data scientists described concerns with data credibility and data quality. A main challenge in the work of data scientists is convincing educators (or other relevant stakeholders without technical knowledge) that data matters, and as one data scientist succinctly noted, "trust in [artificial intelligence] remains to be a consistent challenge within educational settings." Like researchers, data scientists also commented on the quality of data collected by schools and districts and suggested that district partnerships focused on data sharing could improve some of issues around data quality and ease of use.

Table 5.2 shows the topic structure of participants' responses in the post-event survey. The post-event survey question similarly probes participants' perceived challenges and successes with data, though it additionally inquires how the two-day workshop informed these perceived challenges and successes. Within participant roles (practitioner, researcher, and data scientist), the topic structures are thematically similar to those of the pre-event survey, with an apparent emphasis on data visualizations. For instance, practitioner responses in the post-event survey were, again, focused on educators' data literacy, though data literacy more narrowly defined as educators' ability to navigate and interpret their schools' and districts' data dashboards. Researchers and data scientists again discussed issues with data quality and the absence of educator perspective in their work. However, both groups discussed coming away from the ELDA workshop with a better understanding of the types of data visualizations that are most useful for educators: "The biggest challenge as a data scientist using educational data is to identify what kind of analysis that will be helpful for teachers. [This] two-day workshop (especially the data-sprint) exercise was extremely useful in that sense, since I was able to learn thinking from an [educator's] perspective." For researchers and data scientists, the utility of the datasprint workshop underscores the importance of designing and implementing formal structures to facilitate collaboration and information sharing between practitioners and research scientists.

Table 5.2. Post-survey topics and associated high frequency words, by participant profession

Question: What challenges and successes have you experienced using data and evidence in your practices in schools/districts and how does the experience of the two-day event inform this?

	Topic	Word Stems
PRACTITIONER	Building capacity around the data structures/dashboards that the district has implemented	Discuss, Analysis, Biggest, Help, Dashboard, Item, Implement, Improv, Structure
	Being able to navigate and synthesize data from various platforms to create a cohesive narrative that teachers can easily transfer to classroom practice	Inform, School, Create, Easi, Develop, Plan, Reflect, Collect, Account
RESEARCHER	Data visualizations that are comprehensive and comprehensible for educators	Question, Visual, System, Type, Effect, Time, Comprehension, Limit
	Lack of consensus on what type of data and analyses are helpful; researchers don't know what practitioners need, and often the interests of researchers diverge from what is useful to practitioners	Evaluate, Educ, Practice, Type, System, Analysis, Visual, Help, Collect
DATA SCIENTIST	Data accessibility for research and getting user (educator) buy-in	Research, User, Dataset, Complex, Context, Depart, Encount
	What data visualizations are most useful to practitioners, given lack of experience with classroom support. How to identify changes to make based on the data	Experi, Identify, Support, Access, Collect, Limit, Change

Discussion

The 2019 Education Data Analytics Collaborative Workshop offered a rare and important opportunity for practitioners, researchers, and data scientists across the country to think, learn, and build together in a two-day dataspint design. The event responded to the need for joint capacity building in the field of ELDA, a necessary opportunity to advance our collective understanding and use of data in schools. As a data scientist participant, working on a team with practitioners taught me how to identify and approach problems from an educator's perspective, which has in turn influenced how I approach my own work. I left the event with a renewed sense of inspiration and motivation to inform my research with the needs of practitioners – and some new code for data visualizations!

I also left the event convinced that we *need* more opportunities for this type of collaborative work, and results from the text analysis of participant survey responses support this instinct. While educators look for more opportunities to increase their data literacy skills and learn how to effectively use the data dashboards and visualizations supplied by their schools and districts, researchers and data scientists seek occasions to engage with educators about data-driven instruction and data use in schools, broadly. Not only do we need more collaborative events like this one, we also need formal systems, like professional organizations and networks, that facilitate collaboration across ELDA professions by creating opportunities for sustained relationships and partnerships. Future work in the field of ELDA must include designing, developing, and sustaining meaningful opportunities for ongoing conversation and collaborative work that cuts across the research and practice divide.

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CHAPTER 6

Understanding Workshop Participant Movement Through a Temporal Cluster Analysis

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Abstract

Multi-modal learning analytics is an actively growing area of educational research. New forms of modal learning data aggregated across multiple sources has created innovative research opportunities within the learning science community. One area of this research focuses on the application of spatial-temporal analysis of movement data. In this paper, we use participant movement data collected during an NSF grant-funded workshop at Teachers College Columbia University. The data from this workshop was analyzed using the Pythagorean theorem distance measure to determine the proximity of team members to their team's centroid throughout the workshop's scheduled structured and unstructured activities. An Analysis of Variance was

then applied to the distances to determine if was any significance in distances between teams or within structured or unstructured scheduled activities. Results indicate there is a significant difference in mean distances. While physical closeness does not imply participant interaction, looking at trends across groups' spatial positionings can determine if and when opportunities to collaborate occurred. Work in this field has the potential to inform how learners respond to collaborative exercises and events, with the potential to even determine how scheduled events and curricula are designed.

Background

The first author of this book chapter, Chad Coleman, attended an NSF grant-funded workshop intended for school district employees (such as superintendents, administrators, and teachers). The purpose of this two-day workshop was to bring together educators and administrators from the Nassau County, Long Island New York Board of Cooperative Educational Services (BOCES) and educational technology industry data scientists to better understand the needs around education data, with the final outcome of the workshop consisting of a data sprint and visualization prototype built using BOCES real-world education data. Coleman attended as a data scientist to provide guidance into how school districts' data can be harnessed and presented in meaningful ways, with the overall goal being to help schools use existing data to prototype data visualizations. By participating in this workshop initiative, Coleman gained access to data on the participants' physical locations over the course of the day-long workshop. In this chapter, he and his coauthors analyze the participants' movements and positions to better understand the opportunities of spatio-temporal data analysis with collaborative learning environments.

Through this experience, Coleman observed that when presented with opportunities to interact and network with individuals from other educational institutions, participants typically opted to seek out others with the same role or job title as them. Data scientists often interacted with other data scientists, superintendents met with other superintendents, and so on. Based on these observations, Coleman and his coauthors became interested in understanding more about the value of measuring participation movement, interactions, and distance. This experience prompted him to look for significance in their trends of their positioning data. Through his attendance at this workshop, Coleman also gained insight into the extent to which educators' knowledge and familiarity with how to analyze data collected in educational settings may vary; such insight will likely guide future papers and work intended for individuals working within K-12 learning environments.

Introduction

Many educational institutions invite participants to engage in self-guided movement, exploration, and teamwork as part of the learning process (Cohen, 1986). Activities in this style, which range from group projects to browsing "gallery exhibits" or other "informal learning...set-up[s]," typically are designed to provide learners with heightened ownership over their learning, as well as with greater opportunities to collaborate (Ortiz-Vasquez et al., 2017). These approaches, which are rooted in the educational theory of constructivism, are designed to "hold learners in their zone of proximal development" (Driscoll, 2005). These environments also utilize an approach that recognizes the importance of the process undertaken to solve a task rather than a more traditional evaluation of student ability as measured by a terminal assessment. Additionally, communication patterns of students involved in constructivist activities can present insights into learner affect states (Worsley & Blikstein, 2013). However, the immediate or direct value of these activities has historically proven difficult for educators to determine as the activities occur, given how fluid and varied learners' actions and behaviors are during these experiences (Blikstein & Worsley, 2016).

Educational technologies that rely on social constructivist and communities of practice theories consist of a group of people who have a shared purpose or interest meeting and working together regularly to achieve a goal, elevate performance, and enrich knowledge(Hodson & Hodson, 1998). Through recognizing the role that the learner's community plays in the learning process, communal constructivism is an approach to learning in which learners not only construct their own knowledge, but are also actively engaged in the process of constructing knowledge for their learning community by interacting with the environment. The method often involves the use of existing knowledge and the creation of new meanings and new ways of representing these meanings (Rafaeli & Kent, 2015).

Emerging educational technology platforms that utilize game based, virtualized, and immersive elements provide substantive sources of data to profile learners on their engagement, preferences, and trends with educational content (Blikstein, 2013). The growing use of mobile and wearable technologies, or devices that monitor the physical attributes of an individual, such as affect states, yield additional data sources, and ultimately extend the opportunities to broaden knowledge about learner interactions during instructional events (D'Mello, 2013; Lee, 2013).

Combined analysis using data from multiple sources, such as location, time, and interactions among learners during a specific lesson, can be conducted to identify social and relational connections among peers. These new approaches are intended to create a more realistic understanding of learners within their physical environmental context (Eagle & Pentland, 2006). Analytical methods that accommodate large volumes of data, such as clustering learners by types of content interaction, result in new, more accurate predictive models accounting for variances within and between group achievement (Cerezo, Sánchez-Santillán, Paule-Ruiz & Núñez, 2016).

What is Multimodal Learning Analytics?

More recently, technology has opened avenues to enable learning analytics approaches to capture more comprehensive data on learners than educators have been able to gather in the past (Blikstein, 2013). This progress has sparked a new sub-field within learning research, often referred to as multimodal learning analytics. Multimodal learning analytics involves gathering and analyzing data that educators or conference leaders ordinarily would not be able to gather due to its collection either being too time-consuming or potentially even impossible for a single person to gather and examine. Blikstein & Worsley (2016) determine that these "techniques could yield novel methods that generate distinctive insights into what happens when students create unique solution paths to problems, interact with peers, and act in both the physical and digital worlds" (p. 222).

With multimodal learning analytics, researchers could combine insights on learners' text production, speech, handwriting, movements, posture, gestures, eye gaze, and/or affective state (Blikstein & Worsley, 2016). As one likely can surmise, this range of data is too extensive for an individual to collect while also teaching and assisting participants, especially during activities where learners engage in self-guided movement and exploration (Worsley, 2012). While the body of knowledge continues to grow in the field of multimodal learning analytics, in both the insights driven from this research, the data, and technology to conduct the analysis, understanding learner behavior is an active area of continued exploration (Ochoa, 2017).

Combining non-traditional forms of learner data has shown promise through the application of multimodal learning analytics, with significant results in both measuring and comparing behavior related to student learning strategies using data collected on speech, gesture, and electro-dermal activation (Worsley & Blikstein, 2015). Additionally, video data on social actions has been used to catalog and measure participants' observations to identify and measure behavior (Andrade, Delandshere & Danish, 2016). More recently, incorporation of spatial movement data in combination with existing traditional multimodal learning analytic sources has enabled researchers with the capacity to continue exploring research related to cognitive learning patterns among students (Schneider & Blikstein, 2015).

Related Work

Spatio-temporal data analysis has been utilized in a wide range of scientific domains focusing on understanding behavior (Dobra,, Williams, & Eagle, 2015; Versichele, Neutens, Delafontaine & Van de Weghe, 2012; Cao, Wang, Hwang, Padmanabhan, Zhang & Soltani, 2015). Engineering research has used this type of data to understand occupant movement throughout office facilities which has led to advancements in energy system design for improved building energy performance (Salimi, Liu, & Hammad, 2019). Ecologists have utilized data collected from animal tracking devices to understand migratory patterns in human-dominated landscapes to inform conservation or wildlife management (Oriol-Cotterill, Macdonald, Valeix, Ekwanga & Frank 2015), and urban planners have leveraged vehicle movement data to inform the design of more efficient road infrastructure planning (Hasan, Schneider, Ukkusuri, & González, 2013). Through advancements of tracking technology, a wealth of new, highly accurate data has paved the way for movement behavioral analysis in both micro and macro contexts (Worsley, 2014), leading to the educational research community now recognizing new opportunities in understanding learner learning behavior within learning contexts.

One area of interest that has emerged among researchers reviewing data on constructivist learning environments is the participants' physical locations during collaborative or exploratory activities. Recently, researchers have endeavored to use temporal spatial data to infer participants' membership within groups, the location of groups within learning spaces, and the degree of dispersal between group members (Ortiz-Vasquez et al., 2017). In a separate study, researchers assessed if the style of furniture present in a learning space altered the behaviors of individuals during collaborative tasks, with the findings suggesting that seated arrangements led to more time spent working in groups than standing-height furniture (Healion et al., 2017).

Recent studies examining the implication of indoor positioning systems revealed several practical implementations of the technology, such as replacing existing tracking systems to reduce research costs or enhancing existing products to improve capabilities (Luimula & Skarli 2014; Huo, Wang, Paredes, Villanueva, Cao & Ramani 2018). Modern indoor positioning systems, like the *Quuppa Intelligent Locating System™* (https://quuppa.com/), combine an array of trackers fixed throughout a room with wearable smart tags to monitor movement. Low Energy Bluetooth technology contained in these systems have been found to be a highly reliable alternative for tracking natural movement when compared to conventional, more laborious, methods (Colino, Garcia-Unanue, Sanchez-Sanchez, Calvo-Monera, Leon, Carvalho, ... & Navandar, 2019). Experimental learning spaces, such as the Smith Learning Center Theater at the Gottesman Libraries at Teachers College, Columbia University, incorporate these systems in their infrastructure to support research activities (Lan, Chae, Nantwi & Natriello, 2019). However, these systems appear to be a rarity in education beyond cutting-edge learning environments.

Tracking physical movements of students in learning environments has led to greater insights into what is happening in the classroom with hope to improve affordances and supports related to group work (Healion, Russell, Cukurova & Spikol, 2017) by uncovering with features of collaborative student group work are predictive of team success (Spikol, Ruffaldi, Landolfi & Cukurova, 2017). While there is continued interest in this type of learning analytics, there exists a substantial gap of knowledge in this area of multimodal learning analytics, with some researchers declaring a call to action for improved analysis of temporal data within educational learning systems (Knight, Wise & Chen, 2017; Lan, Chae, Nantwi & Natriello, 2019).

Methods

Research supports that temporal spatial data is one area of learning analytics research that presents new opportunities for understanding how individuals interact within educational or collaborative settings. While there is evidence to support this claim, this field is still in its infancy, presenting us the opportunity to contribute to the body of knowledge by analyzing spatio-temporal data in new contexts. Based on this rationale, we were interested in understanding if there are any significant differences between group spatio-temporal data when collected during a collaborative workshop. In this paper, we seek to answer the following questions:

> **RQ1:** Are there any significant differences between groups in team composition in terms of participant distances?

RQ2: Are there any significant differences in team composition during different structured or unstructured events throughout the day?

We hope that by conducting this analysis, we can support the inclusion of temporal spatial data within future learning analytics research by showing that there are significant differences in physical movement data collected on participants during a collaborative workshop. While this analysis does not include any additional learning data to measure the impact or importance this distance has on participant performance, we hope that our results can still provide evidence to support the rationale for future research conducted within the multimodal learning analytics domain.

Data Preparation

Spatial data used for this analysis was collected during a National Science Foundation (NSF) funded Education Data Analytics Collaborative Workshop hosted at the collaborative learning space within the Smith Learning Center - Teachers College, Columbia University (NSF, 2019). The purpose of this two-day workshop was to bring together educators and administrators from the Nassau County, Long Island New York Board of Cooperative Educational Services (BOCES) and educational technology industry data scientists with the goal to better understand the needs around education data, with the final outcome of the workshop consisting of a data sprint and visualization prototype built using BOCES real-world education data.

The workshop consisted of a total of 72 participants, who were designated the specific roles of Educator/Teacher, Administrator or Data Scientist based on their work experience. The participants were then split into 11 smaller teams, with each team consisting of at least one participant representing each role. Teams were then provided the same de-identified sample dataset extracted from the BOCES educational data warehouse and presented with a challenge to work collaboratively as a team to build visualizations and educational data dashboards that best address the needs of the many audiences within the educational system. The table below provides a description of the participant team assignments.

Table 6.1: Team Roles and Team Size

Team Name	**Participant Role**				
	Administrator	Data Scientist	Educator	Staff	**Total**
Arrow	2	3	1	1	**7**
Chevron	1	3	2	1	**7**
Circle	2	2	1	1	**6**
Cube	2	1	0	1	**4**
Cylinder	2	3	1	1	**7**
Diamond	1	2	2	1	**6**
Hexagon	1	3	3	0	**7**
Pentagon	2	1	3	1	**7**
Square	1	1	4	1	**7**
Star	1	2	2	2	**7**
Triangle	1	3	2	1	**7**
Total	**16**	**24**	**21**	**11**	**72**

Movement position data was collected in the form of x and y coordinate JSON log files using Bluetooth tracking devices (Quuppa) that participants were asked to wear throughout the duration of the second workshop day (NSF, 2019). These devices reported the current participants' position within the workshop space at regular intervals, with an accuracy of 0.1 meters. The initial number of records collected throughout the day totaled 3,372,372 movement observations, with the first observation occurring at 08:18:39 AM and the last recorded observation of the day occurring at 04:13:31 PM. The image below provides a sequence of the participant movement within each hour over time. A link to the full sequences can be found under the image, highlight participant (at varying speeds) using all available observations.

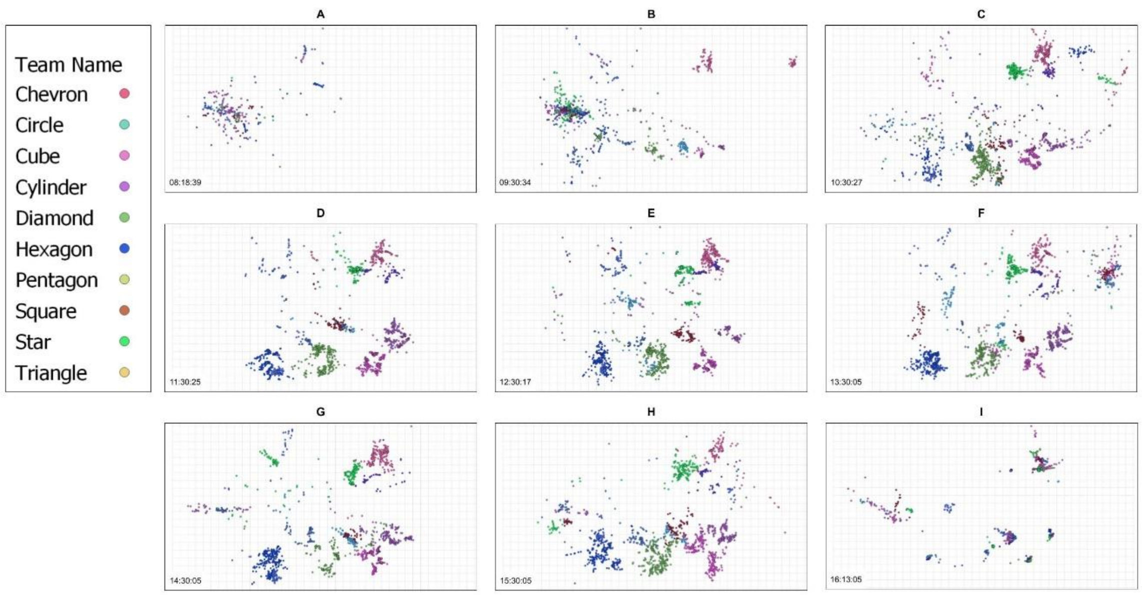

Figure 6.1: Sequence of Participant Movement.
Animated Figure:
Participant Movement (Fast Speed) https://youtu.be/sOC-dTOASgw
Participant Movement (Medium Speed) https://youtu.be/-iqKlRmA0Xo
Participant Movement (Slow Speed) https://youtu.be/h1ZwzRHKzL4

Throughout the workshop event, participants were asked to contribute to various activities related to the data sprint initiative. These activities were then classified into two categories: structured and unstructured events. Structured events consisted of activities where participants were asked to accomplish a defined goal involving close interactions with their team members. Unstructured events are classified as activities that did not involve a specified goal, where participants were given free roam of the workshop, allowing them to interact with other teams. The overall schedule and event category assignment for the day is found in the table below.

Table 2: Schedule and Event Category Assignment for the Day

Start Time	End Time	Event	Event Category
8:00:00 AM	9:15:00 AM	Registration	unstructured
9:15:00 AM	10:00:00 AM	Pre-event activities	unstructured
10:00:00 AM	10:45:00 AM	Dashboard Expo	unstructured
10:45:00 AM	11:00:00 AM	Introduction of datasets	structured
11:00:00 AM	11:15:00 AM	Discussion of Thursday (Day 1) data use priority questions	structured

11:15:00 AM	12:00:00 PM	Datasprint working session	structured
12:00:00 PM	1:00:00 PM	Working Lunch (Lunch provided)	unstructured
1:00:00 PM	1:15:00 PM	Quick break for work, life, and email checks	unstructured
1:15:00 PM	2:15:00 PM	Datasprint continues	structured
2:15:00 PM	2:30:00 PM	Coffee break	unstructured
2:30:00 PM	3:45:00 PM	Final shared discussion and viewing of data sprint	structured
3:45:00 PM	4:15:00 PM	Conclusion and next steps	structured

To understand if there were any significant differences in how teams functioned throughout the day, we first calculated a moving centroid between all members of a team within each minute time block. Calculating a centroid within each time block, as opposed to identifying a centroid based on the location of the teams assigned work table location enabled us to account for any collective movement that may have occurred throughout the day. For example, during the scheduled lunch hour, we will be able to see if participants grouped together, even if they opted to eat at an alternative location within the room. If we limited our analysis to the teams' distances from the work tables, these insights would have been lost. The centroid points were calculated as:

$$C(x,y) = (C_1, C_2) = \left(\frac{1}{n}\sum_{i=1}^{n} x_i, \frac{1}{n}\sum_{i=1}^{n} y_i\right)$$

We then needed to calculate the individual participant distance from each team centroid. This was accomplished by using the Pythagorean Theorem distance formula, a commonly used distance measure used to compute distance between two points of spatial data (Tay, Hsu, Lim, & Yap, 2003). This resulted in a data set containing, at the minute level, an individual participant's location, their team's centroid for that time block, and the participant's distance to that centroid. The last step was to then take an average of the individual participant distance from the team within each minute time block to create the final data for analysis. This was accomplished using the following calculation:

$$d = \frac{1}{n}\sum_{i=1}^{n} \sqrt{(x_i - C_1)^2 + (y_i - C_2)^2}$$

Figure 6.2 below provides an example of this distance calculation in practice.

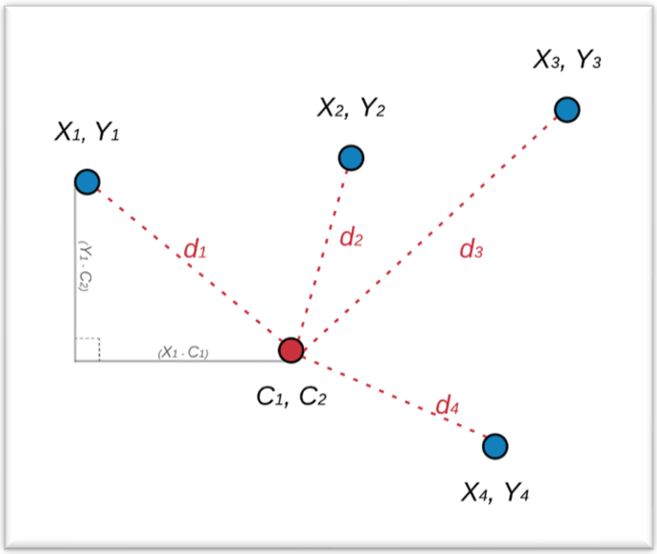

Figure 6.2: Example of distance calculation in practice

The resulting data set contained a minute level time stamp, a category assignment for that specific point in time (categorized as either structured or unstructured), and the average distance for all the team members recorded within that minute time frame, measured in meters. Figure 6.3 shows the average distance from each centroid, for each team over time.

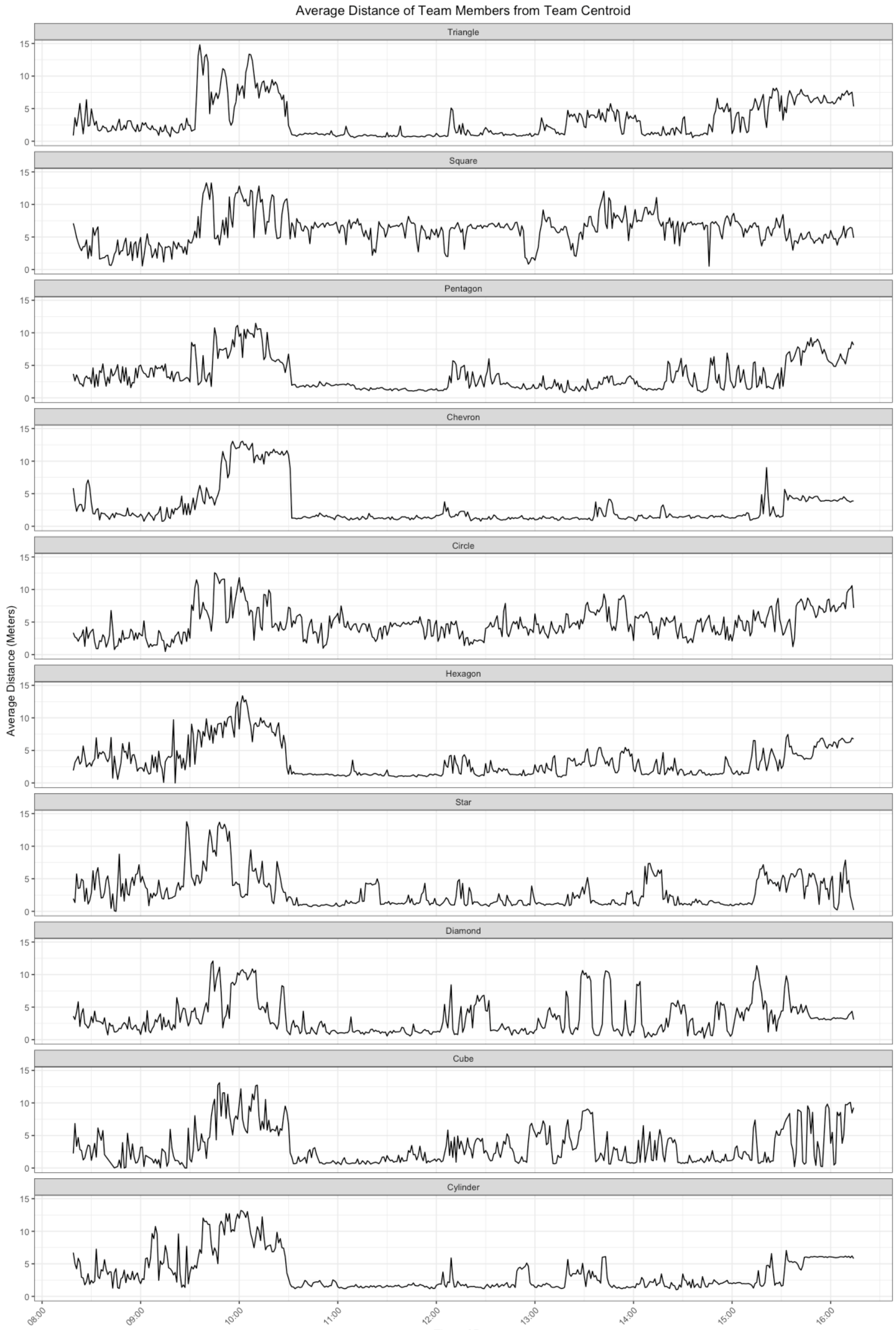

Figure 6.3: Average Distance of Teams within Scheduled Activity

Coleman et al., 2021

Analysis

A factorial design two-way Analysis of Variance (ANOVA) was then conducted on the average distance for each team within each structured or unstructured event. Using an ANOVA, we can test the main effect of each independent variable. In this case, we are testing main effect of team (whether the average distance throughout the day differed based on the subjects' team assignment, ignoring the effects of the event category) and the main effect of the event category (whether distances differed based on the event category, ignoring the effects of subjects' team).

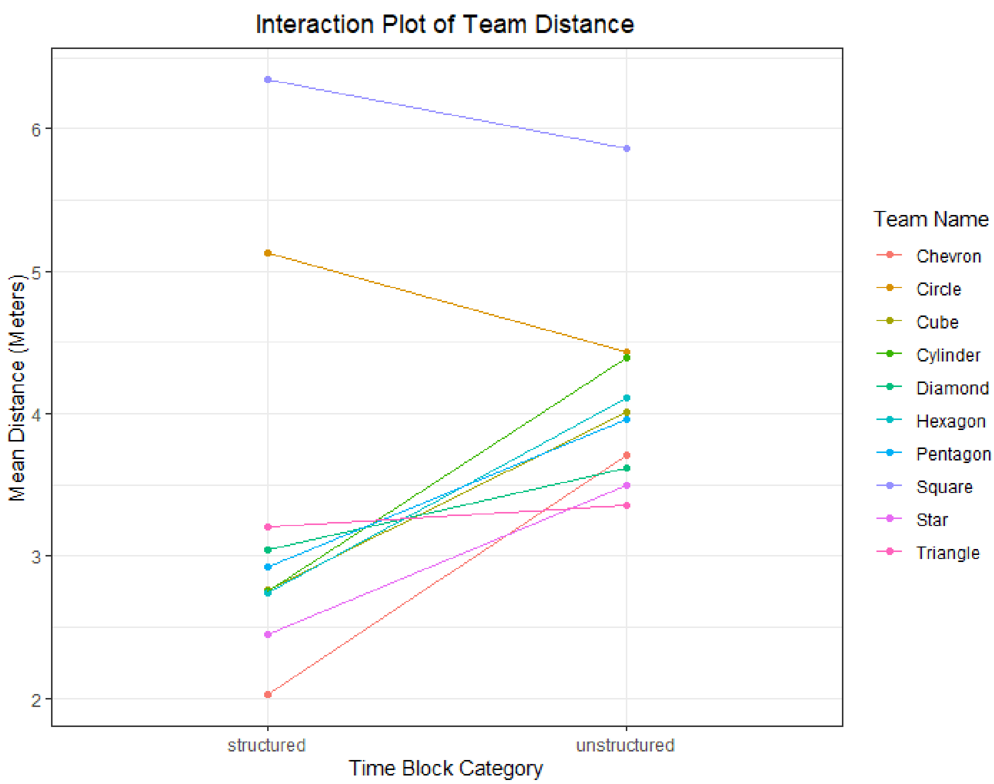

Figure 6.4: Interaction Plot of Team Distances within Activity Category

Specifically, average distances were analyzed with a 2 (Team) x 2 (Event Category) mixed-model ANOVA. The main effect of team assignment on average distance was significant, $F(1,9) = 69.68$, $p < .001$ and the main effect of event category on distances was also significant $F(1,1) = 100.977$, $p < .001$. In order to interpret the interaction of the main effects, a post-hoc pairwise comparison was conducted using Tukey's Honest Significant Test (HSD) to determine where the significance occurred within the ANOVA. We conducted pairwise comparisons on the team, the time block, and the interaction between the team and the time block. The table below shows the findings of the team pairwise comparisons.

Results (Appendix Table 1) of the pairwise team comparison found significant differences between multiple team group pairs. Team Chevron showed a significant difference in team member distance between five other teams: Circle, Cylinder, Hexagon, Pentagon and Square ($p < 0.05$). Circle pairwise comparisons found differences in distance between all other teams in the analysis ($p < 0.05$). Cube showed one significant difference in distance with team Square ($p < 0.05$), Cylinder showing a significant difference in distances between teams Square and Star ($p < 0.05$), Diamond showing a significant differences in distance between team Square ($p < 05$), Hexagon showing a significant difference in distances between team Square ($p < 0.05$), Pentagon showing a significant difference with team Square ($p < 0.05$), and Square showing significant differences in distances between teams Star and Triangle ($p < 0.05$). The Tukey HSD test (Appendix Table 2) showed that the effects of the structured and unstructured activity categories differed significantly in average team distance ($p < 0.05$).

Discussion

One particularly interesting finding from our results was the behavior of two teams, Square and Circle, when comparing distances between structured and unstructured event categories. While all the other teams in the workshop showed the expected behavior of spreading out during unstructured activities and coming closer together during structured activities, the Square and Circle teams had the opposite behavior, with their participant distance actually shrinking during unstructured events and spreading out further during structured events. While our data does not enable us to understand the reason for this behavior, it presents an interesting opportunity for future multimodal data analysis to see if this type of behavior impacts the performance of the participants and their ability to meet any of the objectives defined during the workshop.

Limitations

Our analysis encountered several limitations. Due to technical issues encountered during the workshop, 12 participants did not have matching records for their tracking devices, leading them to not have any reported location data. This was likely caused by the tracking devices not being charged or turned on during the workshop. The impact of this issue was significant to team Arrow, which had 5 of their 7 members not report any data, requiring us to remove this team completely from the analysis. The rest of the missing devices were evenly distributed across the other teams, with Square and Diamond missing data from 2 devices, and Chevron, Cube, and Star only missing one device within their team. This issue further reduced our study sample down to 60 total participants, spread across 10 total teams.

Additionally, the technological instruments utilized within this analysis collected data in an inconsistent fashion, with some of the participant devices reporting back several location observations within a single second, while others may have only recorded data twice within a minute. To address this inconsistency, we reduced the granularity of the data by taking the timestamps recorded in the log file and then rounding them to the nearest minute. We then averaged the x and y position data within each minute for each participant, reducing the initial number of records collected throughout the day from 3,372,372 millisecond level observations to 4,760-minute level average position observations.

Lastly, our analysis excludes any factors that could be used to measure participant performance throughout the workshop. Initially, we experimented with including participant voting data as the participants were asked to vote on which visualization they liked the most by placing their movement tracker on the table of the team they wanted to vote for, but due to the aforementioned technical issues we encountered during the data collection, the sample size became too small to determine any significant differences in voting patterns or correlations between distance and vote.

Conclusion and Future Work

In summation, this analysis reveals the opportunities of spatio-temporal data analysis in determining difference of in team interactions within a collaborative workshop context. Given that this analysis focused on analyzing a single data source (movement data), we are limited in our capacity to conduct any meaningful causal analysis on what occurred during these interactions, as we are lacking additional data needed to extract these insights, these findings support the need for continued research. Future analysis could be improved by the inclusion of audio recorder devices to determine team sentiment (Worsley, 2012), or by creating an assessment to determine the impact that team closeness has on the overall performance of the participants during the workshop (Cerezo, Sánchez-Santillán, Paule-Ruiz & Núñez, 2016). Improving awareness of if or how learners communicate with one another can be used to evaluate the efficacy of group projects of other collaborative work, especially in formal education settings.

Within the field of K-12 education, utilizing data garnered from multimodal approaches to learning analytics will present new opportunities for analysis. Evidence-based understanding of student/learner interactions can greatly impact how educators and administrators establish designs and practices for classrooms (Healion et al., 2017; Ortiz-Vasquez et al., 2017). Armed with this data, administrators, educators, and other school stakeholders may be able to make more informed decisions than they used to make when they were limited to common forms of data such as exam scores, attendance data, and observable behavior to understand learners-- which supports the notion of continued close work between data scientists and educational institutions (Agasisti & Bowers, 2017). Further, educational policymakers will be able to develop better plans for management of educational institutions on a larger scale, such as on a district, state, or national level (Bowers et al., 2019). Regional policies that are grounded in data analysis can unite many schools to incorporate research-based educational initiatives into their classrooms.

Although most applicable to classroom or collaborative learning environments (Healion et al., 2017), the same approaches soon may be applied to informal learning spaces, such as libraries, museums, and after-school centers (Ortiz-Vasquez et al., 2017). When implemented in these settings, multimodal approaches to learning analytics can impact learners of all ages.

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Appendix A: Results of Tukey HSD Team Pairwise Comparisons

Table 3: Results of Team Pairwise Comparisons

Contrast	Estimate	SE	T Ratio	P Value
Chevron - Circle	-1.919	0.167	-11.456	**<.001**
Chevron - Cube	-0.524	0.169	-3.096	0.061
Chevron - Cylinder	-0.708	0.167	-4.228	**0.001**
Chevron - Diamond	-0.467	0.167	-2.785	0.142
Chevron - Hexagon	-0.562	0.168	-3.352	**0.028**
Chevron - Pentagon	-0.578	0.167	-3.448	**0.020**
Chevron - Square	-3.241	0.167	-19.350	**<.001**
Chevron - Star	-0.112	0.168	-0.668	1.000
Chevron - Triangle	-0.415	0.167	-2.477	0.281
Circle - Cube	1.395	0.169	8.244	**<.001**
Circle - Cylinder	1.211	0.167	7.227	**<.001**
Circle - Diamond	1.452	0.167	8.671	**<.001**
Circle - Hexagon	1.357	0.168	8.092	**<.001**
Circle - Pentagon	1.341	0.167	8.008	**<.001**
Circle - Square	-1.322	0.167	-7.894	**<.001**
Circle - Star	1.807	0.168	10.781	**<.001**
Circle - Triangle	1.504	0.167	8.979	**<.001**
Cube - Cylinder	-0.184	0.169	-1.090	0.986
Cube - Diamond	0.057	0.169	0.339	1.000
Cube - Hexagon	-0.038	0.169	-0.226	1.000
Cube - Pentagon	-0.054	0.169	-0.317	1.000
Cube - Square	-2.717	0.169	-16.058	**<.001**
Cube - Star	0.412	0.169	2.432	0.307
Cube - Triangle	0.109	0.169	0.644	1.000
Cylinder - Diamond	0.242	0.167	1.443	0.914
Cylinder - Hexagon	0.146	0.168	0.872	0.997
Cylinder - Pentagon	0.131	0.167	0.781	0.999
Cylinder - Square	-2.533	0.167	-15.122	**<.001**
Cylinder - Star	0.596	0.168	3.558	**0.014**
Cylinder - Triangle	0.293	0.167	1.751	0.766
Diamond - Hexagon	-0.096	0.168	-0.570	1.000
Diamond - Pentagon	-0.111	0.167	-0.663	1.000
Diamond - Square	-2.775	0.167	-16.565	**<.001**
Diamond - Star	0.354	0.168	2.115	0.517
Diamond - Triangle	0.052	0.167	0.308	1.000
Hexagon - Pentagon	-0.015	0.168	-0.092	1.000
Hexagon - Square	-2.679	0.168	-15.978	**<.001**
Hexagon - Star	0.450	0.168	2.682	0.181

Hexagon - Triangle	0.147	0.168	0.877	0.997
Pentagon - Square	-2.664	0.167	-15.902	**<.001**
Pentagon - Star	0.465	0.168	2.778	0.144
Pentagon - Triangle	0.163	0.167	0.971	0.994
Square - Star	3.129	0.168	18.671	**<.001**
Square - Triangle	2.826	0.167	16.873	**<.001**
Star - Triangle	-0.303	0.168	-1.807	0.731

Appendix B: Results of Tukey HSD Time Block Pairwise Comparisons

Table 4: Results of Time Block pairwise comparisons

Contrast	**Estimate**	**SE**	**T Ratio**	**P Value**
Structured - Unstructured	-0.757	0.075	-10.078	**<.001**

Appendix C: Code for Analysis

Function to Clean Quuppa JSON Log Files

```
###### Load Dependencies
library(jsonlite)
library(lubridate)
library(dplyr)
library(tidyr)
library(stringr)
library(rgl)

options(scipen = 999) # Disable scientific notation

#######################
### function parse JSON
#######################
# Description:

# cleaning function to load all Quuppa log files stored in a supplied
folder
# location. The function allows for two arguments, the first is the
path to the
# folder, and the second is the time interval. Quuppa data is measured
at the
# milisecond level, the time interval argument rounds the time stamp to
a
# specified intervale and only retains the first record within that
time unique
# time stamp. This can greatly reduce the data size over long periods
of time.
# The time interval value is appended to the csv file produces by the
function.

# Possible time interval options avilable are:
# clean_quuppa_data(x, ".5s")
# clean_quuppa_data(x, "sec")
# clean_quuppa_data(x, "second")
# clean_quuppa_data(x, "minute")
# clean_quuppa_data(x, "5 mins")
# clean_quuppa_data(x, "hour")
# clean_quuppa_data(x, "2 hours")
# clean_quuppa_data(x, "day")
# clean_quuppa_data(x, "week")
# clean_quuppa_data(x, "month")
# clean_quuppa_data(x, "bimonth")
# clean_quuppa_data(x, "quarter") == clean_quuppa_data(x, "3 months")
# clean_quuppa_data(x, "halfyear")
# clean_quuppa_data(x, "year")

# Example of use: Parses all files in path to one second intervals and
stores as
# unified csv in Quuppa folder.

# quuppa_path <- "/Users/chad/Documents/Quuppa"
```

```
# clean_quuppa_data(quuppa_path, "second")

# Expected output:
/Users/chad/Documents/Quuppa/cleaned_quuppa_second_time_interval.csv

clean_quuppa_data <- function(quuppa_directory, time_intervals){
  files <- list.files(quuppa_path, pattern = '.log')
  total <- length(files)
  pb <- txtProgressBar(min = 0, max = total, style = 3)
  quuppa_df <- data.frame() # create an empty list
  for (i in 1:total) {
    print(paste("Parsing file:", files[[i]]))
    raw <- readLines(paste0(quuppa_path, "/", files[[i]])) # read log
file
    raw <- raw[-(1:4)] # ignore first 4 lines of log file
    json <- grep("^/\\* [0-9]* \\*/", raw, value = TRUE, invert = TRUE)
# get rid of the "/* 0 */" lines
    n <- length(json)
    json[-n] <- gsub("^}$", "},", json[-n]) # add missing comma after }
    json <- c("[", json, "]") # add brakets at the beginning and end
    df <- fromJSON(json)
    df$date <- as_datetime(df$positionTS/1000, tz="EST") # convert unix
epoch time to datetime
    df$date <- round_date(df$date, time_intervals) # Round to 5 second
intervals
    df$date <- format(df$date, format='%Y-%m-%d %H:%M:%S') # specify
formate
    df$position <- gsub("\\c|\\(|\\)", "", df$position) # remove
unwanted characters from position field
    df$smoothedPosition <- gsub("\\c|\\(|\\)", "", df$smoothedPosition)
# remove unwanted characters from position field

    df <- df %>%
      separate(position, c("X", "Y", "Z"), ",") %>% # split position
coordinates to seperate columns
      separate(smoothedPosition, c("sX", "sY", "sZ"), ",") # split
position coordinates to seperate columns

    df$X <- as.numeric(df$X) # convert to numeric
    df$Y <- as.numeric(df$Y) # convert to numeric
    df$sX <- as.numeric(df$sX) # convert to numeric
    df$sY <- as.numeric(df$sY) # convert to numeric

    df <- df %>%
       select(name, X, Y, sX, sY, date) # drop unwanted columns

    quuppa_df  <- rbind(quuppa_df,df) # append data to final frame
    Sys.sleep(0.1)
    # update progress bar
    setTxtProgressBar(pb, i)}
  close(pb)
  write.csv(quuppa_df, # write final frame to csv
            paste0(quuppa_directory, "/cleaned_quuppa_",
time_intervals, "_time_intervals.csv"), row.names = FALSE)
  print(paste0("Saving data to: ", quuppa_directory,
"/cleaned_quuppa_", time_intervals, "_time_interval.csv"))
}
```

Calculate Centroid and Team Member Distance by Time Point

```
library(lubridate)
library(dplyr)

distance_data <- data.frame() # create an empty list
teams <- unique(as.character(df$Team)) # create list of teams
dates <- unique(df$date_by_minute) # create list of time stamps

for (j in dates){
  for (i in teams){
    timeframe <- j
    team_name <- i
    df2 <- df %>%
      filter(date_by_minute == j)
    df2 <- df2 %>%
      filter(Team == i)
    m <- cbind(df2$sX, df2$sY)
    cnt <- c(mean(m[,1]),mean(m[,2]))
    mean_distance <- mean(apply(m,1,function(x,cnt) {(sqrt((x[1] -
cnt[1])^2+(x[2]-cnt[2])^2))},cnt))
    cnt <- as.data.frame(cnt)
    x_center <- cnt[1,]
    y_center <- cnt[2,]
    distance_data  <- rbind(distance_data, data.frame(team_name,
timeframe, x_center, y_center, mean_distance))
  }
}

distance_data$timeframe <- as_datetime(distance_data$timeframe,
tz="EST") # specify formate
distance_data$timeframe <- as.POSIXct(paste(distance_data$timeframe),
format = "%Y-%m-%d %H:%M:%S", tz = "EST")
```

Plot Figures and Images

```
library(scales)
library(ggplot2)
library(gganimate)
library(magick)
library(tidyverse)
library(lubridate)
library(RColorBrewer)

### Load Cleaned Data

df <- read.csv("...\\cleaned_quuppa_1s_time_intervals.csv") # Load
cleaned time
attendees <- read.csv("...\\NSF Education Data.csv") # load participant
data

### Gather PII Boolean into groups
pii <- attendees %>%
  mutate(Quupa.ID = ï..Quupa.ID) %>%
```

```
  select(Quupa.ID, Team, Educator, Teacher, Building.Administrator,
District..Administrator, BOCES..Staff, Data.Scientist) %>%
  gather(Type,j,-Quupa.ID, -Team) %>%
  filter(j==1) %>%
  select(-j)

# specify formats
df$date <- as.POSIXct(paste(df$date), format = "%Y-%m-%d %H:%M:%S", tz
= "EST")
pii$Quupa.ID <- as.character(pii$Quupa.ID)
df$name <- as.character(df$name)

### Merge PII to DF
df <- inner_join(df, pii, c("name" = "Quupa.ID"))

df1 <- df %>%
  group_by(name, Team, Type, date) %>%
  summarise(X = round(mean(X),2),
            Y = round(mean(Y),2),
            sX = round(mean(sX),2),
            sY = round(mean(sY),2)) %>%
  arrange(date) %>%
  mutate(Group = if_else(Type == 'Educator' | Type == 'Teacher',
'Educator', 'Other'))

df1$date_by_minute <- round_date(df1$date, 'minute')

distance_data <- data.frame() # create an empty list
teams <- unique(as.character(df1$Team))
dates <- unique(df1$date_by_minute)

for (j in dates){
  for (i in teams){
    timeframe <- j
    team_name <- i
    df2 <- df1 %>%
      filter(date_by_minute == j)
    df2 <- df2 %>%
      filter(Team == i)
    m <- cbind(df2$sX, df2$sY)
    cnt <- c(mean(m[,1]),mean(m[,2]))
    mean_distance <- mean(apply(m,1,function(x,cnt) {(sqrt((x[1] -
cnt[1])^2+(x[2]-cnt[2])^2))},cnt))
    cnt <- as.data.frame(cnt)
    x_center <- cnt[1,]
    y_center <- cnt[2,]
    distance_data  <- rbind(distance_data, data.frame(team_name,
timeframe, x_center, y_center, mean_distance))
  }
}

distance_data$timeframe <- as_datetime(distance_data$timeframe,
tz="EST") # specify formate
distance_data$timeframe <- as.POSIXct(paste(distance_data$timeframe),
format = "%Y-%m-%d %H:%M:%S", tz = "EST")

distance_data <- distance_data %>%
```

```
  filter(team_name != 'Arrow') # Drop arrow fram data due to high
missing >=5

# write_csv(distance_data, 'team_distance_data_by_minute.csv')

#### Static Plot

p <- ggplot(distance_data[!is.na(distance_data$mean_distance),],
aes(timeframe, mean_distance, group = team_name, color = team_name)) +
  geom_line() +
  scale_color_viridis_d() +
  labs(title = 'Average Distance of Team Members from Team Centroid',
       x = "Time of Day",
       y = "Average Distance (Meters)") +
  facet_wrap(~team_name, nrow = 11) +
  theme_bw() +
  theme(plot.title = element_text(hjust = 0.5),
        legend.position = "none",
        axis.text.x = element_text(angle = 45, hjust = 1))

p <- p + scale_x_datetime(labels = date_format("%H:%M", tz = 'EST'),
                          date_breaks = "1 hours")
# Plot Figure
p

########### Animated Line Plot

library(ggplot2)
library(gganimate)
library(hrbrthemes)

plotData <- distance_data[!is.na(distance_data$mean_distance),]
plotData$hourTime <-round_date(round_date(plotData$timeframe, '15
mins')) # Round time stamp to 15 minute intervals

plotData2 <- plotData %>%
  group_by(team_name, hourTime) %>%
  summarise(averageMeanDistance = mean(mean_distance))

# Line Plot
plot <- plotData2 %>%
  ggplot(aes(hourTime, averageMeanDistance, group = team_name, color =
team_name)) +
  geom_line() +
  geom_point() +
  scale_color_viridis_d() +
  ggtitle('Average Distance of Team Members from \n Team Centroid Over
Time') +
  theme_ipsum() +
  ylab("Average Distance (Meters)") +
  xlab("Time of Day") +
  labs(color='Team Name') +
  theme(plot.title = element_text(hjust = 0.5),
        legend.position = "right",
        axis.text.x = element_text(angle = 45, hjust = 1)) +
  scale_x_datetime(labels = date_format("%H:%M", tz = 'EST'),
date_breaks = "30 mins") +
```

```
  transition_reveal(hourTime)

animate(plot, fps = 10, width = 800, height = 600) # Plot Figure

# Save at gif:
anim_save("line_plot.gif")

# Animated Bar Plot

plotData3 <- plotData2 %>%
  group_by(hourTime) %>%
  mutate(max.value = max(averageMeanDistance)) %>%
  ungroup() %>%
  mutate(text = case_when(hourTime == '2019-12-06 08:15:00' ~ "8:00 AM
- 9:15 AM \n Registration",
                         hourTime == '2019-12-06 08:30:00' ~ "8:00 AM
- 9:15 AM \n Registration",
                         hourTime == '2019-12-06 08:45:00' ~ "8:00 AM
- 9:15 AM \n Registration",
                         hourTime == '2019-12-06 09:00:00' ~ "8:00 AM
- 9:15 AM \n Registration",
                         hourTime == '2019-12-06 09:15:00' ~ "8:00 AM
- 9:15 AM \n Registration",
                         hourTime == '2019-12-06 09:30:00' ~ "9:15 AM
- 10:00 AM \n Pre-event activities",
                         hourTime == '2019-12-06 09:45:00' ~ "9:15 AM
- 10:00 AM \n Pre-event activities",
                         hourTime == '2019-12-06 10:00:00' ~ "9:15 AM
- 10:00 AM \n Pre-event activities",
                         hourTime == '2019-12-06 10:15:00' ~ "10:00 AM
- 10:45 AM \n Dashboard Expo",
                         hourTime == '2019-12-06 10:30:00' ~ "10:00 AM
- 10:45 AM \n Dashboard Expo",
                         hourTime == '2019-12-06 10:45:00' ~ "10:00 AM
- 10:45 AM \n Dashboard Expo",
                         hourTime == '2019-12-06 11:00:00' ~ "10:45 AM
- 11:00 AM \n Introduction of datasets",
                         hourTime == '2019-12-06 11:15:00' ~ "11:00 AM
- 11:15 AM \n Discussion of Thursday (Day 1) data use priority
questions",
                         hourTime == '2019-12-06 11:30:00' ~ "11:15 AM
- 12:00 PM \n Datasprint working session",
                         hourTime == '2019-12-06 11:45:00' ~ "11:15 AM
- 12:00 PM \n Datasprint working session",
                         hourTime == '2019-12-06 12:00:00' ~ "11:15 AM
- 12:00 PM \n Datasprint working session",
                         hourTime == '2019-12-06 12:15:00' ~ "12:00 PM
- 1:00 PM \n Working Lunch (Lunch provided)",
                         hourTime == '2019-12-06 12:30:00' ~ "12:00 PM
- 1:00 PM \n Working Lunch (Lunch provided)",
                         hourTime == '2019-12-06 12:45:00' ~ "12:00 PM
- 1:00 PM \n Working Lunch (Lunch provided)",
                         hourTime == '2019-12-06 13:00:00' ~ "12:00 PM
- 1:00 PM \n Working Lunch (Lunch provided)",
                         hourTime == '2019-12-06 13:15:00' ~ "1:00 PM
- 1:15 PM \n Quickbreak for work, life, and email checks",
```

```
                          hourTime == '2019-12-06 13:30:00' ~ "1:15 PM
- 2:15 PM \n Datasprint continues",
                          hourTime == '2019-12-06 13:45:00' ~ "1:15 PM
- 2:15 PM \n Datasprint continues",
                          hourTime == '2019-12-06 14:00:00' ~ "1:15 PM
- 2:15 PM \n Datasprint continues",
                          hourTime == '2019-12-06 14:15:00' ~ "1:15 PM
- 2:15 PM \n Datasprint continues",
                          hourTime == '2019-12-06 14:30:00' ~ "2:15 PM
- 2:30 PM \n Coffee break",
                          hourTime == '2019-12-06 14:45:00' ~ "2:30 PM
- 3:45 PM \n Final shared discussion and viewing of data sprint",
                          hourTime == '2019-12-06 15:00:00' ~ "2:30 PM
- 3:45 PM \n Final shared discussion and viewing of data sprint",
                          hourTime == '2019-12-06 15:15:00' ~ "2:30 PM
- 3:45 PM \n Final shared discussion and viewing of data sprint",
                          hourTime == '2019-12-06 15:30:00' ~ "2:30 PM
- 3:45 PM \n Final shared discussion and viewing of data sprint",
                          hourTime == '2019-12-06 15:45:00' ~ "2:30 PM
- 3:45 PM \n Final shared discussion and viewing of data sprint",
                          hourTime == '2019-12-06 16:00:00' ~ "3:45 PM
- 4:15 PM \n Conclusion and next steps",
                          hourTime == '2019-12-06 16:15:00' ~ "3:45 PM
- 4:15 PM \n Conclusion and next steps",
                          hourTime == '2019-12-06 16:30:00' ~ "3:45 PM
- 4:15  PM \n Conclusion and next steps"))

plotData4 <- plotData3 %>%
  group_by(team_name, text) %>%
  summarise(averageMeanDistance = round(mean(averageMeanDistance), 2),
            hourTime = mean(hourTime)) %>%
  ungroup() %>%
  group_by(text) %>%
  arrange(averageMeanDistance, .by_group = TRUE) %>%
  mutate(ordering = row_number()) %>%
  mutate(max.value = max(averageMeanDistance))


plot2 <- plotData4 %>%
  ggplot(aes(x = ordering, y = averageMeanDistance)) +
  geom_col(aes(fill = team_name)) +
  geom_blank(aes(y = max.value)) +
  #scale_color_viridis_d() +
  ggtitle('Average Distance of Team Members from \n Team Centroid
Within Activity') +
  labs(fill='Team Name') +
  geom_text(aes(y = max.value / 2, label = text), x = -1, check_overlap
= TRUE) +
  coord_flip(clip = "off") +
  theme_bw() +
  theme(plot.title = element_text(hjust = 0.5),
        legend.position = "right",
        axis.title = element_blank(),
        axis.ticks = element_blank(),
        axis.text  = element_blank(),
        plot.margin = unit(c(1, 1, 8, 1), "cm")) +
```

```
  geom_text(aes(label=as.character(averageMeanDistance)), hjust=1.6,
color="black", size=3.5) +
  transition_states(hourTime, transition_length = 2, state_length = 2)
+
  view_follow(fixed_x = TRUE)

# Plot Figure

animate(plot2, fps = 10, width = 800, height = 400)

# Save at gif:
anim_save("bar_plot.gif")
```

CHAPTER 7

Data Driven Instructional Systems: 2030

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Digital data tools and practices are now ubiquitous in US schools. All public schools collect data on student performance and outcomes and seek to use these data to reflect upon and adjust practices of teaching and learning. Educators are increasingly comfortable using student information systems, learning management systems, computer-adaptive testing and curriculum programs, and digital learning resources in their daily work. Leaders use data from local, state and national data systems to plan, implement and evaluate initiatives and roles. Using digital data systems has become a prerequisite for participation in contemporary schools. Taken together, these digital tools constitute data-driven instructional systems in schools. (Halverson, et. al. 2007)

Data-driven formative feedback in response to failure is a key principle of learning theory. Successful learning depends on receiving clear feedback on authentic attempts at explanation, then trying again with a new hypothesis in an iterative cycle of inquiry (Kapur, 2015). Paul Black and Dylan Wiliam (1998) initially framed effective formative feedback in terms of an oral or written dialogue with learners. In recent years, digital data plays an increasingly important role in providing contextual feedback in learning (Gee 2003). Digital and dialogic data, customized to respond to the activities of learners, has become the prevailing model for how formative feedback can guide learning at scale.

Data-driven decision making tacitly depends on these features of good learning theory in the design of information systems. However, in most school information systems, data are generated *from* the activities of students, but *for* educators and system leaders. In other words, data systems in schools can be formative for the learning of educators but are largely irrelevant to the activities of students. Data collected from student activities provided feedback to learners at the system governance level to guide reforms across the district.

In this chapter, I trace how data systems have become so important in our schools and argue that the role that data will play in our schools is about to undergo a significant expansion. I consider the recent evolution of data-driven instructional systems in schools from the perspective of "who is the learner", or in other words, whose learning is the data constructed to support. In the first stage, guided by NCLB, data systems were constructed to support learning for policy makers, state and district leaders outside the school context (Hamilton, et. al., 2009). In the second stage, guided by ESSA, school principals and teachers became learners in a system that used student outcomes to assess and guide their performance. The next frontier, the third stage, of this evolution will be the integration of student into school data-driven instructional systems. In the early stages, federal accountability policies and market forced sparked the creation of systems were student data were used to support learning for system leaders and educations.

I will argue that in the third stage, new movements such as personalized learning will push schools to embrace a new range of student-centered data practices for teaching and learning. By 2030, data-driven instructional systems in schools will continue to evolve through hybrid practices and technologies that will allow policy makers, school leaders, educators, and now students to access and use information that not only documents overall educational quality but also supports the day-to-day practices of their learning.

Stage 0: Data-Driven Instructional System Pre-NCLB

Digital data systems have revolutionized 21st century schools. It is sometimes hard to see just how significant this recent transformation has been. 20th century schools dealt with data driven decision making in entirely different ways. Famously characterized as loosely-coupled systems, 20th century teachers taught largely how and what they wanted to teach with little interference except when their classroom control broke down. The role of school leaders was to control access to who got into schools (admissions and hiring) and created a safe and responsive school environment around classrooms (Halverson & Kelley, 2017). Teachers were largely responsible for improving the quality of their own work through their choices of professional development.

Of course, 20th century educators always collected data related to their work, but, for the most part, these data were collected locally, stored in files and in gradebooks, with limited ability to share. Teachers built lo-tech systems that assembled information on student work to assign grades; leaders developed similar systems to collect grades into transcripts. School office staff often developed rudimentary financial and administrative tools, often designed around Excel sheets, that tracked relevant transactions. While district and state level offices began to invest in more more complex digital finance and planning technologies, local educators had to rely on analog systems to guide their work.

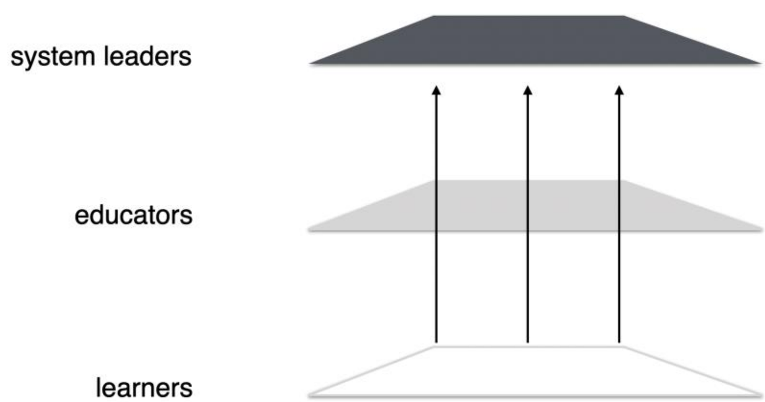

Figure 7.1: *In the NCLB era, data transfers from the student level to the system leader level*

Stage 1: Data Systems in the early NCLB Era (Figure 7.1)

The landscape of data-driven instructional practices shifted with the No Child Left Behind Act of 2002. NCLB required all public schools to use the results of student standardized tests to assess school quality. Disaggregated test scores that demonstrated gaps in achievement outcomes were made public in every state, and schools that could not improve test scores received were designated in need of improvement.

NCLB data systems were intended to support local educators (Hanushek & Raymond, 2001), but were actually designed to support the learning of policymakers, school and district leaders, researchers and community members. In part, this design resulted from the rhythm of standardized testing where students were tested in the fall semester, but the scores did not arrive until the following spring. The untimely reception of the scores meant that educators were always designing to adjust practices that had already happened with students who had already moved on (Stecher, Hamilton & Gonzalez, 2003).

However, district leaders and policy makers learned to use these data to support decisions about school closure and reconstitution and to reallocation of resources. Test score data proved valuable to researchers who learned the value of sharing a common kind of outcome data to support new forms of research at scale. From the community perspective, realtors learned to point homebuyers toward NCLB data to enhance decision making on where to live and local community leaders began to promote their schools with test scores and demographic information (Barnum & LeMee, 2019).

Stage 2: Creating the capacity for educators to learn from data.

The universal press to adjust instructional practice to improve test scores resulted in a number of structural and practical changes in schools (Fuhrman & Elmore, 2004). Even though standardized test scores provided ambiguous information to support specific program improvements, many schools engaged in a variety of reforms to create the capacity for data-driven improvement. Many schools increased instructional time in math and language arts and test preparation time and cut extra-curricular and arts programs (Crocco & Costigan, 2008).

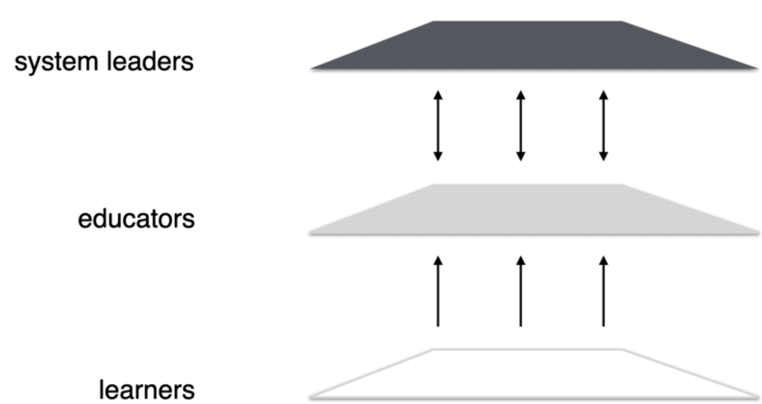

Figure 7.2: *In the ESSA era, schools develop data pathways from students and educators to inform the work of both system leaders and educators*

By 2010, most school systems in the country had now purchased school information systems, school finance systems and were beginning to buy learning management systems, and to design web-based communication platforms (Means, Padilla & Gallagher, 2010). An entire research-industrial complex emerged to designate a list of interventions known to improve test scores across contexts (Burch, 2009). The rush toward data technology purchases created new positions for instructional leadership as technology support shifted from fixing printers to leading data-driven decision-making tools. Schools across the country invested in benchmark assessment systems, such as the ACUITY, MAP and STAR tools, that gave educators immediate feedback on student learning progress. Operationalizing these investments to improve practice called for a new form of literacy for educators who were increasingly expected to make instructional decisions based on outcome measures (Green, et. al. 2015).

The Every Student Succeeds Act of 2015 (ESSA) pushed for test-based accountability for principal and teachers. Schools began to prioritize data to improve teaching by including teachers as data-driven learners (as well as system leaders) (Figure 2). These new data practices invited educators to create data-driven systems to diagnose and address student progress in academics (through Response to Intervention (RtI) strategies) and in behavior (through Positive Behavioral Interventions and Support (PBIS) strategies). These initiatives inducted teachers into the new data process that provided feedback for classroom practices.[2] Teachers are now expected to work with school leaders to generate and use data in continuous improvement cycles (Schildkamp, 2019). These kinds of data are now nearly universally collected and shared by data technologies to facilitate the learning of adults as a new core capacity of schooling.

Stage 3: Integrating students as users into school data practices

As we move forward in the new decade, the frontier for development of data-driven capacity is for students as learners (Figure 3). NCLB and ESSA policies have resulted in data driven instructional systems that give support for teachers, leaders and decision-makers to learn from student demographic, assessment and achievement data. However, the lack of attention for data-driven formative feedback at the student level is an obvious gap in the design of systems that have been developed to assess the practices around student learning, but not to support student learning itself.

[2] Of course, teachers have always been data-driven learners. Teaching is defined by the development and use of low-fi, analog information systems on daily student achievement and interaction, including tools like quizzes, gradebooks, observations and homework. The difference introduced by ESSA was to shift the focus of where teachers get the relevant data from ad hoc, classroom based informal data systems to system-wide technology systems.

Students as learners are left out of much of the contemporary discussion of data-driven practices in schools. Craig Mertler's 2014 ASCD book, for example, defines data-driven educational decision making as a process for educators to examine assessment data to "identify student strengths and deficiencies and apply those findings to their practices" (p. 1). For the first 20 years of the data transformation of schools, students are required to generate the data necessary to guide the work of educators and leaders – but which systems provide data to support the work of learners? Even though policy makers and researchers have not yet fully explored this new area for data-driven instructional support, educators around the world have been experimenting with new practices to include learners in school data practices. Here we will consider how the key practices of personalized learning invite students into the data-driven instructional systems of some schools.

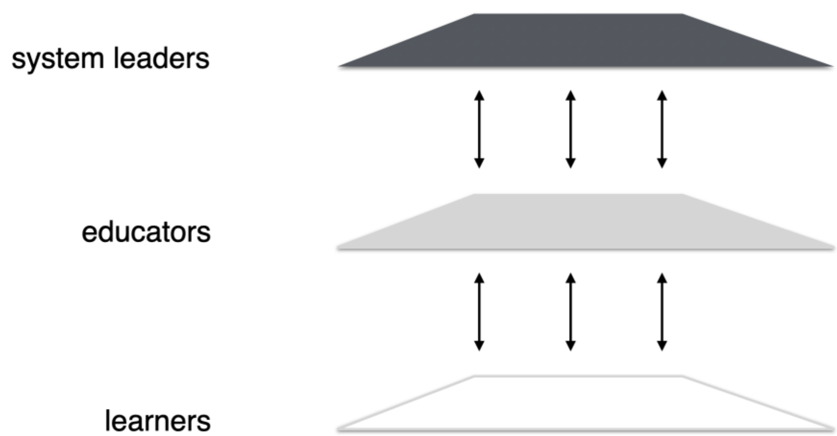

Figure 7.3: *Personalized learning opens up a plane for student interaction in school data systems*

Personalized learning is a collection of schooling practices that place student needs and interests at the heart of the education process (Rickabaugh, 2016). In recent years, personalized learning has emerged as a challenge to traditional models of education that focus on measuring the outcomes of teaching at scale and aggregated measures of achievement. Personalized learning educators bring ideas together from three domains of education practice:

1) traditional education practices such as the individualized education plan (IEP) and differentiation;

2) progressive education practices such as interest- and project-based learning; and

3) new approaches to standards-based instructional practices enabled by data and new media technologies.

Although there are well-defined approaches to personalized learning (e.g. Summit Learning), the variety of components in many programs reflect a more eclectic spirit of grass-roots innovation. Some personalized learning schools focus on technologies and practices designed to improve student test scores, while other schools emphasize community engagement and new media production. In spirit, though, personalized learning educators seem to agree that their approaches

> challenge traditional school designs by moving away from a teacher leading the whole class in a common lesson. Instead, each student can follow an optimal learning path and pace through a mix of instructional methods, including individual- and small-group time with teachers, group projects, and instructional software. (Childress & Benson, 2014 p. 34)

The recent work of my research group has focused on identifying some of the shared features of personalized learning as practiced in American public schools (Halverson, et. al, 2015). Our research involved studying dozens of educators and students at over 20 self-identified personalized learning schools. We found that personalized learning educators work to:

- Create a *culture of agency* in schools by working with students to collaboratively control the pace, place, content, goals and social configuration of learning.

- Engage in *regular, data-driven consultation* with students, centered around teacher-student conferring, to collaboratively develop learning relationships, and assessments.

- Develop unique *socio-technical ecologies* composed of learning management, computer adaptive curriculum and assessment, and new media production tools collected to support local pedagogical priorities.

These kinds of practices open up a plane of authentic student involvement of data-driven instructional practices and likely will change how teachers interact with data as well. (Figure 3).

The socio-technical systems developed to support personalized learning are the foundation for students to become key actors in the school's data-driven instructional system. Developing a culture of agency, for example, invites teachers to co-develop learning plans and assessments with students. Students use learning management tools to select and sequence learning activities and to track their own progress through performance-based assessments. Learning management systems provide a data-rich environment that reshapes teaching practices in response to student choices and cultivates student ability to use the same kinds of resources available to teachers to plan and assess their own learning.

Some schools develop learning management systems on their own out of the ubiquitous Google Classroom GSuite tools. For example, one school in our study built a shared Learner Pathway Google Sheet for each student. This student-curated spreadsheet was used to plan instruction from Kindergarten through 8th grade. It included relevant context standards, a menu of learning activities necessary to meet standards, and links to assessments that allowed learners to demonstrate mastery. The Learner Pathways spreadsheet served as the link between the classroom and parents and came to replace the school report card. Another school developed a customized project management system that allowed students to form groups around shared projects, invited students to choose and document learning standards, and built shared project timelines. The shared timelines became the framework for educators to engage in the projects and to intervene when necessary (Kallio & Halverson, 2020). These learning management systems have successfully created shared data pools for teachers and students to coordinate and evaluate their work in personalized learning schools.

Conferring practices are another area where personalized learning illustrates new possibilities for integrating student voice and choice into school data systems. The conferring practices in personalized learning schools served a variety of functions – they helped educators get to know learner needs and interests, they guided the development and review of learning plans, and they allowed for student demonstration of mastery (Halverson, et. al, 2015). Educators spoke about how conferring helped to build learning relationships with each student through discussing data from a variety of sources. Conferring gives a new student-centered role for data tools such as benchmark assessments. One high school we studied used MAP testing to provide an independent measure of student progress in a computer-adaptive math curriculum. Teachers met regularly with students to use these kinds of data to track learning progress in the Google-based learning management system. Personalized learning conferring practices help schools convert outcomes data into formative information students can use to guide their work.

Personalized learning models are currently in the experimental stage in school districts across the country. The lack of a standard definition of personalized learning reflects a movement in the process of transforming into a collection of interventions as educators and learners test which practices result in better outcomes. My argument is not that all schools should embrace personalized learning, but rather that these cutting-edge schools can open up new possibilities for how to engage students in the data-driven instructional systems that have dominated the recent history of public school innovations.

Conclusion

Like all other institutions, schools moved into the 21st century by implementing technologies to generate and use data for decision-making. I have argued that the initial uses of these technologies in schools was to inform the decision-making of policy makers and system leaders far from the classrooms that generated the data. In the early stages of the accountability movement, the data from these systems was formative for those outside the classroom, but experienced as irrelevant for those closest to the practices of teaching and learning. In the second decade of the 21st century, teachers have been increasingly included into the data-driven instructional systems of schools as the information that guides their practice, through initiatives such as RtI and PBIS, made student demographic and performance data actionable for planning and assessing teaching practices. In the next decade, we will see school data-systems (finally) develop systems to invite students to use system data to guide their own learning. The advent of personalized learning signals are one example of how these new systems might be configured to support student data use. Once students are integrated into school data-driven instructional practices, we can look forward to a new era of instructional practices guided by data-rich formative feedback for leaders, teachers and learners as a promising pathway toward improving outcomes for all students at scale.

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SECTION II

Data Collaborative Workshop Participant Datasprint Team Chapters

CHAPTER 8

Look Who's Talking - Facilitating Data Conversations that Match Data Visualizations with Educators' Needs

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Introduction

As educators, how do we talk about data? More importantly, do educators receive data in a form that is easily digestible and ready to be analyzed in a meaningful way? In some instances, educators access data and need to spend a great deal of time manipulating the data into a form they can make sense of. At other times, data are provided in readily accessible reports and dashboards which are easy to understand but may be missing key data points that would greatly enhance their value. In yet other instances, data are presented in a manner that is fully embraced by educators who rely on such data reports to do their important work in schools. This leads us to another question: *Who creates the data reports for educators and how do those report writers know what the educators need?* In this chapter, I will share my experiences regarding the data conversations that take place between Nassau County educators and those who are responsible for creating the data reports that they

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use. In the context of the NSF Data Collaborative, we now have the opportunity to enrich the nature of these data conversations for the future.

I have a unique perspective to share on this topic as a former public school teacher and administrator for twenty-five years before assuming my current role as supervisor of the Instructional Data Warehouse (IDW) at Nassau BOCES for the past six years. During the two-day NSF Data Collaborative event held at Teachers College, Dr. Bowers prefaced the work we were about to begin in our datasprint teams by highlighting that "this work is *not* about data – it is about *relationships*." Though I have been heavily involved as a partner throughout all phases of this NSF grant with Dr. Bowers over the past four years, and though I knew this to be the impetus for the grant with "Building Community and Capacity" as the first four words in its title, it was not until it was stated so plainly, in this forum, that this really clicked with me. It truly is *not* about the data and *all about relationships*.

Background – What is the IDW?

Before proceeding, it will be useful for the reader to understand what the Nassau BOCES Instructional Data Warehouse is and how it functions. In the context of student data, Nassau BOCES serves as a Regional Information Center (RIC) for fifty-six public school districts in Nassau County on Long Island just to the east of New York City. The public school districts, as required by New York State, submit student data to the Nassau BOCES RIC which in turn loads the data to the New York State Education Department via the Student Information Repository System (SIRS). This collection of data from school districts is known simply as the *Data Warehouse* and is supported by a team of state reporting professionals at the Nassau BOCES RIC that assist district personnel in uploading their data accurately and on time – quite a challenge given the volume of data that must be reported and the strict timelines that must be followed. The <u>*Instructional*</u> *Data Warehouse* (IDW) represents another arm of the Nassau BOCES RIC in which the data are repackaged into data reports and dashboards using a variety of visualizations in the IBM Cognos Analytics platform that are made available for school district personnel. Within our IDW team, we have two groups – the IDW report writing team, and the IDW professional development team. The report writing team is a brilliant technical team of four programmers that creates all of the IDW reports and dashboards but do not have any experience as public school educators. In contrast, the IDW professional development team consists of former school administrators who couldn't code their way out of a paper bag but are very knowledgeable about how to interpret these visualizations and how they should be used by educators. Together, these two groups work together to make decisions about what visualizations are needed, to create the reports and dashboards, and to inform educators about the use of these visualizations.

Data Conversations in Nassau County

As I interact with school educators in a variety of contexts to share with them what data reports are available through the IDW, I will often say "we do not look to the data to give us the *answers* - we look to the data to help us to ask the right *questions*." I cannot recall where the seed of that quote came from, but I picked it up along the way at some point in my career and it stuck with me. This is but one example of how we frame our *data conversations* - the way that we as educators talk about using data. Within our IDW team, questions that arise from our internal conversations between our IDW report writers and our IDW professional developers are many and range from "Is anyone actually using this report? Does it need to be updated?" to "Which new visualization do we move ahead with first? What do our districts need?" We are fortunate that our professional development team has the educational background to inform such decisions and they do receive feedback from district personnel as they present workshops in a variety of formats to Nassau County educators. Yet, when it comes to the frequency of use of the IDW, the data show dramatic differences between districts. As a result, our informal conversations with IDW users tend to be isolated conversations that may involve few or perhaps only one of the 56 school districts that we serve. This leads to further questions: "How can we at the IDW engage in dialogue with school leaders in a more systematic way?" "How can we be sure that we provide them with what they need?" The need for more intentional data conversations is certainly in order.

Before we consider how we can arrive at facilitating more meaningful conversations surrounding data, it is useful to review the nature of the types of data conversations that have been already occurring in Nassau County.

These conversations are the result of the interactions of the IDW professional development team with educators in a variety of forums as detailed in the next few paragraphs.

Three times per year we hold user group meetings to inform Nassau County educators of the newest IDW reports that our report writers have developed. These two-hour meetings typically consist of presentations by members of the IDW team and on several occasions have included presentations made by IDW users from our component districts to highlight how they have been using the IDW data reports and dashboards. Starting in the fall of 2017, we renamed these meetings “Bullseye Meetings” to reflect that we were targeting our focus in the meeting to a subset of our users such as “High School Administrators” as we found it had become difficult to engage the entire audience by presenting on a wide range of reports such that each person attending would be sure to leave the meeting with at least one or two useful take aways. That is, elementary school administrators have little interest in our SAT and Diploma Type reports, and high school administrators are not very interested in our Performance Level Change reports that compare student state assessment results for Math from grade 4 to grade 5, for example. Even with our more targeted delivery of information through “Bullseye Meetings”, the nature of these meetings has continued to be that of a series of presenters providing information to an audience of IDW users. On occasion, conversations have arisen from these meetings that have led to improvements in the IDW. One that comes to mind is when we invited representatives from a high achieving school district in the fall of 2018 to present on their use of our most frequently used report – the Gap report - which compares student performance on state test item response data to a county benchmark thereby examining the performance “gap” between a small group of students in one school and all of the students in Nassau County – this will be described in more detail later on. This conversation led to the development of a new version of the Gap report that allows district personnel to examine Gap data over multiple years.

Another type of professional development that we offer involves district visits. Districts can schedule a half-day session to review their IDW data with their administrative team led by an IDW trainer. Through these district visits, we provide an overview of many of our IDW reports and take a closer look at the data for identified areas of interest for that district. Just as indicated above for our Bullseye Meetings, further conversations have been sparked that have led to substantial improvements in the IDW. In the fall of 2017, I was doing an in-district IDW training in a school district which led to questions about our Regents Maximum Score Report which was a report to help school personnel easily identify each student's *highest* score on the New York State Regents examinations required for graduation. While this was seen as a useful report and was in use by the district, there were critical pieces of information missing from the report such as student disability status and English proficiency status that school counselors would need to have in order to determine graduation requirement status. This conversation led to a collaboration with the Assistant Superintendents consortium of Nassau County which involved the creation of a focus group to review the report in its current form and to recommend changes which resulted in the publication of two new versions of the report – the Regents Maximum Scores Download, and the Regents Maximum Scores Dashboard. The focus group that came together for this very productive conversation consisted of fifteen people representing seven districts and three members of the IDW team. After meeting on three occasions, this focus group had accomplished its goal and we were pleased to share these two new reports with our users across Nassau County which was very well received. We had a similar conversation, albeit much smaller in scale, that arose from the Nassau County Superintendents organization early in 2019 that led to the development of the Initial College Enrollment Outcomes report which allows districts to track the outcomes of their high school graduates who attended a particular college based on National Student Clearinghouse data. These examples of conversations between district level users and the IDW team, though powerful, are relatively infrequent and occur very much in an ad-hoc fashion. In the context of this discussion of data conversations I find myself asking, 'how can we make these types of conversations the rule rather than the exception?'

In addition to our in-district training sessions and our Bullseye Meetings, we offer hands-on training sessions to small groups throughout the year to targeted audiences of teachers, administrators, and school counselors. Very often, the conversations that occur in these sessions reflect our users interest in using data, the competing agendas and lack of time that keep them from using data, and revelations of what reports are available in the IDW of which they were not previously aware. It is always rewarding to see one of our workshop participants get excited about the data visualizations that we have available but at the same time it can be frustrating to see dedicated educators who were not previously aware of what IDW tools they have had available.

The last type of conversations that we engage in with school leaders surrounds the Data Wise approach to utilizing instructional data. We offer a Data Wise (https://datawise.gse.harvard.edu/) professional development course to school level teams as well as a follow up version of the course, Data Wise 2.0, to continue to offer support to participating schools. These courses require a substantial commitment from each building level team as they are run over the course of the school year (not to mention the extensive preparation work for our IDW professional development team). While there is a significant amount of time spent during this course on Data Wise on concepts and protocols, we have learned through experience to structure this professional development to maximize the amount of time that school leaders are engaged in conversations about data and focusing on how to extend that conversation within their schools beyond their Data Wise teams. These are also powerful data conversation, albeit to a relatively limited audience consisting of data teams from just a handful of schools.

In reflecting upon all of these conversations about data that our IDW team is involved in, it strikes me that these conversations fall into two broad categories. The first category I would describe as *informative data conversations* – conversations in which we of the Instructional Data Warehouse advise and answer questions about the data reports and dashboards that we have available for educators and how to best utilize and interpret these data visualizations. *Informative data conversations* are critically important for our users – they allow educators in our region to understand how to get the most bang for their buck out of the data reporting service we provide. The second category of conversations that we have are *inquiry data conversations* – conversations in which we actively collaborate with Nassau County educators to create new data visualizations. These conversations are much more engaging in that, unlike our *informative* conversations, these *inquiry* conversations are two-sided with Nassau County educators and the Nassau BOCES IDW team truly working collaboratively to identify the data needs of school leaders and to meet those needs with a thorough understanding of the available data sets and the myriad of other technical factors that affect the creation of reports. Oft times, the devil is in the details.

Data Conversations at the NSF Data Collaborative

The unique opportunity afforded to all of us attending the NSF Data Collaborative Fellowship was to extend our *inquiry conversations* over the course of this dedicated two-day event to a whole new level of what I might call *elevated* conversations. By infusing data scientists from outside of Nassau County into the mix of these conversations, the *inquiry* conversations that we were able to engage in at this event brought us to an entirely different level. Through the datasprint teams (each identified by a shape), we were all able to learn from each other and create new data visualizations in real time – in particular, there were three datasprint teams that engaged in these *elevated* conversations that have already resulted in changes being made in the IDW and have led to follow-up *inquiry* conversations since. In the next section, I will focus on the work of three of the datasprint teams: pentagon, cube, and circle. The cube and pentagon teams' work each resulted in a re-imagining of two of our most frequently used reports – the Gap report and the WASA report. The work of the circle team has sparked conversation regarding what data are available to districts as opposed to what data are available to Nassau BOCES which is more limited and how we might be able to bridge this gap.

As I work with educators, I am continually touting the power and necessity of the Gap report and the WASA report. In trainings, I will often say, "If I were on a sinking ship, I would get my family in the lifeboat, and then grab the Gap and WASA reports before I hop in the lifeboat myself." The Gap report provides the user with an item by item breakdown of student performance on state assessments by comparing the performance of a group of students (by district, school, or classroom) against a county-wide benchmark. I will often pose the question to workshop participants, "50% of the students got question number 4 correct – what does that tell us?" After the appropriate wait time, and fielding responses from the participants I will emphasize that by itself this data point tells us "absolutely nothing!" I will then go on to highlight that we need a basis of comparison to make sense of the 50% success rate on this question. If 90% of the students in Nassau County got this question correct, then it will lead me in a much different direction than if only 30% of the students in the county answered correctly. The Gap report makes exactly this comparison as shown below:

Gap by District

Sort By: Standard/Key Idea

Standard/Key Idea	Subskill/Performance Indicator	Question #	MC/CR	District%	Region%	District Gap
Arithmetic with Polynomials & Rational Expressions	A.APR.1 Understand that polynomials form a system analogous to the integers, namely, they are closed under the operations of addition, subtraction, and multiplication; add, subtract, and multiply polynomials. --| HSA.APR.A.1	II-26	CR	45.7%	56.1%	-10.4%
Arithmetic with Polynomials & Rational Expressions	A.APR.3 Identify zeros of polynomials when suitable factorizations are available, and use the zeros to construct a rough graph of the function defined by the polynomial. --| HSA.APR.B.3	I-08	MC	94.2%	89.4%	4.8%
Building Functions	F.BF.1 Write a function that describes a relationship between two quantities. --| HSF.BF.A.1	I-16	MC	59.7%	60.3%	-0.5%

The question that naturally follows from the Gap report regarding multiple choice questions is "If the students chose the wrong answer, what wrong answer did they choose?" Hence, we have the Wrong Answer Summary Analysis (WASA) report which answers this question. Note that for question 16, the WASA report reveals that *Response 3* was the correct answer highlighted in green (with 60% of the students) and that *Response 1* was a distractor for this question with 20% of the students choosing this response. In both reports, the user can click on the blue question link within the report to view the actual test item and gain some further insight into student responses.

Wrong Answer Summary Analysis (WASA)

Sort Report By: Skill Tested

Q#	Skill Tested	Region %	Correct Resp	Blank #	Blank %	Resp 1 #	Resp 1 %	Resp 2 #	Resp 2 %	Resp 3 #	Resp 3 %	Resp 4 #	Resp 4 %
I-08	Arithmetic with Polynomials & Rational Expressions: A.APR.3 Identify zeros of polynomials when suitable factorizations are available, and use the zeros to construct a rough graph of the function defined by the polynomial. --| HSA.APR.B.3	89.4%	3			1	1%	4	3%	131	94%	3	2%
I-16	Building Functions: F.BF.1 Write a function that describes a relationship between two quantities. --| HSF.BF.A.1	60.3%	2			28	20%	83	60%	15	11%	13	9%

Being that these two reports are so important for our users going back to the early days of the IDW, it never dawned on me to look for ways to improve upon them. When I arrived at the NSF Data Collaborative, I was expecting to be collaborating on creating new reports, not re-examining our existing reports - that was all about to change. These two reports are so much a part of what we do in the IDW, I suddenly felt like the fish that is not aware of the water in which it lives.

Team Cube: Re-imagining the Gap Report

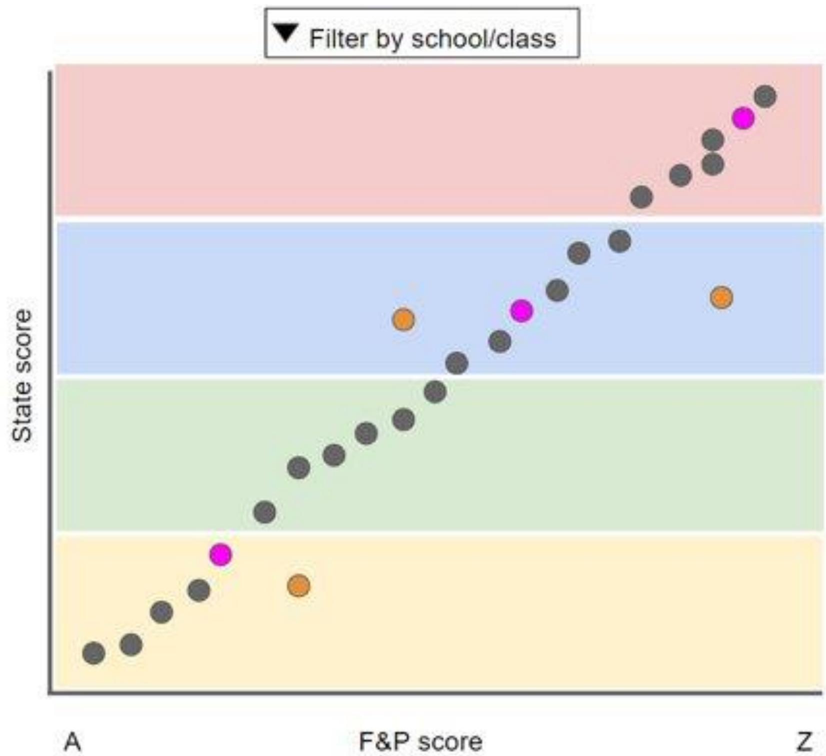
I was fortunate to be a member of Team Cube. On this team, we decided to work with the mock data set provided to create a new version of the Gap report that would make it very easy to identify instructional strengths and target areas of improvement at the teacher level over multiple years in a single report. This represented a current need expressed by our IDW users so I was pleased to see the direction this group was going. The opportunity to develop this prototype with a Cognos programmer on our team resulted in a very productive brainstorming session. Within our limited time frame, we were able to come up with the following visualized version of the Gap report which grouped test items by curricular domain thus revealing areas of strength as well as areas of needed improvement. While the existing Gap report provides the same information after some manipulation, the benefits of having this in a readily digestible form served the needs expressed by the educators in this group.

Team Pentagon: Re-imagining the WASA Report

Team Pentagon came to a conclusion very similar to Team Cube regarding the development of a data visualization that would allow users to see at a glance which question items on a state assessment had the most significant distractors that would lead to better understanding of student strengths and deficits. Once again, the information provided in this version of the report is the same as the original WASA but presented in a manner that makes it much easier to see which test items had the most significant distractors. The green bars in the positive direction indicate correct responses while the stacked bars going below the x-axis indicate the number of incorrect responses for each question.

Team Circle: Re-imagining Available Data

Team Circle took an entirely different approach as compared to Pentagon and Cube in that this group decided to not be restricted by the mock data set provided to all teams. Rather, this team chose to work with another actual data set of Fountas and Pinnell data provided by one of their team members. To me, this highlighted an ongoing issue that hampers our ability to create IDW reports that school personnel want and need for data that is available within districts but not available to the Nassau BOCES RIC as such data are not reported to the state. Team Circle's determination to use an additional data source, along with new capabilities of Cognos as presented in the Data Expo earlier that day certainly got me and other members of the IDW team thinking about how we could accommodate the needs of educators to create visualizations for data sets that are not available regionally.



Continuing the Data Conversation

At the end of this two-day event I recognized the need to continue the rich data conversations that we had just started. The NSF Data Collaborative was a huge undertaking – the culminating professional development event of a four-year grant partnership between Teachers College and Nassau BOCES. This was supposed to be the end – I could now see that it was, in fact, a new beginning. This was an opportunity to approach our Nassau County data conversations moving forward with a new found commitment to engage in more *inquiry* conversations that systematically bring together those who create the data visualizations with those who use them to make decisions for the benefit of students.

Upon return to Nassau BOCES, as a team we continued the conversation internally at first with a debrief of our team of eleven who attended the NSF Data Collaborative. We prioritized what we took away from this experience and we arrived at three conclusions. First, we recognized the need to continue the inquiry data conversations that we had engaged in with the sixteen participating districts at this event and to extend these conversations to include all of the fifty-six districts that we serve in Nassau County. Second, we came to realize that not only did we need to move ahead with creating new reports with visualizations, but that we really needed to examine the visualizations in existing reports to provide educators with tools that make data analysis as user friendly as possible. Finally, we determined the need for additional support for our Cognos report writers in the form of targeted and on-site training to be done in-house with a Cognos expert that can address our needs.

Nassau BOCES team reconvenes the week after the NSF Data Collaborative

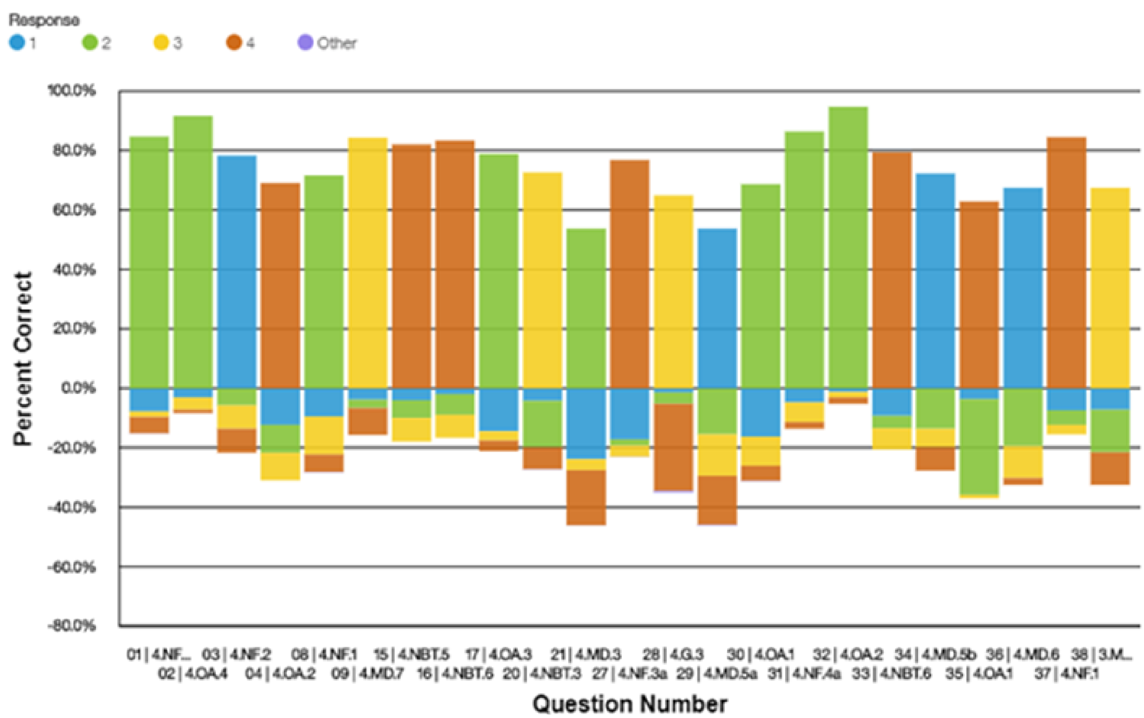
So we rolled up our sleeves and got to work with the very first task being to upgrade our version of Cognos 11.1.0 to Cognos 11.1.4. This was critical for the purpose of leveraging additional Cognos visualizations and especially to explore the possibility of providing district designated "power users" to upload their own data sets and to then create their own data visualizations to be shared within their own district (inspired by the work of Team Circle). Within a month, this transition to the new version of Cognos was complete. During this time, our team also dug into the work of creating a teacher version of the Multi-year Gap report (based upon the work of Team Cube), and a new visualization for the WASA report (based upon the work of

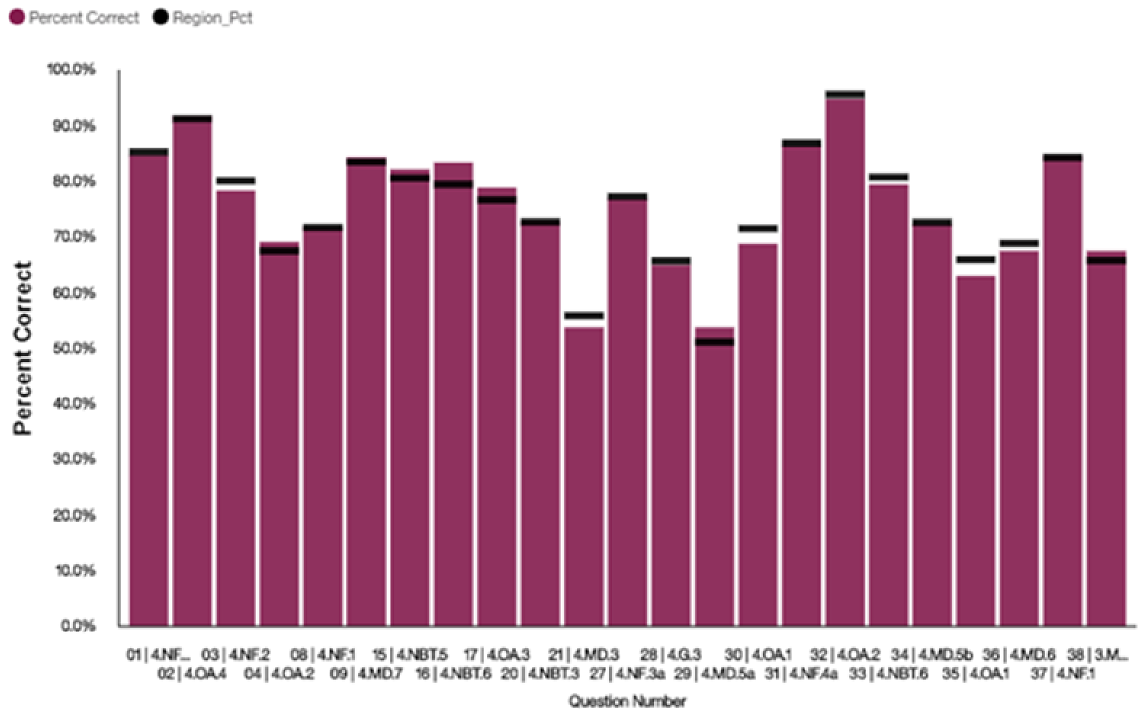
Team Pentagon). However, based upon our experience from the NSF Data Collaborative, we knew that the creation of these visualizations would not be the end of our work – it was time to go back to the educators in the field to get their input.

Before proceeding with the teacher version of the multi-year Gap, we reached out to four NSF Data Fellows coming from two districts to discuss the development of this data report. This focus group came together for a meeting in January to give the educators an opportunity to advise the IDW team on what aspects of these data would be most important. Included in this conversation were some of the data problems that arise in a multi-year report such as teachers changing schools within a district, teacher name changes, and the like. This was a helpful first step in further developing a new visualization for the multi-year Gap report.

Looking back, it was a tall order to ask educators with very busy schedules to attend the two-day event in December, especially with an extended commute for both days. However, the feedback from those who attended was so positive that we decided to cancel our February Bullseye Meeting – which typically involves an *informative data conversation*. Instead, we decided to invite all of the NSF Data Collaborative Fellows back for an afternoon session at Nassau BOCES so that we could continue the *inquiry conversations* from December and receive feedback from the educators in the field regarding the work that we have done so far and the direction that we are heading. On February 11, 2020 we were so excited to see more than half of the district participants return for this follow-up session! Using a very similar format to the NSF Data Collaborative, we designated participants into groups named as countries (rather than shapes) to engage them in small group dialogue with regard to the work done on our new versions of the Gap and WASA, as well as the prospect of being able to upload their own data sets to create custom dashboards. We collected their feedback and have used that feedback to make key changes that we would not likely have thought of on our own. Some highlights of this feedback were to give the user the option of what columns to include or exclude on the Gap report, to filter the new WASA visualization by state learning standard, and to provide users with *templates* of data files that they could use to upload for customized reports. The power of engaging our IDW team members in purposeful inquiry conversations with our end users has proven to be a valuable strategy that we look to expand upon moving forward.

During this February follow-up meeting, we highlighted our IDW version of the re-imagined WASA report that grew out of Team Pentagon's work. This visualization is slightly different than what Team Pentagon created with each response item having its own color regardless of whether the answer is correct or incorrect. The correct response is indicated above the x-axis with the distractor items being displayed below. One data point that was missing in this new visualization from our original WASA report was the regional percent correct which is critically important to have a basis of comparison as discussed previously. This proved to not be a possibility in this version of Cognos, so we created a second visualization of the Gap report to appear directly below the visualization for the WASA which would provide the user with this information at a glance. Additionally, on the basis of our follow-up meeting, we also allowed for the user to be able filter this report by curriculum standards which further simplifies the analysis for the user. In the end we had actually created a combined Gap/WASA visualization which allows for much quicker analysis by our end users.





Data Conversations for the Future

So how do we proceed from here? We know what types of conversations we want to have moving forward – but how do we do so in a manner that draws in more of our IDW users? How do we do so in a manner that is respectful of limited time for educators with tight schedules? These are the questions that we find that we as the IDW team are asking ourselves as we look ahead and as indicated earlier, it is all about asking the right questions. We still need to have our *informative data conversations* – educators need to know what data visualizations they have available and how to use them. But what we need to do better is to develop a structure such that our *inquiry data conversations* are no longer ad-hoc events but that they become a part of our systemic practice. We will continue to meet with this core group of NSF Data Collaborative Fellows and reunite from time to time but more importantly, we will be calling on them to invite their colleagues from other districts into the conversation. The days of creating IDW visualizations without district input are over – it may take a little extra effort on our end to accomplish this and I would have to conclude at this time that this will become a priority moving forward.

Pratt, 2021

In conclusion, I am compelled to refer to Dr. Steven Covey's analogy of 'sharpening the saw' - habit number seven in *The 7 Habits of Highly Effective People*. Simply put, Covey states "We must never become too busy sawing to take time to sharpen the saw." The power of the *inquiry data conversations* presented here I truly see as our opportunity to take a little extra time to sharpen the saw. Our talented staff of IDW report writers spend a great deal of time cutting down trees. It is only right to give them a sharp blade to use. Saws need to be sharpened continually to be effective tools. The *inquiry data conversations* discussed in this chapter are our sharpening tools. We know how we will be proceeding with our IDW team and the districts that we serve in Nassau County - we will be sharpening our saw by purposefully engaging school personnel in the process of developing visualizations collaboratively through *inquiry* data conversations. The question remains for other organizations to consider in this context, is "how can my organization sharpen the saw?"

CHAPTER 9

A Meeting of Three Interconnected Worlds: Reimaging Data for Practitioners

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July marks the end of one school year and the preparation for the upcoming school year. Building administrators wait with baited breath for the release of the state assessment scores so that student placements, class assignments and AIS schedules can be adjusted and finalized. August arrives and the work of deciphering the multiple pages of data, based on a single point of measure, begins. Questions that a building principal seeks to answer immediately include: How did my students compare to other students in our district? to others in New York State and in Nassau County? Are we closing the achievement gap? As the building leader, a more critical task is to decide how I am going to share this information with others in a manner that makes sense, in a comprehensive way that speaks to successes to be celebrated and actions to be taken. The one page summary presented by the media is a superficial cliff note that, in and of itself, gives us incomplete, unusable information. So, the journey of poring through pages and pages of scores begins so that data are disaggregated to generate “notices” and “wonders” about growth and challenge areas based on grade level, ethnicity, gender, economic status, etc. Additional questions emerge: For which state standards did we demonstrate growth? Which standards represent key strands that are still an area of concern? Did students in some classes demonstrate mastery in targeted state standards while others struggled? How do the findings from this single point of measure compare to benchmarks and other assessments? More importantly, how do I share this information in a meaningful way with the professionals who have the power to act upon it? How can this be done without spending countless hours clicking through multiple reports and slides to get to the bottom line—how can these data inform my instructional practice? Who can assist us so that data be consolidated and accessed easily in a visual format?

This was the precise question posed to us by Dr. Bowers at the NSF Education Data Analytics Collaborative Workshop at Teachers College. Educators, administrators, data scientists and researchers were placed in teams to discuss how to visualize data to make it a pragmatic and accessible tool for the practitioner. It was a collaborative effort, a "one stop shop" working experience, where professionals from different areas in the United States and Canada gathered to discuss the content and design of educational data reports. Teams consisted of researchers, data scientists and multi-tiered educators (central office and building level administrators, and classroom teachers). I was fortunate enough to be a member of Team Cube, which consisted of a building principal, a superintendent, a BOCES data administrator and two data scientists.

After learning about our backgrounds, the members of Team Cube formulated our guiding or essential question, "To what extent can we identify specific areas of instructional strengths and needs?" We examined a variety of visualization designs such as scatter plots, line graphs, pie charts, etc. and decided that our choice of visualization would have to conform to the following criteria: ease of use, relevance of data, and pathway to instructional intervention. "Ease of use" questions that we considered included: How many clicks before accessing the data "picture?" How can we create a picture that is worth a thousand words, or 5 data pages, in a snapshot? "Relevance of data" discussions focused on the number of years of data that should be readily accessible as well as item analysis considerations and gap reports. Finally, "pathway to instruction intervention" discussions, the ultimate purpose for developing this tool, focused on effective instructional strategies and tools that professionals can replicate. Other considerations our team discussed were student access to data with the goal of student ownership of their learning.

The tentative answers to the questions emerged. Team Cube decided to focus on the Algebra Regents. We wanted to identify the top strengths per school within the district and county over the past 3 years (see Figure 9.1).

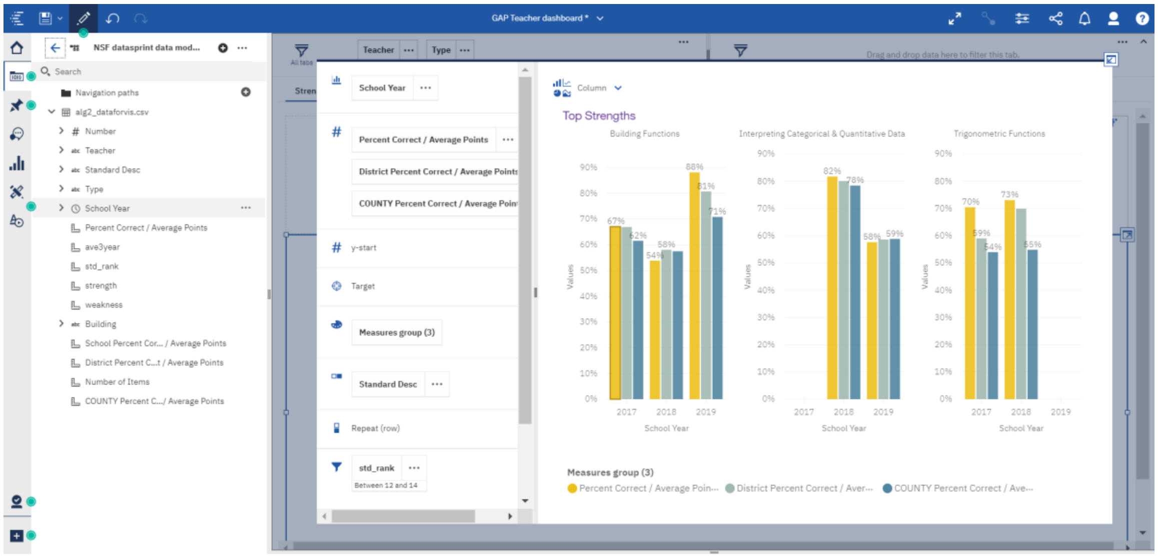

Figure 9.1: *Data Slots. Algebra Regents: Top Strengths, 2017-2019*

Why look at the strengths? Because we believe it is important to see where our strengths lie and where our challenges are. Because we need to establish a culture where administrators and teachers alike can reach out to colleagues who have expertise in identified areas. Similarly, our team members discussed the necessity to identify the major challenges per school within the district and county over the past 3 years.

Next, the team discussed "drilling down" to identify teacher gaps over the past 3 years as related to the top strengths and top challenges. The why? Because we want to give educators access to historical data that informs them on the effectiveness of their practice. In addition, we also wanted to see, at a glance, the number of questions targeting the identified skill or standard in order to determine the validity of data (see Figure 9.2).

Along with the ability to identify strengths and challenges, the team discussed how to access an assessment item map to examine the question format (i.e., multiple choice or constructed response) and the standard being targeted by each question. This would then enable educators to conduct an item analysis. These reports already exist, thanks to the diligent work of the data professionals at Nassau BOCES who prepare these reports and place them in the Instructional Data Warehouse (IDW). The question posed to our data scientists was how to configure the data so that it is easy to access and simple to read. We've only begun to scratch the surface.

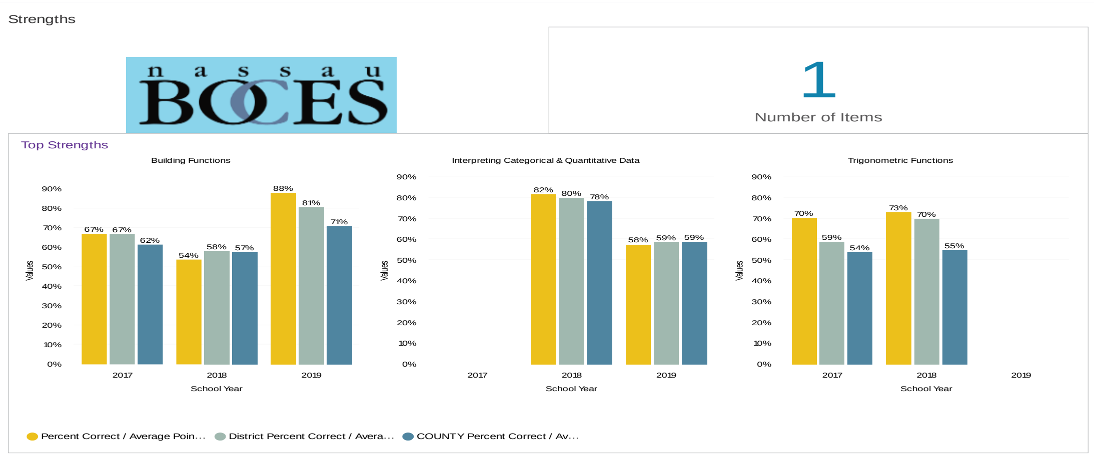

Figure 9.2. *Gap Teacher Dashboard*

The NSF Education Data Analytics Collaborative Workshop at Teachers College was an invaluable experience. It was a venue where researchers, data scientists and district wide, building level and classroom educators sat together to share ideas aimed at promoting the effective and consistent use of data to inform and drive decisions that impact the academic success of our students. Hearing the different perspectives and practices of professionals from across and outside the United States, from those who work in the field of education and those whose expertise is in research and data coding was an eye-opening experience. It was the marriage between research and practice. Having the researchers and data scientists listen to the voices of the practitioners, having the practitioners express their concerns and their needs made for a rich exchange of ideas in this Think Tank. As a result of these rich conversations, the data scientists began to create the visualizations the team had discussed. They created, displayed their work and modified it based on our immediate feedback.

This was just the beginning, the springboard, of a partnership representing the future field of Educational Leadership Data Analytics (ELDA). “Education Leadership Data Analytics (ELDA) is an emerging domain that is centered at the intersection of education leadership, the use of evidence-based improvement cycles in schools to promote instructional improvement, and education data science” (Bowers, Bang, Pan, & Graves, 2019). As a building principal who oversees the data trends in my school and a member of the Superintendent’s Cabinet who examines the patterns in scores based on disaggregated data, I recognize the dire need for the ongoing collaboration among educational leadership, educational data scientists and educational researchers if we are to make effective use of the data. Without the ability to make informed decisions based on the data, we run the risk of having students take assessments for the sake of having scores reported in the newspaper—the antithesis of the true purpose of assessments.

After designing a possible template (see Figures 9.1 & 9.2), our team received feedback from other teams who participated in the NSF Education Data Analytics Collaborative Workshop. The comments from our counterparts in other groups revealed that our proposed visualization has the promise of resulting in reflective and introspective educator practices and systemic change (see Table 9.1).

Teachers can improve on a year-to-year basis using the visualization.
Administrators can use visualization to understand what a teacher(s) need to be more productive.
Visualizations can identify leaders as bright spots and can use them to guide other teachers.
Teachers can narrow down based on standards by year.
The group is working on a teacher dashboard for the GAP reports.
Will give a 3-year analysis at a glance.
Item analysis for broader topic areas and identify key ideas greater than standards. Questions around key ideas. The data visualization will represent and calculate teacher/building/district with a dotted line representation the country average.
How do we identify specific areas of instructional strengths and weaknesses: - district discipline - 3 years period of practices and area of improvement - country comparison by foci (ie. Finance). Goal is to identify 3 areas of strengths / 3 areas of improvement (focus area)
Quick view of strength areas. Hypothesize as to the why: - researches need to be lathed - raises questions - validities teachers strengths - check in the item level

Table 9.1. *Basecamp Written Data/Feedback*

The two days of intensive work left our team members wanting for more. It confirmed our sentiments that time is of the essence if we want to see the impact of data analysis on instructional practices. Several members from the Long Island team reconvened a few months later to discuss how to make this data visualization a reality.

July is now only two months away. This is the time where principals and district level administrators wait for the state assessment results. Except this summer, we will not be receiving any new data due to the coronavirus pandemic. How will students be placed in classes? What data will be used? I have decided to keep students together in their classes and move the classes up as a whole. Those classes were created based on academic, behavioral and social-emotional data. But that data, as we know, is now dated. Other variables will need to be considered. Benchmarks will need to be administered and analyzed upon our return if we are to address the COVID slide that the majority of our students will experience. Teachers and administrators will need to have an "at-a-glance" view of test results to identify skills and standards in need of attention. We will need to look at attendance information, distance-learning data (e.g., How often did students connect with their teachers? How often did they complete their assignments? Did they understand the tasks assigned?) and health statistics. We are at a critical juncture where we can safely predict that blended learning will be our "new normal." Making data visual will be essential to ensure its effective use.

References:

Bowers, A.J., Bang, A., Pan, Y., Graves, K.E. (2019) Education Leadership Data Analytics (ELDA): A White Paper Report on the 2018 ELDA Summit. Teachers College, Columbia University: New York, NY. https://doi.org/10.7916/d8-31a0-pt97

CHAPTER 10

Building on each other's strengths: Reflections from an education data scientist on designing actionable data tools at the 2019 NSF Data Collaborative

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Introduction

Educational agencies, particularly in the K12 sector, are increasingly seeking and utilizing data scientists to help their organizations make sense of the copious amounts of data at their disposal. While there seems to be widespread agreement on the usefulness of data professionals in education, organizations struggle to effectively utilize their talents. Data professionals arrive in the educational sector with varied talents including deep methodological training in statistics, research design, and/or data visualization (Bowers et al. 2019). However, many (this author included) lack deep experience in instructional design, the science of learning, and/or school management. On the other side of the coin are education leaders that are experts in designing rigorous, high quality lessons and managing teams of teachers, but lack a conception of the possibilities and complexities of data

Data Visualization, Dashboards, and Evidence Use in Schools

D'Amico, 2021

analytics. The result is educational data scientists that do not understand how to create data tools to help educators and educational leaders that do not understand the tools data scientists possess to assist with educational decision making.

The 2019 National Science Foundation (NSF) Data Collaborative Event was a bold initiative designed to create the conditions for these different individuals to successfully collaborate with each other. The event brought together a diverse collection of data scientists, technologists, academics, and education administrators and practitioners to participate in a two-day data sprint. Teams articulated numerous educational questions and created analyses and visualizations to help educators on the ground answer those questions. While a rewarding experience for those able to participate, the intent is that we can broadly share our learning from these two days as a model for other educational agencies across the country. An extension of this work would be for participants or others to build out their own data sprint like teams in local organizations to improve data driven decision making and improvement.

But, acknowledging the need to work together is easier than actually implementing effective collaboration. I will share my reflections on what happened during this event to create productive collaboration between two sets of colleagues with deep, but not always overlapping, expertise: educational data scientists and education leaders/practitioners. There are three inter-related topics that education professionals should consider in standing up their own local teams devoted to Education Data Leadership Analytics (ELDA): 1) the necessary traits for a successful group, 2) the process for arriving at a key question or problem, and 3) the process to design metrics and visuals to assist practitioners. In will discuss each of these topics in detail, sharing what worked well in my own data sprint team. I will end by sharing the experiences I have had, both positive and negative, establishing and working in a collaborative ELDA team in my own district.

Necessary traits of a collaborative work group focused on data use

One of the reasons the NSF Data Collaborative meeting was so successful was the thought put into selecting participants and dividing them into data sprint groups. The organizers ensured that each data sprint team had a diversity of members from different functional areas (educational leaders / practitioners and data analytics experts) and different backgrounds (school based experience in addition to statistical/research based experience) united by a common commitment to inquiry and using data.

As education organizations consider setting up similar groups, they should expect variation in the specific organizational roles that serve in the group. For example, during the NSF Data Collaborative, I was paired with a superintendent from a small district who takes a significant role in thinking about school and classroom instructional data. In contrast, in my own large urban district with thousands of students, our superintendent does not have the bandwidth to be involved in conversations related to detailed school and classroom data. The critical consideration is not in what specific organizational roles help with this work, but rather in ensuring a diversity in the functions, backgrounds, and perspectives of individuals. This diversity allows group members to build off of each other's strengths and ideas, compensating for the knowledge any one individual might lack.

The importance of the beliefs and soft skills of members cannot be understated. When all group members commonly think that data can be used to drive actions that improve results for students, energy and time does not have to be expended convincing others of the value or purpose of the group. Rather, for those that might be skeptical of the utility of such a group, they can more easily be convinced by the successful execution of a visualization or analysis the helps guide the actions of school leaders.

The other traits that were common among our group members, but not necessarily selected for by the organizers, were humility and a willingness to listen. Successful collaborative work requires individual members to admit the limits of their own knowledge and openly listen to the perspectives and ideas of others. The benefits of the group's diversity are lost if there are a few dominant individuals that push the conversation and agenda. An ability to listen to other perspectives and recognize the value in them helps lead to a stronger final product.

As I mentioned, the participants of the Data Collaborative Event benefited from the work of the organizers to ensure the best conditions for collaboration existed. Other educational organizations starting this work will need to exercise their own thoughtful reflection to create effective collaborative groups within their own contexts. I will suggest some potential strategies later, as I discuss how I have engaged in this work in my own school district.

Articulating guiding values, a key data question, and expected actions

Educational data scientists are fortunate to have extensive data sets at their fingers. An effect of the focus on education accountability is that local and state educational agencies are required to track and report on students' demographic characteristics, assessment scores, behavior incidences, attendance, with repeated measures over time for each student (Piety 2013). This wealth of data also poses a problem. Superintendents, principals, and teachers are left with a jumble of data points and signals, unsure of what to watch and how individual pieces of data might be combined to uncover otherwise unseen insights. Data scientists are left wondering which analyses or visuals to prioritize as the most impactful for school and central office based educators.

One of the most important tasks of an ELDA group is to identify and prioritize the specific data related questions that will most benefit the organization. As part of the data sprint, groups followed a protocol to generate potential ideas sparked from existing data, categorize the ideas into themes, and then rank the themes along the dimensions of possibility and priority. The data we had available to use was student performance results on New York state assessments for schools with data in the Nassau Board of Cooperative Education Services (BOCES) data warehouse.

This process isn't the only way narrowing can happen and the best approach to take will depend on the context of your organization and its maturity in using data. Some questions might naturally arise from issues that have been observed in classrooms. Other questions might emerge based on summary analyses that have been previously performed. Regardless of the mechanics of a process, from my experience, the key factors in successfully identifying and prioritizing a data question are establishing guiding principles for the work and practicing shared leadership.

Our group agreed on three principles to guide our work: ease of use, relevant data, and a connection to instructional intervention. All three principles forced us to consider the perspective of the intended user as we developed our question. Our answer would need to be intuitive for users, include data that connects to users' day to day work, and helps drive users to actions that improved instruction for students. The third principle also centered our work on the core mission of educational agencies: improving instruction and educational outcomes for students. While there are lots of interesting ways to look at and analyze data, if the results didn't help drive improvements in how we could serve students, then they would be of limited use. As we thought about the priority of different topics and questions, those that aligned with our principles scored the highest.

I previously discussed the necessary beliefs and traits of group members that would help groups succeed in their collaboration. These traits are important because they help create shared purpose, group social support, and voice for group members. These are the necessary conditions for shared leadership to take place and for individuals of such diverse backgrounds to build off each other's expertise (Carson et al. 2007, Rath & Conchie 2008). Shared leadership is the idea that rather than a single leader directing all of the activities of other group members, leadership is a rotating role. Rather than competing to exert influence over others, group members recognize the times when they should follow the lead and expertise of others, while also being comfortable to assert their own leadership when appropriate to their expertise.

Given the guiding principles we had established, I allowed the members with instructional expertise to take the lead in articulating potential questions to be answered by the available data. They are the group members with the greatest experience in delivering instruction to students and positioned closest to end users that will utilize the tools we build. Following their lead does not mean disengaging from the conversation. I worked to better understand the perspective of the education leaders by asking questions to clarify any misconceptions I had and to help them hone and refine the questions they put forward.

Education data scientists are used to taking general questions from internal and external stakeholders and obtaining the necessary details that make it possible to go from question to answer with the available data. At this point, data scientists should begin pushing education leaders to consider who would use this data, the best level of aggregation for the data, and over what timespan the data should cover. In this manner, our group was able to go from a broad comment on the need to understand standard level assessment data to a more specific question of "How can we help teachers and principals identify specific areas of instructional strength and weakness?"

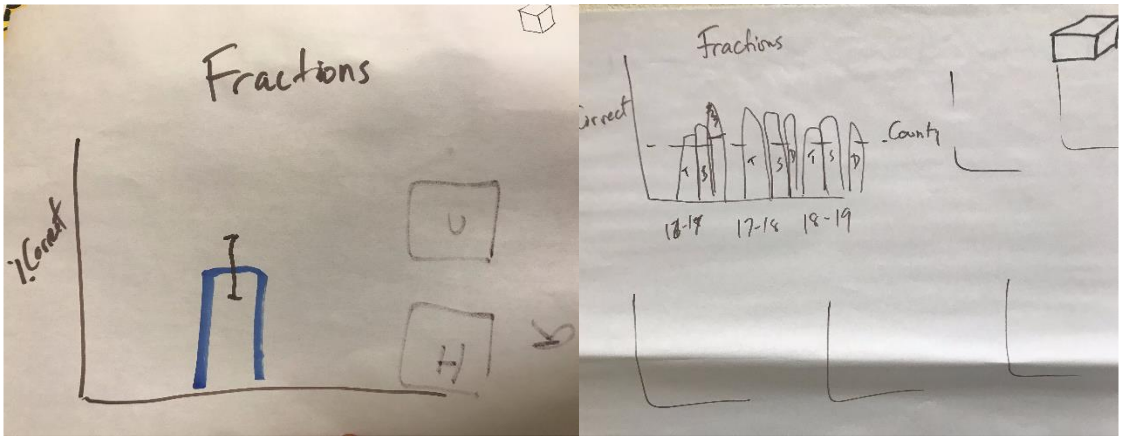
Given one of our guiding principles was to inform instructional practices and interventions, we continually thought of what actions we wanted principals and teachers to be able to take based on the answer to our question. The goal was to identify for individual teachers the key ideas in the standards where their students have historically performed well in addition to the areas where their students have been the weakest. Teachers would review the data at the start of the year to help them identify and replicate the instructional techniques they use in their areas of strength while directing their attention to the standard key ideas where they will need to revise their lesson plans and strategies. Principals would review the data to understand what supports they would need to give to individual teachers and identify any schoolwide patterns that might inform general professional development needs.

Iteratively designing metrics and visuals to support actions

The previous stage was very much driven by educational leaders and practitioners. Once we had agreed on a question and the associated actions we hoped users could take, the data scientists began to exert leadership. This stage would require decisions on how to define strengths and weaknesses, how to best visualize the data, and how to structure the data to achieve the visualizations needed. Given their expertise, this is where education data scientists are positioned to lead by explaining different analytic options and visuals to other members of the group and soliciting feedback. The guiding principles remain an anchor at this stage, helping to focus our attention on some options over others. The educational practitioners in the group also helped push our thinking in considering what data and summarization was most relevant and easiest to understand for users.

This is where an iterative design process proved most helpful for our group. The data scientists would establish initial design options aligned with the guiding principles. The options would be presented to educational practitioners for either feedback or to decide between different options. Utilizing this type of feedback loop helps keep the analysis and visual design responsive to the needs and thoughts of our target users. It also ensures that data scientists do not go too far down a pathway that does not meet the needs of users and could require significant amounts of work to be redone. The amount of time taken between design and feedback is up to individual groups.

To shorten the amount of time between design and feedback, our group drafted potential designs for quick feedback and adjustments. Examples of these drafts are shown in **Picture 10.1**. Each graph would show a standard key idea (collecting multiple individual standards) from a state assessment and the percentage of correct responses related to that key idea across all students tied to a teacher. In effect, our visual displays the percentage of correct responses in a key idea. In our discussions, we decided it would be helpful to show multiple years of data at once and to create comparisons between a teacher's performance in an area with school and county wide aggregate data.



Picture 10.1: *Examples of visual design drafts*

These changes went toward improving the instructional decisions that could be made from the data. Principals could identify the teachers that were standouts in their school or county. These teachers could then help model best practices for others. The visual also encouraged a growth mindset for *all* teachers. Even if examining their strengths, teachers would be able to identify room for improvement if their strongest areas still lagged behind the aggregate performance in their school or county.

As our group thought about the visuals, we simultaneously grappled with how to best define strengths and weaknesses. Our intuition was that we did not want to leave the interpretation of a strength or weakness up to the user, as this would make using the data more difficult and create inconsistencies in how users considered their data. These concerns were confirmed via feedback from the educational leaders in our group. The final metric we designed to determine the strengths and weaknesses, while simple, achieved our goal.

For each teacher and subject, we averaged the total percentage of correct answers in each standard key idea across all three years of data that were available. These averages were then ranked, with the top three areas for a teacher identified as their relative strengths and the bottom three areas identified as their relative weaknesses. There are certainly more sophisticated techniques we could have used to identify strengths and weaknesses. For example, we might have estimated a model that predicted each student's performance and then measured the extent to which a teacher's students exceeded or lagged behind these expectations. Our decision to use a simple average was a result of our guiding principles. Based on feedback from our educational leaders and practitioners it was clear that teachers often looked at the percentage of correct responses by individual standard or key idea. Our goal with this project was not to get teachers and principals looking at different data, but instead to provide structure and consistency in how they interpret and use the data.

To structure the data to work in the visualization, we merged the flags for areas of strength and weakness into a file with student performance aggregated by school year, teacher, subject, and standard key idea. This data structure allowed us to create slicers in our visualization so that an individual teacher could be selected and the data displayed would shift to the strengths and weaknesses of the selected teacher. This again went toward ease of use, allowing users to focus on the specific person of interest, rather than having to view graphs for multiple people at once.

Picture 10.2: *Final Visualization*

D’Amico, 2021

The final visualizations we created are in **Picture 2**. There are many possible extensions for others looking to build from this initial work. One direction our team considered but ran out of time to implement was error bars to help users in comparing their performance to school and county performance. Currently, the visual relies on the users themselves to make the decision when they are significantly above or below other groups. Assisting with this interpretation would further improve the ease of use for the visual.

Replicating ELDA groups in other organizations: advantages and challenges

Working collaboratively and creating our final visual was made easier by the planning and preparation of the team at Columbia University that organized the event. While our visual was shared and commented on by other participants, it did not have to face the scrutiny and adoption of our targeted user group. As others hopefully start collaborative data work in their home organizations, they will be faced with issues and challenges that did not exist in the more controlled setting of the event. Since participating in the event, I have been working in a cross-functional district team to provide leadership and guidance around using data. While our group would make no claim to being an exemplar of implementation of this work, we have learned a number of lessons that extend the insights from the event.

Take advantage of work streams that already exist

Simply setting up a cross-functional group to give guidance on the analysis and use of data can be a challenge. True collaboration requires a significant investment of time and energy from participants and for many educational organizations, staff are already handling multiple roles and responsibilities. Even if colleagues agree with the value of such a group, they might be reluctant to participate and to add yet another meeting to their calendar with associated to-dos. In my experience, one avenue around such objections is to place such a group in the context of other work that is already happening.

In Cleveland, our data experts had already been working to revise the roles and responsibilities associated with our data driven cycle of improvement. This included specifying what data was available, what analyses would be released and when, and our expectations for how others could use this data. Parallel to this, experts in our curriculum and instruction team had been creating decision trees that outline the different instructional strategies teachers could use, depending on where students were at. There was clear overlap between the two pieces of work, with both intended to initiate changes in instructional practice in response to data. Bringing these two groups together to align efforts as part of a unified data leadership group was made easier since it did not involve extra work, but rather an alignment and enhancement of each of our individual pieces of work. Strong relationships between individuals in the group and chief level encouragement for this alignment further helped.

Examples from others can accelerate your progress but only to a point

In Cleveland, the data we used to align the work of our team was the standard level results from our state assessments. Our question was: "How could standard level results for the district influence the supports and professional development that need to be provided?" This work was not dissimilar from the work of my own and many other datasprint teams during the ELDA 2019 Collaborative event. I shared and used a number of things I had learned at the event with the rest of the group.

Building off of the work and efforts of other organizations and districts is an easy way to accelerate progress in your own organization. Rather than feeling the need to re-invent the wheel, collaboration and sharing between organizations is itself an example of iterative design that can lead to better data tools. As organizations focused on learning and teaching, we should not fear this type of sharing. However, we also must recognize that building off of external models can only bring our internal efforts so far.

Organization specific context is relevant in successfully implementing an initiative, including efforts to use data for continuous improvement. Organizations should not expect to simply take an idea off of the shelf and implement it as is. Internal stakeholders will need to be provided opportunities to provide feedback, helping them to have a stake in the decision. When it comes to data work specifically, there are additional considerations.

For example, while shared code can help organizations, there are also limits to its usefulness. With many states giving different assessments, there is not always consistency in what information districts are provided and certainly no consistency in the format. As an example, in Ohio, while teachers can access a report showing how their students performed on individual items and standards, no district level report for all teachers is available. Since districts only get a file with the of how all students in the district performed on individual items and standards, our we are stuck with an analysis at a district level, rather than the teacher level analysis that was completed with data from New York. Due to these challenges, our own district's use of standard level data aims to inform the types of district supports and interventions that are available, based on the content strands that we consistently show weakness in as a district.

Additionally, the proliferation of numerous education technology tools (including assessment platforms, student information systems, learning management systems, etc.) means that data often is not similarly structured across districts, unless common systems are used. As a result, code cannot necessarily be shared and immediately work, but will require revisions from local data scientists. As a result, as data scientists produce their code with an eye toward sharing it more broadly, they will need to devote effort to writing code as flexibly as possible. This means allowing other users an easy way to define the schema of their own data and feed these different schemas into algorithms or analyses.

Have a multi-modal plan for training and professional development

Finally, groups will need to think through how to prepare stakeholders to use any data tools that are created. This is why articulating expected actions based on the data is as important of a piece as specifying the question. These use cases form the learning goals for any training plan and help inform the different activities that need to be designed. Just as with students, the learning should involve a gradual release where the use is modeled for all participants, participants practice the skills together in small groups, and finally participants practice the skills independently. These learning experiences need to be engaging and interactive. Also, when the actions are tied to work that participants already have to do, it is easier for them to make connections between how the tool can help them do their work, rather than feel like an addition to their work.

Besides designing engaging learning opportunities, organizations will likely face challenges in simply arranging time for the learning. As we used our data in Cleveland to identify the supports and training needed to improve in our specific areas of weakness, we have struggled to think through the mechanism to train teachers in the use of these supports. Especially in a system our size, we cannot necessarily expect to reach all teachers with an in-person training. As we and others develop our data tools, we must think about multi-modal learning opportunities that include in-person sessions, online group sessions, and on-demand tutorials to answer questions for users as they arise.

Conclusion

Data driven continuous improvement cycles continue to have significant promise for positively altering education outcomes for students. As the organizers of the NSF Data Collaborative argue, delivering on this promise requires providing greater opportunities for education leaders and data scientists to collaborate at national meetings and to receive training in a number of core competencies. The 2019 Data Collaborative also provides a framework for education professionals to accelerate their own data practices, even if they cannot travel to a national conference or event.

I experienced the power of iterative design to help my individual team build a stronger data visualization. Having more and more groups convene collaborative ELDA groups is a continuation of this iterative design and identifying the necessary conditions for data scientists and education practitioners to collaborate. The key to unlocking this learning will be to contingent on us professionals communicating with each other and working to create more opportunities for experts involved in this work to convene and share their experiences. Just as I have attempted to share my insights to this work, I hope the readers of this article will consider their own next steps to engage in this work and to share, at any level (local, state, nationally) their learning from it.

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CHAPTER 11

Using data to pair students and teachers for enhanced collaborative growth

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Introduction to the event

National Science Foundation's Education Data Analytics Collaborative Workshop was a 2-day event held on Dec 5 – 6, 2019, at Columbia University's Teachers College in New York. These two days were packed with discussions and hands-on activities to see how we can improve the integration of analytics in all schools under the region's district school board. We had access to real de-identified data and several school principals, superintendents, administrators, data scientists and thought leaders from the education analytics area. We all gathered under the same roof to tackle the challenge of infusing analytics into the education systems to improve student performance.

We were divided into diverse groups to facilitate cross-sharing of information and skills and were given the task of brainstorming the needs of an educator. Once identified, we had to iteratively code and build visualizations that would help fulfil that need. We also had several thought leaders from the industry, such as Prof. Richard Halverson, who gave a very

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insightful keynote speech. Multiple other speakers presented on various topics related to education analytics and gave demos of their products. This really enriched the workshop and gave us many takeaway lessons to reflect on and implement as we went back to work the next day.

I attended the event as an Advisory Offering Manager for IBM Cognos Analytics, a business intelligence (BI) tool familiar to many educators as the Nassau BOCES have their Instructional Data Warehouse (IDW) reports designed in Cognos Analytics. As the Offering Manager (commonly known as Product Manager), I drive the implementation of new features centered around customer feedback and innovation. This event was a perfect opportunity to learn how educators use Cognos Analytics, the roadblocks they are facing, and how we can help solve them. I gave a presentation on the latest innovations from the lab, including relevant topics such as Cognos's artificial intelligence (AI) assistant, forecasting and the new interactive dashboards. It was great to see the excitement around all the unique possibilities for unbiased data discovery and exploration that will be possible when the BOCES IDW adapts the latest version of Cognos Analytics.

Overall, it was incredible to see so many educators taking an active part in enabling analytics at their institutions. The event was planned and executed thoughtfully and purposefully. I am confident the results from it have been and will keep driving the education analytics field forward. Several attendees, including myself, walked out having learnt a lot of new information and with concrete action items for changes we wanted to implement based on what we learned. Effectively, resulting in a more data-driven education for our students who will be the leaders of the next generation.

Industry outlook

In the industrial age, the more physical hard work a person would do, the higher he/she would get paid. In the 21st century, in the 4th industrial revolution, this is no longer the case. Technology has disrupted many industries, from supply chain to health care to finance and many more. Data analytics is one of those disruptive technologies. In this information age, a person can get ahead by simply uncovering insights from his/her data. A person no longer needs to work physically hard to achieve more; he/she can work smarter based on insights from data analytics and can achieve higher success.

Several industries have tremendously leaped forward through analytics and data visualization. The education sector is rapidly adopting analytics and is yet to unlock its full potential. This is certainly something we hope to achieve, and workshops such as this help us get one step closer towards that goal.

Over the years in the data analytics industry, we have seen an increase in the adoption of self-service analytics. More and more non-technical users can now create their own interactive dashboards and reports with their data and have started using analytics to make their decisions. They like the ability to slice and dice their data, filter it as they like, and explore it to unearth hidden insights.

Looking ahead, AI in analytics will be changing the game. We started seeing increased integration of AI in analytical tools, which increased the potential for unbiased data discovery and has accelerated the process of creating analytical assets. An example of this is the AI assistant in Cognos Analytics. Through natural language understanding (NLU), natural language processing (NLP) and natural language generation (NLG), the AI assistant can communicate with users in natural language. Any user can generate a full-fledged dashboard just by saying “Create Dashboard”. Features like this lower the barrier to entry for analytics. Users with minimal to no technical training can start exploring their data and can build their own dashboards and reports. AI will also help increase the adoption of data analytics in all industries, including education. It is only a matter of time when we will be speaking with our devices for analytics, just like we do today with smart assistants by saying “Hey Google” or “Hey Siri”. Teachers, Principals, Superintendents and soon enough, students will be interacting with their data, asking questions and getting answers in natural language.

The unprecedented COVID-19 pandemic accelerated the adoption of technology in many schools. Previously, this adoption might have taken several years. Many schools adopted digital teaching platforms in order to continue teaching. One of the direct benefits of this is the higher number of student-specific data points we can now easily collect. We can then use these to create more robust data visualizations, informing and helping schools improve their method of education. The future of education analytics has just been accelerated, and it has a lot of potential.

Visualizing a data-driven strategy for pairing the best teachers with students for enhanced collaborative growth (our solution)

Why - the key question we wanted to answer was to what extent/how can we help teachers and principals identify specific instructional areas of strength and weaknesses. As we started out, one of our top priorities was to make sure the visualizations we ideate are easy to understand, are actionable for teachers and can have a direct impact on students.

Who - our primary target audience for the dashboard was teachers and principals. However, superintendents, assistant superintendents, and department chairs can also benefit from this dashboard.

When – the visualization is most valuable at the time of curriculum planning, during the start of each academic year, or during teacher reviews. The dashboard can show comparisons for the past three years. Based on the data available, the number of years can be increased or decreased.

What - we created an interactive dashboard with clustered column visualizations that show a particular teachers' top 3 subjects of strengths and weaknesses. This dashboard can further drill down to a report with more details as needed. The dashboard can also be filtered to select different teachers and question types (MC vs CR). Figure 1 below shows how this looks like in a Cognos Analytics dashboard. This dashboard can further drill-down to a report with more details as needed.

How – the data used is already available today in the IDW. After applying some transformations through R, the data is visualized in a dashboard. A teacher or principal will have access to an interactive dashboard where they can perform their analysis.

Figure 11.1: *Strengths tab in a Cognos Analytics dashboard*

R Code

To achieve this result, we used R to perform some transformations on the data before we visualized it. As MC and CR questions have different grading scales, we had to quantify the scores first. The same transformations were applied for all three years of available data.

```
#IMPORT ITEM ANALYSIS
#ALGEBRA 2 DATA
#2019 ASSESSMENTS
item_alg2_2019 <- read_xlsx('Raw Data/NSF Data Collaborative/Item Analysis/2019/Sample Item Analysis Download Algebra2 Jun 2019_FINAL.xlsx') %>%
  select(-2, -4)

item_alg2_2019_long <- item_alg2_2019 %>%
  gather(question, answer, -`Student Name`, -`Student ID`, -Score, -Level, -Gender,
         -Ethnicity, -Disability, -Poverty, -LEP, -Building, -Teacher, -Assessment,
         -`School Year`, -`Disclaimer`, -`MC Total`) %>%
  separate(question, into = c('Question', 'Type', 'Correct Answer / Maximum Points'), sep = ' ', remove = TRUE) %>%
  mutate(`Correct Answer / Maximum Points` = as.numeric(`Correct Answer / Maximum Points`),
         answer = case_when(answer == 'a' ~ `Correct Answer / Maximum Points`,
                            TRUE ~ as.numeric(answer)),
         mc_correct = case_when(Type == 'MC' & answer == `Correct Answer / Maximum Points` ~ 1,
                                Type == 'MC' & answer != `Correct Answer / Maximum Points` ~ 0,
                                Type == 'CR' ~ round(answer / `Correct Answer / Maximum Points` , 2)))
```

Figure 11.2: *R code for Item analysis of 2019 data*

To increase the ease of use of our visualization, we imported the "Item maps". This enabled us to use descriptive names rather than acronyms for the various subjects. For example, instead of showing "I-20", we displayed "The Real

Number System". This significantly increased the ease of use of our dashboard, making them easier to read and adopt for teachers and principals.

```
#IMPORT ITEM MAPS
#2019 assessments
map_alg2_2019 <- read_xlsx('Raw Data/NSF Data Collaborative/Item Maps/2019/Assessment Item Map Regents Common Core Algebra II - Jun 2019.xlsx')

#COMBINE ITEM ANALYSIS WITH ITEM MAPS
item_map_alg2_2019 <- item_alg2_2019_long %>%
                      left_join(map_alg2_2019, by = c('Question', 'Type'))
```

Figure 11.3: *R code for joining "Item analysis" with the "Item map"*

In order to create a comparison, we also aggregated the data at the district and county levels.

```
#SUMMARIZING DATA AT DISTRICT LEVEL
alg2_district_summary_stdyear <- item_map_alg2 %>%
                                 group_by(`Standard Desc`, Type, `School Year.y`) %>%
                                 summarize(`District Percent Correct / Average Points` = mean(mc_correct, na.rm = TRUE))
```

Figure 11.4: *R code for aggregating data at the district level*

Finally, all the separate files proceeded by all the transformations were packaged into one .csv file for visualizing in Cognos Analytics.

```
#COMBINING SEPARATE FILES TOGETHER FOR FILE LOAD IN COGNOS FOR VISUALIZATION
alg2_dataforvis <- alg2_teacher_summary_stdyear %>%
                   left_join(alg2_school_summary_stdyear, by = c('Standard Desc', 'Type', 'School Year.y')) %>%
                   left_join(alg2_district_summary_stdyear, by = c('Standard Desc', 'Type', 'School Year.y')) %>%
                   left_join(items_per_year, by = c('Standard Desc', 'School Year.y')) %>%
                   mutate(`School Year.y` = ymd(`School Year.y`)) %>%
                   left_join(alg2_gap, by = c('Standard Desc' = 'Standard.Key.Idea', 'School Year.y'))

write.csv(alg2_dataforvis, "alg2_dataforvis.csv")
```

Figure 11.5: *R code for packaging files and the transformations applied into one .csv file for visualization*

Dashboard Design

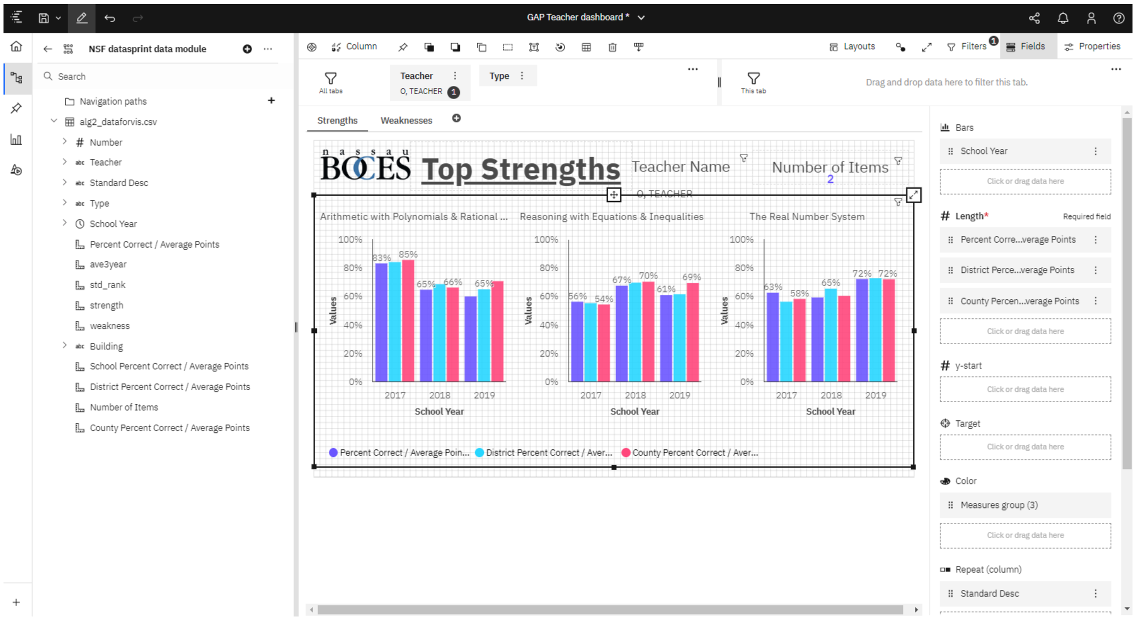

Figure 11.6: *Data slots in a Cognos Analytics dashboard*

We uploaded the .csv into Cognos Analytics 11.1.7 and designed a dashboard on top of it. We created two tabs, one for strengths and one for weaknesses. We also added the "Teacher" and question "Type" columns in the "All tabs" filter. This would allow us to filter on the teacher and question type we want for both tabs at the same time. For branding and giving it a more personal feel, we added the Nassau BOCES logo on the top left of the dashboard. On the top right, we displayed the number of items that were accounted for to render the visualization below.

A column visualization was chosen for simplicity, primarily due to its ability to show clustered comparisons very effectively. The test subject name is shown on top of each respective visualization. The y-axis of the visualization shows the percentage of marks students received; "Percent Correct/Average Points" – for the selected teachers' average, "District Percent Correct/Average Points" – for the district average, and "County Percent Correct/Average Points" – for the county average. The x-axis of the visualization shows these KPIs across the past three school years. We used different colours to differentiate between the three KPIs.

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To have the same clustered column visualization repeat for various subjects, we added "Standard Desc" to the repeat slot. It was then filtered on "std_rank" to show the top three in the case of the top 3 strengths visualization. This limit is flexible and can be changed to show more or fewer strengths as needed. The same process with the bottom three was repeated to create the top 3 weaknesses visualization.

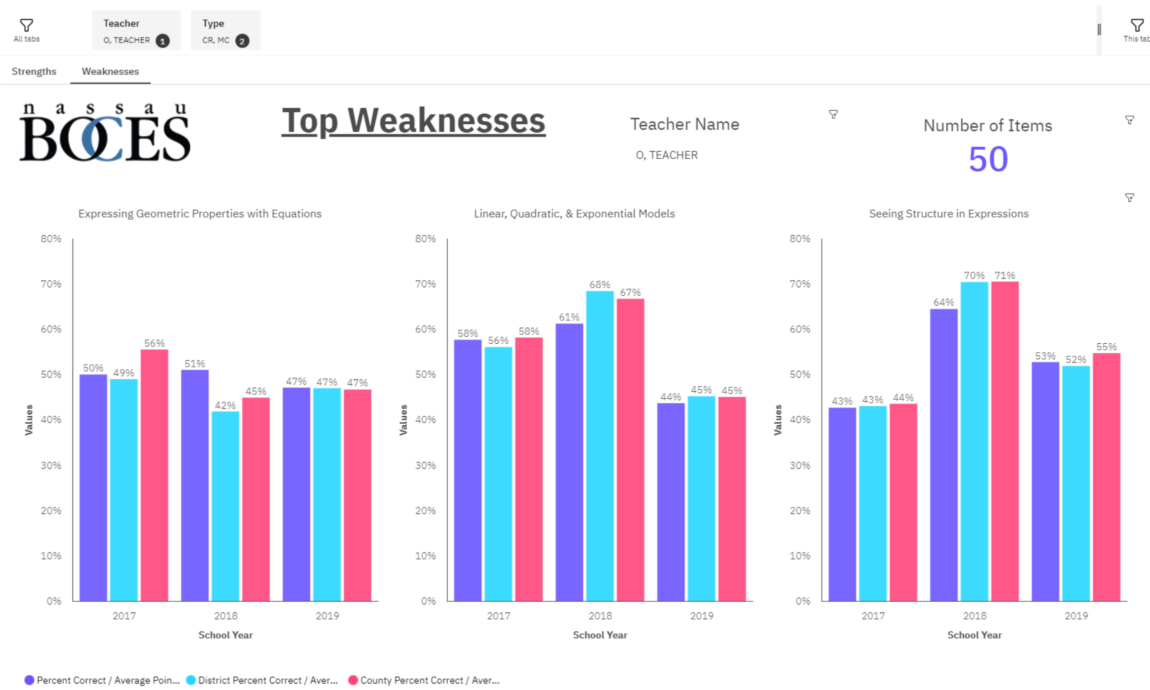

Figure 11.7: *Weaknesses tab in a Cognos Analytics dashboard*

The dashboard provides an excellent high-level overview of the selected teacher's top 3 subjects of strengths and weaknesses. However, if the teacher or the principal wants to see the breakdown of this result and analyze the data at a more granular level, we defined a drill-through navigation path that would give them the details they need. By selecting any of the columns in the visualization, the teacher/principal can drill through to a Gap report. A Gap report contains a regional comparison of student performance data at a much more detailed level. All the filter selections for the school year, the question type, and the teacher are retained, and the Gap report is run using the same filter selections. The Gap report also highlights additional details, such as the building the course was taught in, along with breaking down each item into more granular detail. An example of this report can be seen below in Figure 11.8.

NSF Gap Report

Number	Teacher	Standard Desc	Type	School Year	Percent Correct / Average Points	Building
1	M, TEACHER	Arithmetic with Polynomials & Rational Expressions	CR	2017	80%	Sample SHS
2	M, TEACHER	Arithmetic with Polynomials & Rational Expressions	CR	2018	74%	Sample SHS
3	M, TEACHER	Arithmetic with Polynomials & Rational Expressions	CR	2019	64%	Sample SHS
10	M, TEACHER	Building Functions	MC	2017	69%	Sample SHS
11	M, TEACHER	Building Functions	MC	2018	68%	Sample SHS
12	M, TEACHER	Building Functions	MC	2019	76%	Sample SHS
13	M, TEACHER	Conditional Probability & the Rules of Probability	CR	2017	47%	Sample SHS
15	M, TEACHER	Conditional Probability & the Rules of Probability	CR	2019	59%	Sample SHS
17	M, TEACHER	Conditional Probability & the Rules of Probability	MC	2018	60%	Sample SHS
18	M, TEACHER	Creating Equations	MC	2017	24%	Sample SHS
20	M, TEACHER	Expressing Geometric Properties with Equations	CR	2019	46%	Sample SHS
21	M, TEACHER	Expressing Geometric Properties with Equations	MC	2017	49%	Sample SHS
22	M, TEACHER	Expressing Geometric Properties with Equations	MC	2018	40%	Sample SHS
24	M, TEACHER	Interpreting Categorical & Quantitative Data	MC	2018	81%	Sample SHS

NSF Gap Report

School Percent Correct / Average Points	District Percent Correct / Average Points
78%	78%
71%	71%
54%	54%
67%	67%
58%	58%
81%	81%
49%	49%
58%	58%
62%	62%
25%	25%
47%	47%
49%	49%
42%	42%
80%	80%

Figure 11.8: *Gap report with additional details*

Application and benefits

For the post-event survey question: "For the two-day event, please describe the data visualizations that you found most applicable to your context and role, and why.", one of the attendees replied saying that "The visualization of the top three strengths and weaknesses as reflected in a Gap report for state assessments. This was most valuable because it helped us to identify how we can provide the user with further assistance in examining Gap reports over time."

The quote very concisely captures how educators can use this visualization today to improve the Gap report experience. Here are some more practical applications:

1) *Cultivate collaborative learning through pairing and mentorship* – as we can identify the top strengths and weaknesses of teachers, this opens up great potential for teachers to grow professionally and learn directly from experts. For example: if we identify teacher A as an expert in a subject, and teacher B is weak in that subject, they can be paired. Teacher A could mentor teacher B through discussions, sharing tips and tricks, shadowing in class, and more. Teacher B can significantly accelerate his/her learning and can greatly benefit from Teacher A's experience. Teacher A could be getting help for his/her weak areas from another teacher as well; it is a circular cycle. This mentorship can occur within the same school, within the district or even across the county. This cycle will collaboratively raise the education quality standard of the school, district, and county's teaching community.

2) *Track growth of a teacher in particular subjects* – as we have test score percentiles for several years, we can track how a teacher improved over the years compared to his/her score percentiles from previous school years. If we notice growth, this could be used as one of the KPIs used to promote teachers. If we notice no growth or a decline, this is an indicator, and it would be a great time to have a conversation on what we can do to help the teacher grow in that subject.

3) *Selecting the best fit substitute teacher* – if a teacher is absent for a day or a semester, picking another teacher to teach the subject will be substantially easier. The principal or the department chair making the decision can look at their teacher roster, find who is available, and select the best teacher to teach the subject based on this visualization. This data-driven selection will ensure the students will get the best quality education from their new teacher and that the teacher will enjoy teaching what they are comfortable with. It is a win-win for the students, teachers and the principal as well.

4) *Higher quality content development for new courses* – if we need to select a teacher to teach a new course, or if we need to select one teacher to record content for an online course, we can find the best teacher to do so based on

the same criteria mentioned above. The principal or the department chair making the decision can look at their teacher roster, find who is available, and select the best teacher to teach the subject based on this visualization.

5) *Create a balanced and holistic teaching roster, even while hiring* – it is crucial for a school to have at least one expert teacher per subject. If all the teachers of a school are experts at teaching one or two subjects and there are no strong teachers to teach some of the other subjects, it affects the students' quality of education. The principal or department chair can use this visualization to identify which subjects are strong and which subjects are weak in their school. They can work with other schools to balance their teaching roster through pairing and mentorship. Additionally, they can hire new teachers accordingly to balance things out. Having this visualization helps identify which strengths to look for while hiring.

6) *Strive for excellence through competition* – as a teacher can compare where he/she stands compared to the percentiles of the district and the county, this visualization can be used as a tool to inspire and motivate teachers to push beyond the limits and aim higher. To encourage them to grow and be the best they can be in the district and the county.

As can be seen from the many use cases above, this is a simple yet powerful visualization that is timely, actionable and specific.

Conclusion

Teachers, principals, and educators are busy professionals who play a major role in our societies' success. To ensure we empower them with the best insights, we need to ensure we provide them with accurate and actionable data visualizations. The National Science Foundation's Education Data Analytics Collaborative Workshop helped spark insightful discussions and brought together thought leaders from the education sector, seeking to brainstorm visualizations that can address the several educator data use needs.

As a result of collaborating with a diverse group of educators, we were able to create an interactive dashboard that showcased a teacher's top 3 subjects of strengths and weaknesses. The dashboard user, for example, a principal, can filter to focus on a teacher he/she wants. It empowers them with test score percentile comparisons of that teacher, the district's percentile and the county's percentile for the past three years. We can use this data visualization to answer several key questions, including how teachers and principals can identify specific instructional areas of strength and weaknesses to cultivate growth through mentorship, select the most capable teacher for teaching a course, and strive for excellence by competing throughout the county.

To enhance this dashboard, having historical data for more than a few years can help us with tracking growth over a more extended period, and as well, would empower us to do forecasting to project the growth for the upcoming years. Using the latest version of the analytics tool, in this case, Cognos Analytics would also help the users take advantage of the latest and greatest features they already have access to.

Looking ahead, an actionable and timely data visualization such as this one can really help accelerate the growth of numerous teachers, consequently raising the education quality our students will be able to benefit from. Additionally, as the unprecedented COVID-19 pandemic accelerated the adoption of technology in many schools, we will be able to collect a higher number of data points than we could previously. We can then use them to create more insightful data visualizations. The future of education analytics has just been accelerated, and it is very promising.

CHAPTER 12

Team Arrow's Path to Trust and Value: Getting the Right Data for the Right Task to the Right Person at the Right Time

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Like other data sprint teams at the 2019 NSF Education Data Analytics Collaborative Workshop, Team Arrow spent two engaged and enthusiastic days at Teachers College, Columbia University thinking, talking, and designing for educational data use. Unlike some other more responsible and diligent teams, Team Arrow may have cut a few corners along the way to completing several of the "suggested" data sprint activities. We may have used the provided data set a bit less and left the workshop with fewer (if any) lines of usable code. Yet, somehow, in a shocking upset (especially to us), Team Arrow's work together, at the end of the workshop, received the most votes of confidence from fellow attendees. While most teams admirably drilled down on the dataset, working through the details of engaging visualizations, we were drawn to the big picture, designing for educational data use through the lens of value, trust, and the full range of a community's needs, tasks, and roles.

There were six members of Team Arrow. We included a reading specialist, an elementary-school principal, and an assistant superintendent (each from a separate district in Nassau County), along with a Regional Information Center

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supervisor for the whole of Nassau County, one Ivy League professor of Data Science, one rather distinguished professor of Educational leadership, and the current author, a recent PhD graduate from Teachers College and a member of the team organizing the event.

From the very first icebreaker, led by Dr. Bowers and Dr. Graves, Team Arrow hit it off. Conversation was loud and lively. We were excited to have a full range of stakeholders at the table (from teacher to principal to superintendent to countywide data manager to data scientists and researchers), and we were all invested in doing the best we could with the time we had: we wanted to find and fix obstacles, to take advantage of our different vantage points on schools, and to move forward the creation and use of evidence for the sake of students and their learning.

Exploring Together

We started strong, with our initial brainstorming sessions homing in on five themes. We were concerned about **(1) Data Use, Data Usefulness, and Data Usability**. During an earlier session on Day 1 of the workshop, I had shared visualizations of how teachers and principals used the Nassau BOCES data warehouse over time. Two of these visualizations seemed to resonate with the team and to frame our work over the next day. One visualization, in particular, showed the peaks and valleys of how educators accessed online student data throughout the school year (Figure 12.1), with large spikes in use aligning with state testing events, but otherwise much lower levels of online activity. One member of the team referred to these low-activity periods as "Data Deserts." In Team Arrow, we were not content with Data Deserts. We asked, "What is the best way to make data relevant all the time?"

The second visualization showed usage in the system for more than 180 reports in the data warehouse. This visualization made clear that while a small subset of reports had extensive use by school leaders and teachers, the vast majority showed little to no use over the course of the school year. I wonder now whether these two images, viewed together, oriented the team towards a common, paradoxical problem of data use in schools: Educators love data; they have access to a lot of data (more than 180 reports in this system alone); yet we have Data Deserts. While a wealth of information is contained in report after report, only a small fraction of that information is being used and only during a few key weeks of the school year. From this paradox, I think, followed the inter-related, hard-to-pull-apart questions of our first theme--Are the data being used? Are they usable? Are they useful?

While we, as educators, were clearly not there yet, we wanted the answer to all these questions to be "Yes."

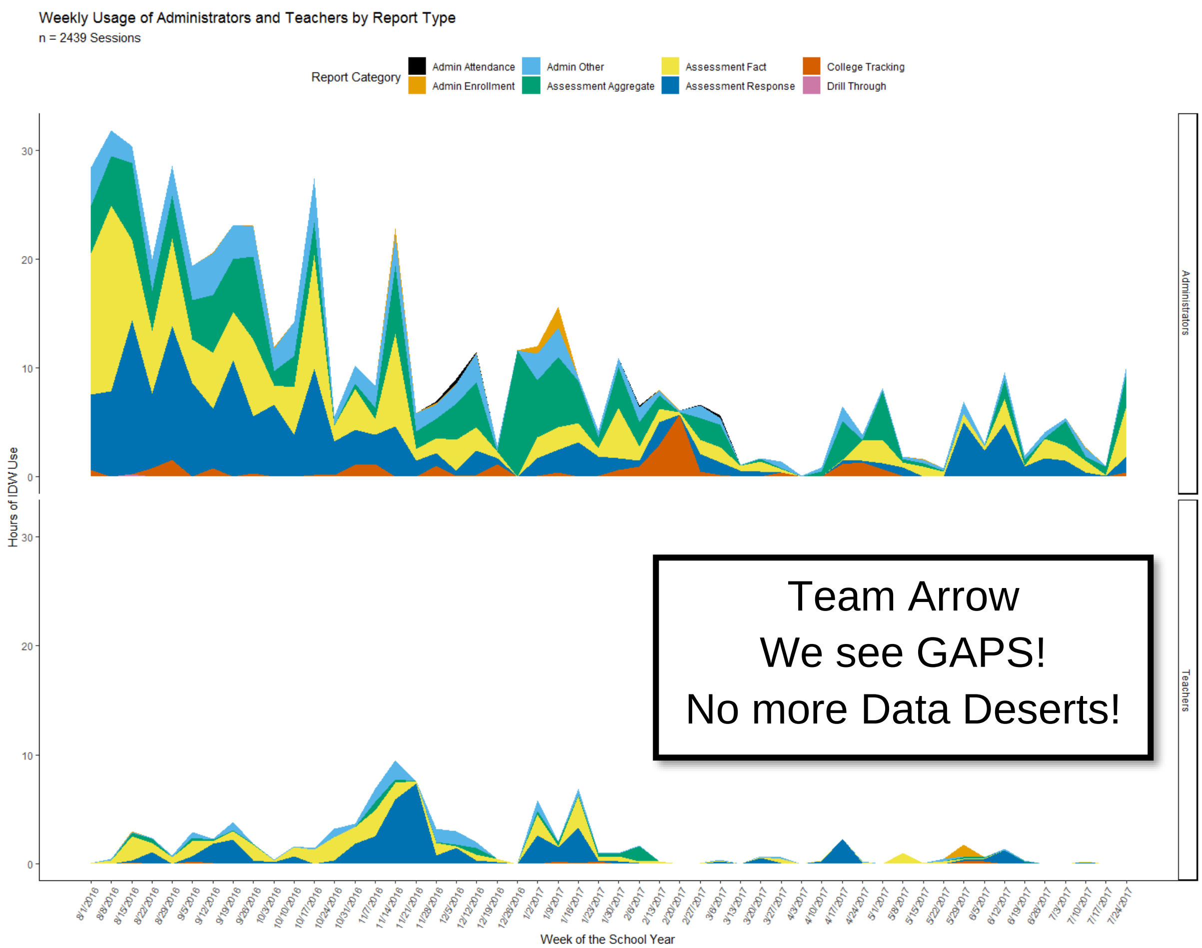

Figure 12.1. Weekly Usage of the Nassau BOCES Instructional Data Warehouse for Administrators and Teachers

Next, we turned to the problems of integration. If the data were not yet useful, perhaps this was because they were too siloed, too disconnected, and unable to present the bigger picture or narrative of a class, a school, or a district. If siloes were the problem, then integrating different sources of information might be one way to make our information more valuable. We decided that the Nassau BOCES data warehouse needed to integrate with other systems. And we wanted those systems to integrate with even more, other systems. We wondered, perhaps naively, how the creators of edtech platforms might integrate on their own initiative. We asked, "How do they get the opportunity to integrate their data?" However, reading this question after the fact, it seems to assume that edtech companies are dying to integrate their student information as much as users want to see it integrated and that they only fail to do so because of unseen forces holding the data apart. That may not be the way the industry works.

We wanted modular data dashboards of "other" data sources. "Other," I think we meant, than standardized testing. We wanted longitudinal views, clickable for depth and detail. We decided that **(2) We want it all altogether.**

Then, once it was all together, we needed to take **(3) Next Steps and Actions with Data**. We recognized that Data's usefulness and analysis are time specific—"Is this data useful now?" had to be asked and the answer attended to. Will teachers have enough information from these reports to make informed changes? If not, why were we sharing them? Do these reports help identify next steps? Most do not. Does that mean that the information on its own is not worth sharing? Could we see student achievement on a continuum of past, present, and future? What would a picture of that future achievement look like? Usefulness and Next Steps were contextual, we thought. Schools are different and need different things. What was useful to one school would not be useful to another.

Lastly, we thought about trust. Even if we were able to deliver for educators the most useful possible information and the clearest possible next steps, without a trusting **(4) Building Climate and Culture,** data use was going nowhere. We wondered what best practices were out there for embedding data analytics in school culture. We wondered about the role that principals play, how their leadership could enhance or deter the use of evidence. How principals might act to integrate Data Teams with other mission-critical, school-based teams (and why weren't those teams using data too?). Even with a supportive principal, though, we thought that having access to data (even access provided by impressive looking dashboards) was never enough for the community. Access alone showed little impact on how evidence was used to make classroom-, or building-level decisions. Making sense of information takes time and motivation, and we wondered if teachers had enough of either (or even if they should). Would we rather have an ELA teacher take their few spare moments to work on an inspiring new unit, to reach out to a disengaged student, or to pick up a few new tricks in Google Sheets? In any case, we were suspicious that mere access to information would do much to change behavior.

The antidote, we thought, was the power of protocols and structures in schools. If data access and awareness could somehow connect to schools' community and climate, perhaps through every day (or every week) practices and protocols, then evidence might have a fighting chance to make a difference. And perhaps this understanding that community was the key was why we took a different path on day two of our data sprint. We considered the available dataset of state testing results, and a data scientist in the group worked magic in R to layer state test scores and community demographics over each other in a fascinating map of Nassau County. At the same time, though, it seemed clear that building better visualizations for state testing data alone might not move the needle far enough in building the community's trust in information or motivating the action from evidence that we wanted to see. We had big thinkers on our team, and we wanted to think about big obstacles. What was keeping the data apart? How could we bring it together? How could we create trust and drive action?

In discussions across the table, we began to suspect that a key to supporting educator *action* was to put front and center how many different and specific education *actions* (plural) there really were. We fully acknowledged that educators have different roles and perform different tasks and that even the same educator makes different decisions at different times of the year. Prioritizing this variation across roles, tasks, and time put us on the path to the next stage of our thinking. We decided that we wanted to design a platform that would "give the right data, to the right person, for the right task, at the right time." To design this system, we would start from the place of practitioners' needs and we would build trust in information by delivering value.

Designing Together

With our four key themes in hand:

(1) Data Use/Data Usefulness/Data Usability.
(2) We want it all altogether.
(3) Next Steps and Actions with Data.
(4) Building Climate and Culture

We came up with a guiding question for our work:

How do we bring together data in one place and make it easily accessible AND usable for a wide range of stakeholders?

In order to bring together multiple data sources into one view, we naturally started thinking about dashboards. Drawing on work in their district, one member of the team shared a dashboard targeted at Guidance Counselors that brought together metrics on grades, attendance, and discipline in one view. This was a great start, but we wanted more: more metrics, more information, more audiences. We wanted "The Mother of all Dashboards".

However, as we kept adding functions and metrics to the "Mother of all Dashboards", we were reminded of the 180+ reports in the Nassau BOCES data warehouse, most of which were only viewed a few times over the course of the year. Probably, we thought, if sharing more reports does not cause educators to use more reports, then cramming more widgets onto a dashboard will not lead to better, or even more frequent, use of information. We wondered, would it really be one dashboard, after all, or many personalized dashboards, with educators seeing the information most relevant to their work at the time of the school year when it was most relevant (and not seeing the information that was not). As Figure 12.2 suggests, in the next iteration of our idea, each educator would access a role-specific dashboard, containing a shifting set of information, that depended on their needs at that moment in the school year. During the data sprint, we started calling this idea “Seasonal Dashboards”.

Or, Many Dashboards

	Teacher	Principal	Superintendent
Fall	Dashboard	Dashboard	Dashboard
Spring	Dashboard	Dashboard	Dashboard
Summer	Dashboard	Dashboard	Dashboard

Figure 12.2. *Team Arrow Final Presentation Slide, “ Or, Many Dashboards”*

To make our seasonal dashboards a reality, we would need several things:

- We would need funding and a willing pilot district.
- We would need a process for gathering feedback about which activities were critical for which educators at different times of the year. Some key information could be easily obtained, through prescribed reporting or budget timelines. Other information might be inferred by looking at how educators used reports in the current data warehouse over the course of the year. But, to fully understand these demands, we would need to talk to teachers, principals, specialists, guidance counselors, and superintendents (and maybe even one day students and parents).
- We would need a method for selecting the most important information for viewing at different times of the year, a kind of calendar analysis for ranking the priority of key events at different weeks in the school year.
- Most technically, but critically important, we would need automated access to a wide range of student information systems and other online applications. To build sustainable seasonal dashboards, we would need better connectivity to a wide range of specialized online applications,

where the metrics that we badly wanted to bring together were all siloed separately away.[2]

We would need all these things, but that day we started with the expertise at the table, drafting out a calendar of what we saw as critical and common activities over the school year. Instead of starting with the data, we started with the decisions, a bit of backward design for data use. In our remaining half day of work, we did not finish our brainstorm, but I include a slightly cleaned up version (Table 12.1) to paint a clearer picture of the kinds of information we saw making their way onto the seasonal dashboard.

As we got closer to our final presentations, members of each team were asked to take a tour of the room, checking in with different groups and then leaving written feedback at "basecamp" about what they had seen on their journey. While we did not have access to this feedback while we worked, it was exciting to see in retrospect, how travelers from other groups understood and appreciated the concepts we were working towards, leaving comments like:

- "They will be putting all data into one place for all stakeholders - superintendent, assistant superintendent, principal, assistant principal, teachers, students, and parents."
- "Identify different stakeholders: superintendents to teachers; present relevant data to all throughout the year; data may change during year."
- "Each stakeholder [gets] what data each needs; attendance, behavior, testing, assessments, standards - benchmarks"

[2] At this point in our conversation, I must report that Team Arrow significantly digressed. We began to understand more clearly how obstacles to data integration were going to be the most critical set of obstacles we had to overcome. With a superintendent, a Regional Information Center (RIC) supervisor, edtech experts, and practitioners all at the same table, we allowed ourselves a deep dive into the myriad structural obstacles our seasonal dashboards would run up against. As we tried to understand these critical issues, we moved past the task of designing a usable visualization and well into the domain of business models, procurement cycles, education politics and policy, and APIs.

Was it possible? Could Nassau BOCES and the RIC somehow leverage their networks, their working groups, their internal expertise, and their regional purchasing power to create data sharing agreements and common data delivery protocols that would connect vendors, districts, and the BOCES itself. As we talked, we realized that schools were bringing information together for staff in ad hoc Google sheets, but lacked consistent technical expertise; districts were building their own, more elaborate, dashboard systems, but lacked capacity and leverage with vendors. So, perhaps the solution did lie with the regional, the countywide organization, the BOCES and the RICs, that were small enough to represent and respond to their communities, but still large enough to advocate for sustainable solutions to data integration?

But we digressed.

Table 12.1 *Monthly Adaptive Dashboard, Calendar Brainstorm by Team Arrow*

<table>
<tr><th></th><th>Student
(Learner-level)</th><th>Content-Specific Teacher
(Classroom-level)</th><th>Principal
(Building-level)</th><th>Superintendent
(District-level)</th></tr>
<tr><td rowspan="2">July</td><td colspan="4">Advanced Placement Testing Reports</td></tr>
<tr><td></td><td></td><td></td><td>Year-end student data
Staff performance review</td></tr>
<tr><td rowspan="4">August</td><td colspan="4">State Testing Results</td></tr>
<tr><td rowspan="3"></td><td>Student Profile/Portfolio:
Achievement Scores
Services received
Writing Samples</td><td colspan="2">Enrollment information:
summary, details on demand, changes by subgroup
Updates and Information on entering students</td></tr>
<tr><td colspan="2">Classroom-level Profiles:
Achievement levels, ELL, IEP, 504, Behavior</td><td></td></tr>
<tr><td></td><td>Task-specific Student Profile for rapid placement of students in classes</td><td></td></tr>
<tr><td rowspan="3">September</td><td colspan="4">NWEA MAP fall results: (at student, class, grade, building, and district levels)
Benchmark I testing results: ELA and math
(performance on state standards by grade-level for principals and superintendents)</td></tr>
<tr><td rowspan="2"></td><td rowspan="2">Student interest surveys</td><td colspan="2">Chronic absence summary indicators: weekly and ongoing</td></tr>
<tr><td>Decision support dashboard for chronic absence: history, student achievement</td><td></td></tr>
<tr><td>October</td><td colspan="2">Instructional reading levels</td><td>Tailored report for data team and RTI meetings</td><td>Tailored report on RTI progress monitoring</td></tr>
<tr><td>November</td><td colspan="3">Tailored report for parent-teacher conferences</td><td></td></tr>
<tr><td>December</td><td></td><td></td><td></td><td>Trimester student reports
(Where applicable)</td></tr>
<tr><td>January</td><td colspan="4">NWEA MAP winter results
Benchmark II testing results: ELA and math</td></tr>
</table>

Hawn, 2021

<table>
<tr><td></td><td colspan="2">Instructional reading levels</td><td>Tailored report for data team and RTI meetings</td><td>Fiscal information for budget development</td></tr>
<tr><td>February</td><td colspan="4">Semester 1 grading and credit accumulation reports
Updated predictive analytics</td></tr>
<tr><td>March</td><td></td><td colspan="3">ELA and Math Gap analysis in preparation for state testing</td></tr>
<tr><td>April</td><td colspan="2">Instructional reading levels</td><td></td><td></td></tr>
<tr><td rowspan="2">May</td><td colspan="4">NWEA MAP spring results
Benchmark III testing results: ELA and math
Analytics for students at risk of failing State Regents testing</td></tr>
<tr><td></td><td></td><td>Tailored report for data team and RTI meetings</td><td></td></tr>
<tr><td rowspan="3">June</td><td colspan="4">Tailored reports and decision support for reflecting on learning and practice, gathering feedback, evaluation, recommendations, and planning next steps</td></tr>
<tr><td></td><td colspan="3">Prompting and completion feedback for consolidating school year records and collecting survey information on students, teachers, and principals</td></tr>
<tr><td></td><td colspan="2">Tailored reporting to support class grouping for next school year</td><td></td></tr>
</table>

- "Timely information to improve their practice; whole-child picture will be in one place."
- "It provides a real-time fluid representation of each child based upon multiple measures."
- "It is applicable to all stakeholders."
- "Missing data elements were key (i.e.: portfolios, etc.)"
- "Bring to the surface the relevant information to help guide instruction."
- "Accessible data: can't love one dashboard, rather multiple dashboards for different people at different times of year?"
- "Guidance for various stakeholders based on available features in a given dashboard."
- "Needs of users: data not currently in the system."

Finally, at the end of the second day, in our two minutes to present, we sold our vision of seasonal dashboards, and as attendees milled around casting their votes, we had more than one enthusiastic conversation about our design and more than one conversation sharing an attempt, by a different school or district, at a similar idea. One superintendent from another district described how they had created their own seasonal dashboard by simply embedding a list of linked reports within a calendar of the year.

Taking Team Arrow's work one small step further, I have included a mockup in Figure 12.3 of one principal's view of a seasonal dashboard. While the range of widgets in this mockup is limited to the kinds of student information discussed by Team Arrow during the workshop, it is easy to imagine additional layers of information drawn from student and staff surveys, from students' homework and classwork behaviors, from students' usage of online systems, from geographic and demographic information associated with schools' locations, or even knowledge of teachers' instructional methods.

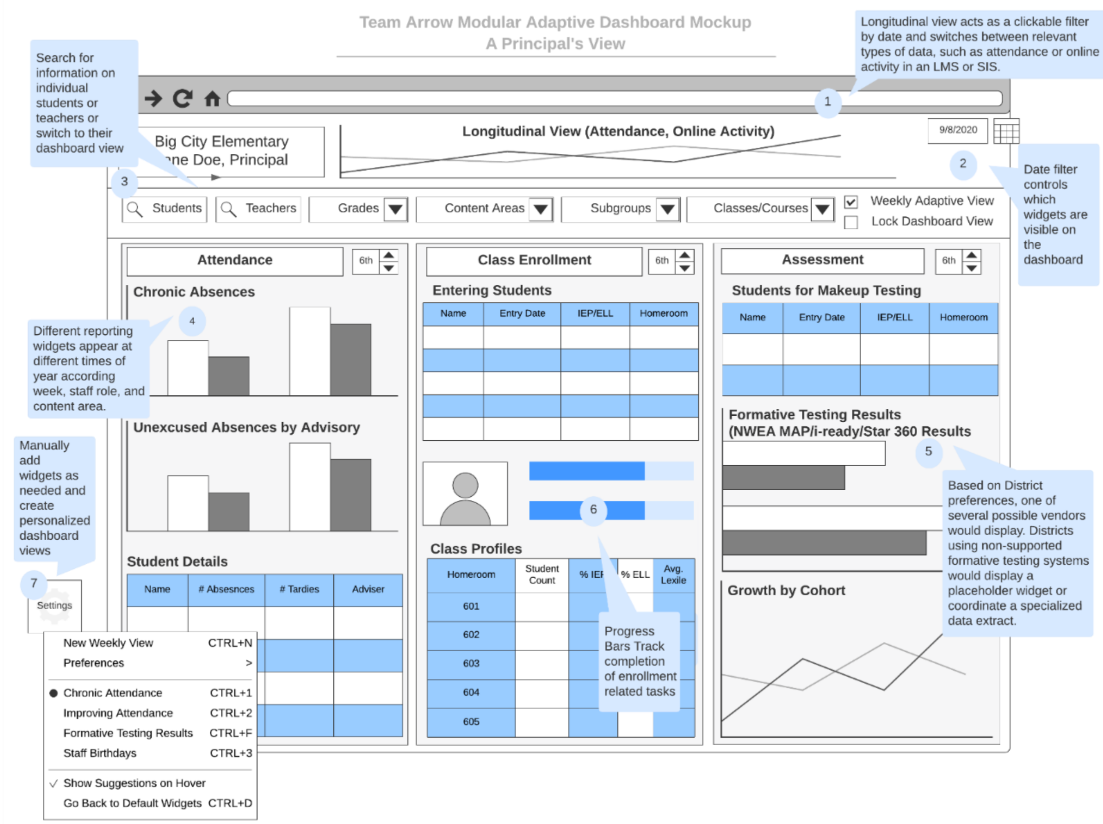

Figure 12.3. Adaptive Modular, "Seasonal" Dashboard Mock-up

While Team Arrow may have approached its work at the NSF Collaborative Workshop at a more macro-level than some other teams, we demonstrated, I think, the potential of this new style of collaborative analytics workshop. We explored and clarified solutions to challenges that educators face in accessing and using information, particularly as they integrate and harness new sources of data. With innovations in data science, business informatics, and recommender systems continuing to trickle slowly down to everyday use in education, we at

Team Arrow look forward to someone stealing our idea and making it a reality. After all, when one stock trader sits down to buy or sell equities, they can have at their fingertips vast amounts of integrated metrics, sentiment analysis, and up-to-the-minute, targeted content. When a teacher, principal, or superintendent prepares to make a decision with lasting impact on children's lives, we hope that soon they will be able to access the information they need with half the ease, confidence, and completeness. In the meantime, we look forward to the next iteration of the Data Analytics Collaborative Workshop to refine our aim, stay on target, and follow instructions just bit better (all puns intended).

CHAPTER 13

Educational Data Workshop: What Does Success Look Like and How to Realize It

Burcu Pekcan
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Introduction

Data is a critical part of educational practices in schools to prepare students for future success. Education data use can have a transformative power on teaching and student outcomes. Schools collect a huge amount of data both quantitative and qualitative with the intention of maximizing student learning. Data can inform education practitioners about student needs and provide opportunities for the schools to evaluate their educational practices so they can augment student achievement. But how close are we to our goal in educating all our students equitably? Are we using data effectively in our schools? What type of information can inform our daily practice? Which data tools inform us best in our contexts to calibrate our practices for maximal impact on our student outcomes? Research shows that despite the willingness to actively use data, most teachers and principals have limited access to data and limited data analysis skills (Datnow et al., 2007), lack the knowledge and skills for how to use data for instruction (Marsh, 2012), lack the proficiency in triangulating data to make effective evidence-based decisions (Vanlommel, & Schildkamp 2019), and schools have difficulty executing effective data use practices (Ebbeler et al., 2016). As the amount of data collected increases, there is a growing need for professional learning to address the data use needs of educators at each level of the educational organizations.

Professional Development (PD) activities around data use are essential investments. PD help reinforce capacity building in schools to make effective use of data. In their study which investigated how four high-achieving elementary schools use data for their instructional decisions, Datnow, Park and Wohlstetter (2007) emphasized the importance of investing in PD on data-informed instruction. They showcased that professional development was effective in building the capacity of educators in the schools they studied. They suggested that training on data use alone is not enough, but the principals and teachers should seek to integrate data use into regular evidence-based improvement cycles.

The NSF Education Data Analytics Collaborative Workshop was one forum for training and arming educators with data capable of enhancing their practice. They describe their goal as:

> "Currently across K-12 education, schools and districts are investing in Instructional Data Warehouses (IDW) and School Information Systems (SIS) in an effort to provide actionable information for educators to inform evidence-based practice and decision-making. Yet, across research and practice, much work remains to understand the types of data to display that are most helpful to teacher, principal, and central office decision making, as well as what types of data dashboards, visualizations, and UX best serve the needs of schooling communities. This work requires insights from both educators in schools as well as the current work of education data scientists working at the intersection of research and practice. As part of a larger National Science Foundation funded project, we are gathering educators and education data scientists together for an exciting interactive two-day event to learn together through a datasprint design-based collaborative workshop. The goal of the event is to work to understand the needs of educators around education data and data dashboards, and then iteratively build prototype visualizations and code together to help address educator data use needs across the system." (Bowers, 2019)

I participated in this NSF workshop as a teacher and researcher. The usual PD in education is more directed rather than collaborative, making this an engaging experience where teachers could provide input directly into the goals of the PD session. Before elaborating on my participation in this forum however, I would like to focus on how data use can affect educator practice and then discuss a model for evaluating PD. This model is important because it highlights the main goals that educators should strive for as they invest their time and resources for professional growth.

How can data change instruction?

Our nation and schools are home to a diverse body of students with different needs. Representing the very communities they live in, students come from different backgrounds and bring with them different combinations of preparedness before they can meet national standards on their way to becoming productive members of our society. Data, data use and evidence-based practices can be leveraged to allocate educational resources effectively and to improve student outcomes. Yet, it is often a challenging task to distinguish data which educators really need. Furthermore, schools often keep data in many formats. Teacher observations for example are often stored in a paper format in an administrative office, while most student data might be found in various electronic databases or even online portals. Integrating these data sources and making holistic inferences about students becomes an arduous task. Vanlommel and Schildkamp (2019) found that teachers do not triangulate data extensively. According to the "Teachers Know Best" report prepared by Bill and Melinda Gates Foundation (2015), there is a great need to have longitudinal data systems which portrays student growth over time as well as mechanisms that allow students to track their performance. Such systems can even forecast future growth trajectories and pinpoint challenges in each student's learning so that instruction can be personalized. Another research team identified managing and prioritizing data as one area of improvement (Datnow et al., 2007). In their study, teachers indicated their desire for a data management tool that can present various types of information in an organized way and present longitudinal data of a student's progress.

A vital need is to have user-friendly tools and visualizations when working with data. Stakeholders with different proficiency levels with data should be able to access the data easily and be able to make sense of data. *Georgia's Information Tunnel* (GIS) is one example of a user-friendly longitudinal data system that promotes evidence-based decision making in schools (Data Quality Campaign, 2020). For example, Figure 13.1 was inspired by a visualization based on GIS which shows student absences for one student over time. Seeing the trend over time arms teachers with context that they otherwise would have missed – there was a dramatic spike in absences between 2008 and 2009. Observing individual student trajectories in such detail gives educators one more tool to better understand their students. Notice how simple the graphic is too – the main takeaway can be deduced almost instantly. The GIS system prides itself on putting such actionable data in the hands of teachers.

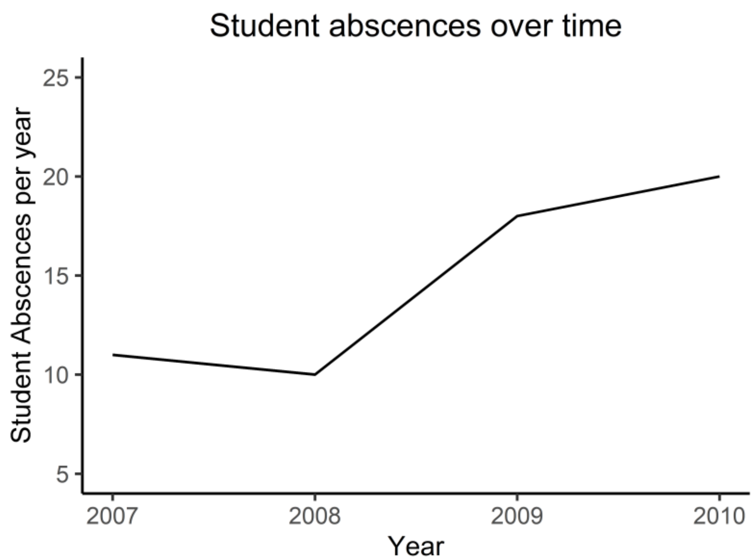

Figure 13.1. *Visualization showing student absences overtime*

Through the linked state level resources to district data, the teachers, principals, district leaders, and parents gain information relevant to their roles such as identifying best practices or observing each student's growth to ensure student achievement (Data Quality Campaign, 2020). On the other hand, new assessment technologies such as computer-adaptive tests measure the student learning through adapting questions' difficulty level based on student's answers. It provides prompt academic information on student learning; which standards are mastered and where the gaps are so that the teachers can tailor their instruction according to the student's needs.

My experience as a teacher has taught me that educators are inundated with many ideas that could conceivably improve their practice. This is especially true in regard to data use or technologies centered on educational data. Keeping data practices learner-focused is essential if its transformative power is to be effectively harnessed. At its very best, data use in education can bring together a school community as they develop a common understanding about their shared educational challenges and successes. It breeds accountability and clarity as to where a school community sits. These ideals are embodied in DuFour et al.'s (2004) notion of a PLC. Lin (2017) observes that "A PLC explores how an organization can be built around the virtues of collaboration, collective inquiry, and continuous improvement, and argues that such organizations are vital for a revival in education" (Lin, 2017, p.1). Creating a self-sustaining culture of inquiry around routine data use to improve students' educational outcomes is an ideal worth striving for.

Education stakeholders increasingly use different types of data to improve educational systems, experiences and outcomes (Campbell & Levin, 2009). Education data takes different forms from student demographics, to testing outcomes and student behaviors, as well as informal observations. When educators agree on clear expectations of what their students should know, they can gather the reliable and valid data to track progress towards the key learning milestones. Schildkamp (2017) calls this a "sense-making process" where the educators use their own experience, understanding, knowledge and expertise when integrating the data points.

Based on this evidence the educator makes educational decisions, through whether personalizing instruction or adjusting the learning environment and experiences to keep the student on track for success. Such activities include setting goals for the student, creating action plans for individual students, reteaching the topics that students did not grasp, implementing small group interventions and scaffolding the activities, and challenging the students who show mastery of content (Schildkamp et al., 2017). Data use in schools can improve student learning when the needs of students inform lesson plans (Campbell & Levin, 2009).

PD can address the data-use gaps

Under the No Child Left Behind Act of 2001, and now ESSA, the states, districts, and schools are held accountable for the achievement of the students they serve (U.S. Department of Education, 2019). This elevated the use of data in schools rapidly, but for accountability reasons. While the elevation of data use has continued since the 1990s, the motives have shifted from accountability reasons toward a greater emphasis on accelerating student growth. Some limitations hinder teachers' effective use of data however. Many educators and administrators at both school and district levels still lack adequate data literacy and training to use what is often an overwhelming amount of data in a meaningful way. Lacking an intuitive and easy method for retrieving or visualizing data to guide practice exacerbates this issue. The

GIS example from above is the exception to the usual chaotic manner that schools store and make access available to their data. At their best, school or district level data systems can facilitate or direct ongoing professional development and create evidence-based data inquiry cycles.

Datnow et. al (2007) studied four high-achieving school systems that adopted effective data-driven decision-making practices. Those systems started with setting goals for student learning framed by established system-wide norms for data use and promoting the mutual accountability between educators at all levels of the system. They invested in an informative and easy-to-use data system which provided them information on students for multiple dimensions. They built a support system where educators that are competent with the data analysis were designated to provide help. With continuous professional development and clear data protocols educators were supported in their use of data. These data-use accelerated students learning (Datnow et al., 2017). The authors emphasized the importance of investing in PD on data-informed instruction and concluded that an ongoing professional development had an important role for building capacity around data use and data management systems in all schools they observed.

Other research found evidence on the positive effects of PD on data use. Schildkamp and Kuiper (2010) stated that training the teachers on how to turn data into evidence-based decisions is necessary. Staman et al. (2014) studied the effects of professional development on the attitudes, knowledge and skills required for data-driven decision making. They found that PD was effective to increase the knowledge and skills of teachers, principals and coaches on how to interpret the output of the system. Hoogland et. al (2016) clarifies that while professional development is crucial to teachers' competence for the analysis, interpretation, and use of data, it is essential to develop teachers' skills in the use of data systems. Since there is a wide-spread need for data literacy among the educators, teaching the basic knowledge in data use is usually the main goal in data PD efforts. However, the trend switched from a one-shot PD model to an ongoing engagement in data use practices. This initiates a culture of inquiry supported by relevant data use and enhances teacher knowledge through collaboration and support. Both PD and professional learning communities seek to build skills that can be used in an ongoing manner in their practice as educators. However, the most important factor for quality PD is whether it retains a learner-focused emphasis. Student achievement is mediated by teacher practices, so a training which improves teacher practices can trickle down and improve student outcomes.

What does good Professional Development look like?

PD is an intentional process that aims to improve student outcomes by systematically improving some part of the educational process for students (Guskey, 2000). It cannot be stressed enough that PD should primarily strive to improve student outcomes. Successful PD efforts recognize that the link between PD and student outcomes must be mediated by some change in the educational process, whether it is a change in instruction, curriculum, pedagogical strategies, textbooks, or school policies. Guskey and Sparks' (1996) model shows how the connection between PD and student outcomes ultimately depends on how educators and administrators adapt their practices. Their model is useful for clarifying what a successful data-driven workshop meetup between educators and data scientists looks like, bearing in mind that a data workshop is a form of PD that educators can receive.

Guskey and Sparks' model posits that the quality of PD is affected by factors which they group into three broad categories: content characteristics, process variables, and context characteristics. Guskey (2000) describes the content characteristics as the "what" of professional development. This factor outlines the knowledge and skills that lie at the heart of a PD effort. Process variables refer to the "how" of PD. They clarify the format, organization and planned activities. Context characteristics delineate the "who," "when," "where," and "why" of a PD endeavor. In the context of a data-based workshop, the who can be agents from a range of different levels of the education process, including teachers, administrators, principals, district officials and data scientists. These three factors serve as the input into a PD session, and they are key in laying the groundwork for high quality professional development (Guskey, 2000). The essential feature of Guskey and Sparks' model is that high quality PD by itself does not directly influence student outcomes; PD only indirectly affects student outcomes through other causal mechanisms. In the third column of their model, there are three indirect mechanisms for how PD can ultimately affect student outcomes.

The most obvious and widely discussed is through a change in teacher practices, be they gains in pedagogical or content knowledge, classroom management techniques, or through integrating data use into their practice. Guskey (2000) writes "teacher knowledge and practices are the most immediate and most significant outcomes of any PD effort. They are also the primary factor influencing the relationship between PD and improvements in student learning" (p. 75). Few would contest this claim. The Guskey and Sparks' model also identifies school administrators practices as another mechanism for affecting changes in student outcomes. While administrators do not typically directly affect student learning, Guskey (2000) cites two examples of how they indirectly affect students. On the one hand, administrators interact with teachers on a daily basis, whether it's through supervision, coaching, evaluation or supporting teachers with various ad hoc requests (Deal & Peterson, 1994). On the other hand, administrators have a direct hand in shaping school policies. This includes school organization, assessment, textbooks, discipline, attendance, grading practices and the provision of extracurricular activities (Guskey, 2000). Administrators therefore can do much to affect the climate or culture of a school community, which can have a large effect on student outcomes. Lastly, the model also suggests that parents are an important stakeholder in the education process. Keeping parents involved in their children's development and school activities can improve student learning and motivation. While parents do not directly receive PD, their involvement can be affected by teachers, administrators, and the wider school climate.

In the fourth and final column of their model, Guskey and Sparks (1996) place improved student learning outcomes. Again, this placement emphasizes that the ultimate goal of PD in education should always come back to how it affects student. Student gains can be demonstrated in a number of ways. Most typically, schools are interested in gains in student achievement as measured by assessment scores, standardized tests, or portfolio evaluations. However, other measures like student attitudes, attendance, homework completion, behavioral indicators, can also be relevant. These gains can be evaluated on an individual level or at the class or school level. When looking at the school level, schoolwide enrollment in honors classes, participation in school or extracurricular activities, or participation in honor societies may be considered (Guskey, 2000). The relevant learning outcomes ultimately depend on the goals and nature of the PD and the participants in that PD. Guskey (2000) acknowledges that there are some missing mediators in the pathway from PD to student outcomes. In the context of the present chapter for example, school principals and district officials are absent from their model. Even so, the important aspect of their model is the understanding that gains in student achievement must be mediated by some change in the educational process. This change can affect any stakeholder in the educational process, including teachers, administrators, principals, or even parents. To bring the focus back to workshops centering on data use, Monroe (this volume) provides an excellent example of how such a PD setting can ultimately affect student outcomes through indirect changes in the educational process.

Writing about a workshop that brought together data scientists and educators from other levels of the educational process, Monroe (this volume) discusses how the stakeholders reached a consensus about building a tool to address student truancy issues. The challenges posed by truancy are well documented, so the buy-in was there and a clear objective for the workshop quickly developed: to build a data tool that could automatically generate letters addressed to parents explaining the extent of their child's truancy problem. This tool was based in the R environment and was quickly developed and completed within the workshop. All educators brought back with them a tangible tool to help assuage the truancy issue. This time-saving tool for administrators tasked with reaching out to parents could serve as an important step in developing a wider plan to combat truancy and has a strong chance to improve a student's attendance record. Viewed from the vantage point of Guskey and Sparks' (1996) model then, the mediating pathways from the PD workshop toward affecting student outcomes is clear. Administrators can effortlessly notify parents of their child's truancy issues. If the parents are able to motivate their child to attend school, then student-teacher contact time is increased. Theoretically, this should improve student learning.

Setting goals for a data workshop

> Is success necessarily the same for all participants in a workshop (teacher, principal, district officials, etc.) as they have different foci and different needs?

This interesting question can, in part, be answered qualitatively based on some research and on my experiences in the NSF Data Collaborative Workshop. Data workshops aim to give educators data tools to understand the whole picture of student learning, both where they came from and where they need to go. Such workshops present training opportunities which exemplify best practices for the use of educational data. Do all educators need the same tools and data to understand where their students are and what they need to flourish? Not necessarily. Broccato, Willis, and Dichert (2014) paint a picture of how needs at different levels of the educational system differ. They asked education practitioners at different levels of the system (e.g., teachers, principals and superintendents) what information about students or schools would be most useful for carrying their roles in the educational system. They also asked what the ideal longitudinal data tool would provide to teachers to help them make better decisions. Superintendents wanted to have information on a wide range of information about individual student to teacher and comparative data for schools (Broccato et al., 2014). For principals, student and teacher achievement information was perceived to be the most helpful information. Teachers focused specifically on their own students and classes and desired a state-wide longitudinal data system where they could see data over time and be able to compare. The responses showed overlaps as well as unique differences between the needs of stakeholders at different levels. This suggests that the attendees of a data workshop, as diverse as they can be, might have very different needs depending on which part of the education process they come from.

The NSF Education Data Analytics Collaborative created the space for educational leaders at different levels of the school system and data scientists to collaborate in creating informative data visualizations that will help educators best serve the students. Given the wider audience in attendance in this particular workshop, "success" in affecting student outcomes looks quite different depending on whether one is a teacher, principal, superintendents, or administrator. A key motivation behind our collaboration was to understand the data needs of the educators at each organizational level including types of data, data tools and to explore and be explicit about these different needs. While all educators seek to improve student outcomes, a teacher, principal, and administrator meet this end goal in very different ways. The way these actors harness data therefore should reflect how their position is likely to mediate the link between a data workshop and student learning.

A data sprint team design was used to enhance the interactions and exchange of ideas. A data sprint team can be thought of as teams which are made up of teachers, coaches, administrators, researchers, and data scientists. Coming from different levels of the educational process then, teams were formed of members with varying perceptions around the use of educational data. For example, educators from the district level focused on how student learning could be meaningfully compared across schools. Teachers emphasized (1) data that captures each learner's mastery of common core learning standards, (2) how to increase teacher access to school-wide data, (3) how data can inform instruction, (4) how data can be used to visualize student learning trajectories over time, and (5) how training can be tailored to specifically address effective data use. The researchers in the group were interested in expanding the use of evidence-driven practices, narrowing their attention to those efforts which directly improve student outcomes. They wanted to bridge the gap between the scientific research community and education practitioners. While the viewpoints of each educator reflected their own position within the educational system, everyone acknowledged that effective data use would mean different things for educators with different roles within the system. But of course, creating a comprehensive dashboard to address all of these concerns simultaneously is not possible or even necessary.

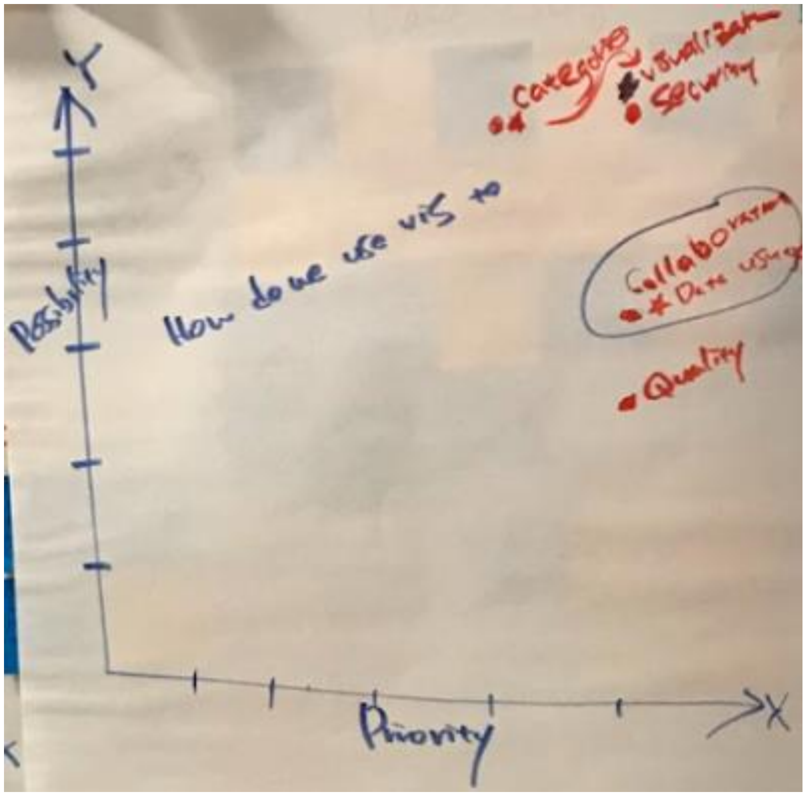

Figure 13.3. *Team Chevron scatterplot showing the priority and possibility of themes around data use*

To help build a consensus around the use of educational data, in team Chevron we centered our conversations around data usage, collaboration, data security, data quality, and visualizations. We then mapped each of these themes onto a scatterplot to compare the relative priorities and possibilities as shown in Figure 13.3. We went through intense discussions, weighing the tradeoffs and our debates on data priorities and possibilities shaped/resulted in our question of interest that would help us best serve our students with the data in hand. These discussions raised our awareness about different points that were new to us seeing from another stakeholder's view and why it is important. We developed a shared language about our collective viewpoints about what was the most important for us to know about our students. We also had to weigh what was possible to create in a short data workshop. It was very eye-opening to hear each member's different perspectives about which ones of these ideas are most urgent and applicable to integrate in the evidence-based practices in schools that we are part of and how to do it. The data scientist supported us in focusing on the most actionable suggestions. One aspect of effective PDs that is suggested by Darling-Hammond et al. (2017) is the provision of expert support and coaching. Having the expertise of data scientists can help educators understand what is and is not possible in a visualization. This made the experience more realistic and kept the discussions pragmatic. After exchanging ideas, we came to a shared consensus and generated a question that would guide us in our work to address the needs of the students we work with through a data visualization. NSF Education Data Analytics Collaborative Workshop was a unique event in how it brought together educators at all levels in an intellectually and physically engaging way. Hunzicker (2011) argued that teachers benefit from PD when they are engaged in discussions, simulations, visual representations, and problem-solving exercises that are relevant to their contexts and their students.

In the end, a consensus formed around the essential goal of advancing student learning. Specifically, in creating a data visualization that would best address the needs of our students, our guiding question was: “To what extent can teachers use data to explore student achievement by standard to help improve instruction?” With this question in mind, we aimed to build a visualization that could give us information on the math performance of 5th graders on three common core math standards. As Guskey’s model highlights, the intention of the NSF data collaborative was to ultimately impact student outcomes.

Our Visualization to Invigorate Change in Practice and Student Outcomes

Our data scientist coded and helped create the visualization displayed in Figure 13.4. The mastery for each standard was determined by a correct response to a diagnostic question designed to measure mastery of the corresponding standard.[2] For example, for standard “5.MD.5b” which relates to “Geometric Measurement: Understand Concepts of Volume and Relate Volume to Multiplication and to Addition”, a student was asked to find the volume of a rectangular prism. The snapshot provided in Figure 13.4 shows one time point where mastery was assessed for these three points.

[2] From a measurement point of view, a single question is not considered sufficient for measuring mastery (Chatterji, 2003). But we had to work with the data that we had in the allotted amount of time.

Our main goal was to have a simple visualization which could highlight a story that would be immediately obvious to any educator. Although Figure 13.4 only shows data for three standards, we had data for many more 5th grade mathematics standards which we could have added to the visualization. This simple bar graph communicates student proficiency levels so that teachers can easily understand where their class stands as a whole relative to some specific standards from the common core learning standards. This visualization is interactive so that when an educator clicks on one of the standards, they will see a list of students who have mastered that skill. Since assessments measure the mastery of standards within each grade level, the tool is also well-suited for administrators or principals. In sum, educators can see which students need support with one click.

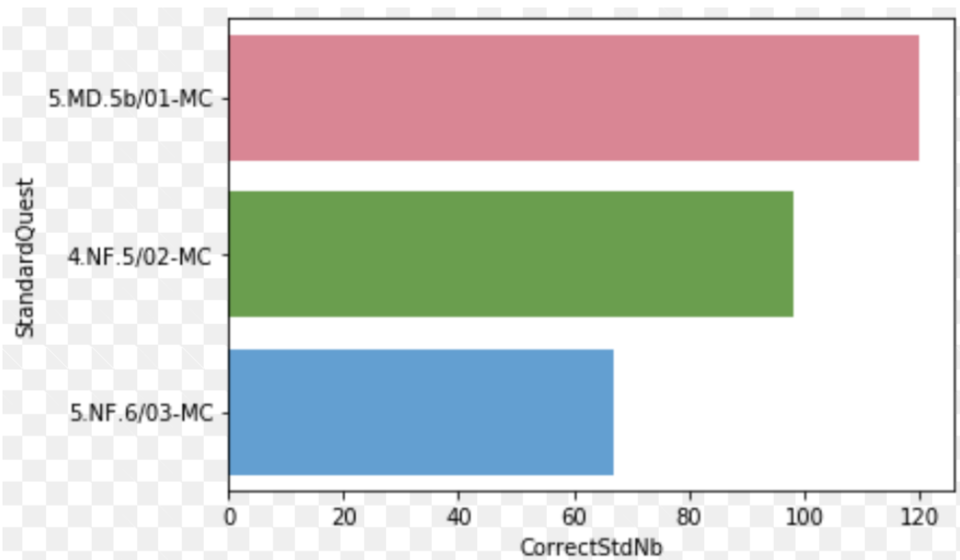

Figure 13.4. *Visualization showing student mastery for three 5th grade mathematics standards*

This visualization has the potential to affect the teachers' instruction and impact student outcomes through providing actionable data-driven insights. All educators need evidence about the learning rates and potential gaps of their students, regardless of their different data proficiency levels. A teacher who can easily read the information from a chart will be more eager to look at the data again before planning his/her instruction. They will also see the picture that the graph presents clearly so they will be aware of the gaps in student learning and will create activities that will close these gaps. With the information provided for weaknesses and strengths, this visualization can be used to enhance teaching practices and augment student learning. By identifying key trends by standards, the educators can pinpoint the gaps and roots of the problems. This will help narrow gaps in student learning and allow teachers and administrators to take timely actions and tailor instruction to individual learners. Action plans highlighting learning gaps can facilitate the allocation of resources in an effective way. This increases the efficiency of teaching practices, which are a key mediator in improving student outcomes. Goertz (1997) states that school level data can be used to address equality, adequacy, and efficiency and that school-level educational outcome measures show the efficiency of an educational organization.

Not all students are at the same performance level and it is important for teachers to know where their students are, what they need, and the best practices to address their needs. Using a visualization like the one we created can also provide opportunities for building capacity around data in schools. Teachers can provide quick interventions to help students catch up with their peers. If this is a school-wide trend, then staff can collaborate around data and develop a common language to identify the issue and then adapt their methods and strategies. By taking a time series approach, they can even identify when the gaps developed and perhaps address the root causes of these trends. Such practice makes schools operate like professional learning communities where continuous improvement becomes the norm (DuFour, DuFour, Eaker and Karhanek, 2004).

The visualization approach shown in Figure 4 can allow teachers and admin to see the students with the highest achievement and identify the teaching practices in those classrooms and share these best practices that teachers learn from each other to improve their students' success. Moreover, this type of visualization will help involve teachers in high-evidence low-inference discussions and will strengthen the collaboration among teachers in honest and trusting conversations to evidence-based data inquiry cycles (Bowers et al, 2019). Teachers will decide on next steps for their instruction and these evidence-based decisions can best serve students as long as the educators ask the right questions depending on their context and use the right data.

Concluding remarks

It is more urgent than ever to educate our students well academically and emotionally for ensuring a just nation and world. It is very urgent that we as educators gain the adequate skills to make the most powerful educational decisions based on evidence to accelerate student growth. Teachers are in the front lines fighting to change a student's life by equipping them with adequate competencies. This makes them well positioned for enhancing student perceptions, understandings, beliefs, attitudes, and tolerances. Data use is critical for our education system to operate on facts when shaping the future of our students. This is particularly needed in today's world that suffers from pandemics, global crises, unjust institutions, and leaders that ignore what data says. This chapter shed light on the importance of stakeholders collaborating to find the tools that can best serve their needs to drive change in their students' growth.

Being inspired by Guskey's (2016) model for evaluating the effectiveness of Professional Development in education, I believe that data workshops should be student-focused in the sense that the design of the activities should yield meaningful impacts on students through the pathway of altering the practices of teachers, administrators, or district officials. This is, after all, the reason that educators go to work each day, and the reason that many of them became educators in the first place. A successful data workshop then should create the opportunity for the teachers to link the workshop contents back to student contexts, since teachers are present in the students' environment on a daily basis. The workshop content should help teachers meet the distinctive needs of their students through offering a context-based design of activities.

One important aspect of data workshops should be the participation of actors from different levels of the educational organization. Sharing and listening to a variety of perspectives that reflect particular roles in the same system such as teachers, leaders, data scientists and researchers allows for deep understanding of the contexts and a consensus in determining priorities and possibilities. This active participation helps build the culture of expert support where the expertise is shared to build on the current knowledge. This is a powerful way that can bring change to perspectives, beliefs, and attitudes of the educators who then may reflect this change into their daily data practices or development of the data tools. While the necessity of participation of educators at each level of the system cannot be ignored, I strongly believe that the teachers have to have the biggest input in the process since they have the clearest mediating pathway for linking PD to student outcomes. As I mentioned before, teachers have the first-hand impact on student achievement, therefore, they have the most knowledge on which levers to pull in the most powerful ways to accelerate learning. If we are striving for better student outcomes through strengthening our fact-based practices in educational settings, it is imperative for data workshops to address teachers' diverse demands.

Of course, we cannot ignore the importance of data scientists in data workshops. Their technical skillset makes them well-suited for specifying and reaching an achievable outcome. School systems rely on their expertise and skills to answer difficult questions. Their work influences how teachers perceive student progress. The perception of the teacher might change depending on the dashboards they use. But this is a two-way street. Educators are on the front lines and intimately involved with guiding students, so their input in directing and framing the energies of data scientist cannot be overstated. It is the teachers who knows the students most closely and the ways that can impact student learning to the highest extent.

Evidence-based educational practices are key to enhancing students' human capital. Effective data workshops can be the platform in which educators collaboratively find the tools that can greatly benefit them in making evidence-based decisions and transforming student outcomes.

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CHAPTER 14

Data Science in Schools: Where, How, and What

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Background

As a current Data Scientist working in the professional world, I perform various technical tasks using data to derive meaningful stories. That includes a wide scope of work such as extracting transactional raw data from the client's database, transforming it into meaningful information like Key Performance Indicators (KPIs), developing machine learning models, and deploying it into the production environment by building visualizations and dashboards using business intelligence tools. The sector and data that I mostly deal with are education and health in international development. I have an academic background in Statistics, Mathematics, Economics, Learning Analytics, and Computer Science (on-going) dreaming to develop a real Artificial Intelligence (AI) in the education sector one day. Hence, when I received the invitation from Dr. Bowers to participate in the NSF data collaborative event as an educational data scientist expecting to perform data science tasks on the spot, my first reaction was, literary, "What? Real-time?". Usually, data scientists' work requires a time commitment to deliver the findings from data. That could be due to time consumption in testing and choosing best models, appropriate visualizations, familiarity with the tools, etc., but mostly, it takes enormous time to digest and clean the data and discuss the research question with the client, i.e. "what do you want to know?".

Lee, 2021

With the excitement and ambiguity in mind, the D-day reached. I was assigned to the group called “Chevron” where we had a fantastic combination of experts from the field. Such as leaders from Nassau county BOCES sharing rich experiences providing insights on warehouse data; a renowned scholar who provided in-depth background ideas, bridging the school’s demand and supply from the real world, and practitioners from schools who were great resources sharing what kind of research questions that they had in the usual daily life using data collected from learning management systems and beyond. During the two days of the workshop, this amazing group collaborated successfully, gathering ideas, sharing questions, understandings and challenging each other. As a data scientist, it was my big privilege working with these people as well, since in the real world there were not many chances to learn what is required from practitioners.

Data science practice during the event

Where did we start?

One of the main objectives of the event given to participants was to perform a data science practice with real data retrieved from the Nassau BOCES data warehouse. To do so, there were several discussions that participants as a group had to go through. First and foremost, we had to identify what kind of data-driven questions that we would like to answer. For instance, some practitioners were curious about how students’ absenteeism data correlates to student’s performance data on assessments. Other practitioners were wondering how data can help in improving the school environment. Depending on which beneficiaries you were in (e.g. teachers, principals, superintendents, etc.), ideas and suggestions varied. In the initial stage of the talk, there were a lot of back and forth discussions since for me as a data scientist, it was important to assess and evaluate the questions promptly and provide feedback to teammates whether those are possible to deliver with the given data in a limited time. In the same sense, I was also assisting in what kind of data we received for this task and what types of analysis are doable. Finding an appropriate research question process took a significant amount of discussions and thoughts but finally, we came up with an agreement to explore “to what extent can teachers use longitudinal data to explore student’s achievement by standard?”.

How did we find the answers?

Once we set up the question, the next step was to examine how we can find that answer with the available resources. In contrast to the initial discussion, this process was mainly led by a data scientist who has the most knowledge and experiences in manipulating and presenting data. However, it was not only the data scientist's work since I was the last person in the group who was actually understanding the background of the BOCES data warehouse while other teammates already had some sort of experience. We started to dig more into the datasets together, identifying what kind of information do we have and trimming down the unnecessary information. During the process, we were able to narrow down more details with the research question such as "what grade should we use?", "what subject of assessment to analyze?", "how effectively can we present those findings?", etc.

Especially, with the guidance from Dr. Bowers' research resources, our group was very excited about choosing the visualization to tell our stories. At first, everyone was fascinated by a variety of possible visualizations. We were being imaginative like little kids who just received the Christmas present drawing charts in the white paper examining whether our variables can fit, and findings can be visually represented well. Yet, the fancier the visualization looked, we found that it was more difficult to share the stories clearly. Of course, if someone spends time and is willing to understand what the picture is saying, that would work. But we wanted something simple and strong that everyone without technical knowledge can understand. This was particularly emphasized by our group practitioners who were actually working at schools on a daily basis since for students, teachers, and administrators, not many people can commit time to study the result if it is not intuitive due to the other bulk of duties. Eventually, we decided to go for a simple bar graph which is common but apparent.

The last procedure of the data science practice was coding, one of the crucial competencies that makes data scientists unique. For this exercise, I used an object-oriented programming language called "Python" in the Jupyter notebook environment, which is widely used for data scientists along with "R". Based on the discussions that I had with the group, I started importing relevant dependencies (e.g. packages for the data frame, visualizations, etc.) and cleaning data. This process was very tricky (and I assume all data scientists in this event felt the same!) since our group task was not using the variables given in the dataset but creating a new feature by joining different datasets. The datasets were also not cleaned which needed a lot of manual manipulation in a short amount of time. But finally, I was able to deliver the expected bar graph.

What did we learn from data?

Figure 14.1 shows visualization during the planning process and after the actual coding with real data. As described in the research question, we were curious about the number of students in the current 6th-grade class who answered correctly by grade 5 math standards. This was an important indicator found by teachers since each standard in the y-axis measures different competencies and those are not from a single dataset but from combinations of different assessment results which made it difficult for teachers to conduct an analysis. For instance, if there are fewer students who got correct answers to certain standard questions, teachers can assess and adjust the curriculum focusing on filling the gap. The final visualization made with Python depicts only part of the standards due to limited time. Yet, it clearly shows that there are fewer students who got the correct answer for question 5.NF.6/03-MC compared to question 5.MD.5b/01-MC. If time had allowed, we were hoping to disaggregate data by class, school, district, and make it into a dynamic visualization so as to build interactive dashboards.

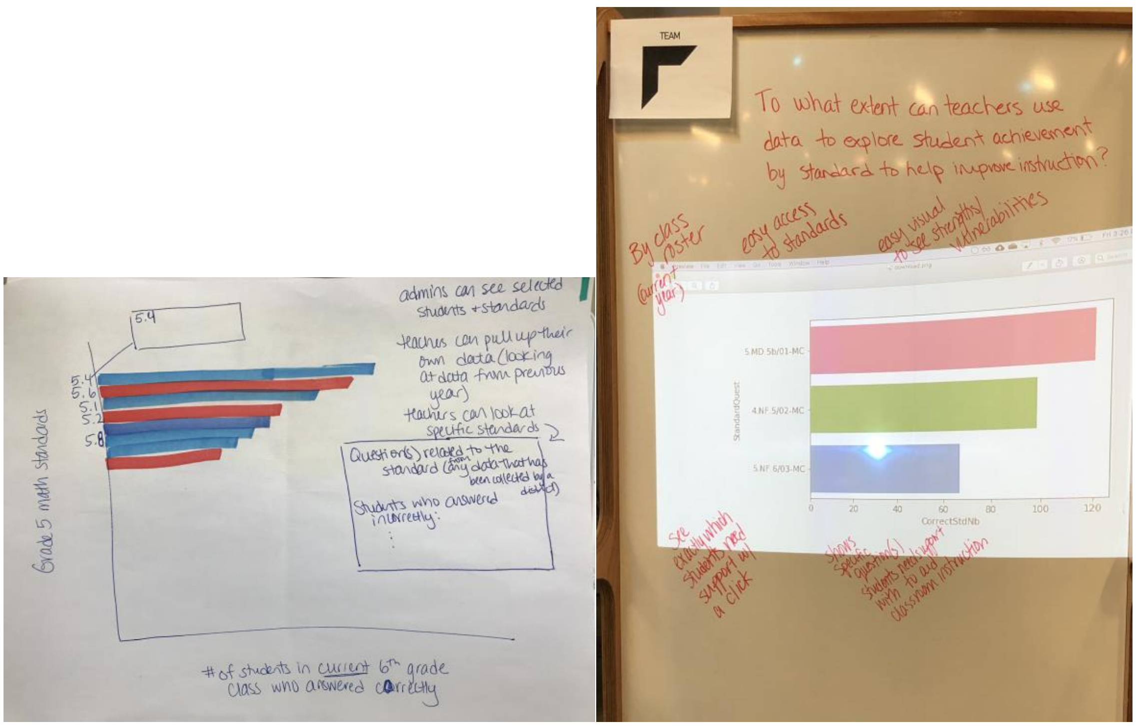

Figure 14.1. *Bar chart (left) during the group discussion and after (right) coding*

Challenges

What do we want to know?

One of the challenges that most data scientists confront today in the real world is to communicate with the beneficiaries (e.g. clients, senior managers, colleagues, etc.) and find out what do we want to learn. This question is more obvious and relatively easy to answer if the target is clear. For instance, in the business world, one might want to know how we can optimize the product line that will affect profit using available data. A data scientist will discuss with various professionals including marketers, engineers, decision-makers, etc. to find out where to retrieve data, how to clean and transform it into meaningful information and visualize it to senior managers for their insights. During the exercise in the NSF event, I was very impressed by our colleagues in learning how many brilliant ideas that they had on data analysis. Principals and superintendents were curious about finding the evidence in improving the school and teaching environment. Teachers were full of thoughts referring to their practical experiences in elevating student's learning. Yet, although we were able to bring up many ideas, it was not easy to come up with one consensus agreement since the significance of questions varied between stakeholders.

How can we get that?

During the event, the key difference that I found from the business world that made educators[2] reluctant to conduct in-depth data analysis to improve their tasks is that there were not many channels that teachers/principals can use to retrieve raw data. For instance, for the business corporations (or any organizations that possess mature data infrastructures), if a data scientist agreed on one research question, he/she consults with the data engineers and finds out where they can get the data. However, in the normal school environment, unless teachers/principals put in much effort to find out where and what kind of data the school IT team stores, it is very time-consuming and challenging to turn this into action due to other busy duties. In our group discussion as well, it was surprising to see how school stakeholders are disconnected from the BOCES data warehouse except for the researchers from higher education. Teachers knew that school and district administrators were collecting data. But they were not aware of where is that data going and how can they request to receive it afterward.

How to do it? What is Data Science?

According to the Harvard Business Review (Davenport and D.J., 2012), a data scientist is identified as "the sexiest job of the 21st century". No wonder, the salary of data scientists is one of the top tiers that many young graduates

[2] Note: Educators here applies to non-tertiary levels such as elementary, middle, and high schools.

would like to enter. Likewise, the technical skills that the industry is expecting from data scientists are high and demanding. Maybe that's why a lot of people are intimidated and feeling new to data science. But actually, this is not true. Data science is not a new area. Perhaps it's a new area for those people who didn't have statistical data analysis or business intelligence techniques (e.g. building data-driven dashboards with KPIs) background in the past. However, if you were already doing this work, it is not that much different from what traditional data analysts were doing except for the fact that the volume and structure of data are somewhat more complicated. Due to this, there is a need to have some data engineering skills (e.g. knowledge in database and programming language). Once you receive data, the preliminary analysis process (i.e. exploratory data analysis) and developing models are the same (or pretty much similar by the fact that the engineering side is using pre-defined algorithms). In that sense, the NSF data science event was an excellent opportunity for professional data scientists to learn how educators are responding to this new regime.

First and foremost, I would like to know how educators were reacting to coding. The biggest difference between traditional statisticians and data scientists in terms of conducting an analysis is programming skills. Most social science analysts widely use programs such as SPSS, which has an intuitive Graphical User Interface (GUI) that makes statistics fairly easy to use. However, as data have become more complex, the open-source tools that do not require a license, such as R and Python, are gaining the spotlight in data science since everyone can contribute and share code, and develop and contribute to open code libraries. Yet, this does not mean that traditional statisticians do not code. There is quite a bit of coding required with more sophisticated tools such as SPSS (using syntax), STATA, SAS, etc.

To understand how educators are familiar with the data science world in our group, I was introducing what kind of work data scientists are doing in the field, what kind of skills are required, and how to do these things through demonstrating the coding process using live coding. Although it was true that most of my colleagues in my group were not exposed to Python or R coding before this event, they were attentive and open to new learning. Furthermore, the good thing was most of the participants were familiar or somewhat familiar with basic statistics that they need to perform for their analysis. It was just a matter of the "method" (i.e. which analysis tool) that they decide to choose to deliver the data-driven stories.

Data Science for whom?

When all groups finalized and shared data science exercises during the event, there was an important lesson that we learned. Who is this data science for? Data science results are highly related to research/business questions that audiences want to know using their data. Although choosing the right visualization to effectively tell the results are also an important aspect to consider, the most crucial thing in the data science projects is whether this research question is helpful for analysts, decision-makers, and the organizations. In that sense, the scope of data science questions can be wide. Selecting an appropriate question that will fulfill the requests of the beneficiaries is very important.

Lessons learned and the next step

Reiterating the appreciation to Teachers College, Columbia University Dr. Alex Bowers and his research team, Nassau county BOCES team, and all participants contributed to organizing this fantastic event on data science in education, I believe this was a huge stepping stone for everyone in the education sector allowing us to learn more about data science at schools. Considering the current reality that most data science professionals are working in an industry where they can access strong data infrastructures due to their high demand, it was a good opportunity for data scientists to meet educators on the spot and interact together.

Through the event, first I've learned that it is crucial to advocate and introduce the concept of data science at the school level. It does not have to be fancy showing flowerlike visualizations, complicated coding, and inferring that data science is intimidating or some special thing that only mathematical aliens can perform. Rather, there should be a perception that thanks to technology, there are many open source libraries and automatic machine learning tools that users can easily access. The most important thing here is to have basic competency in knowing how you can build data-driven research questions and whether you can interpret the results. The middle process can be helped in various ways, such as data scientists performing, using auto processing tools, etc. Those basic competencies can be learned in many ways such as taking capacity building training from higher education, enrolling in courses from free MOOCs provided by renowned institutions, or jumping into the field directly improving from mistakes. There is no one answer. Bowers, Bang, Pan, and Graves (2019) found in their 2018 Education Leadership Data Analytics (ELDA) summit that "the domain and market are ripe for more capacity building offerings for teachers, leaders, central office staff, and researchers throughout education". Yet the current offerings from the market are not perfect covering all three aspects of ELDA, which are "education leadership, evidence-based improvement cycles, and data science". As a data professional working in the education sector for several years, this is very true. Unfortunately, there is a lack of leadership in the education sector recognizing the importance of data use. Although there is training on data science for executives, there are not many courses for school leadership that assist in understanding why and how data can improve the education environment. This could be due to many reasons but at most, I found that the misperception toward data science for non-technical people especially in the education sector is the toughest climbing segment of this journey.

The second lesson learned that I want to stress is the urgency of establishing communication channels between stakeholders and data scientists. Realistically speaking, not all teachers and educators can be data scientists. Not everyone needs to have those skills unless it is required for daily tasks. However, during the group work at this event, I realized that educators are eager to share their data-driven ideas and turn them into reality. Yet, they were just not sure where to start, who to speak with, and how to do it. This is one of the big challenges that most organizations have where they are not equipped with effective data processing infrastructure. Unless it is a special type of school such as charter schools where the organization can afford professional data analysts/scientists dedicated to doing data work for teachers and principals, in reality, it is indeed difficult to secure data professionals in the regular public schools. But if there is something in between, for instance, researchers from higher education, data experts from nonprofit organizations who can bridge the gap, who listens and delivers on a school's request, there then is much less of a burden expected for educators to perform data science tasks. The only thing they need is the minimum competency that they can share ideas for the research questions and understand and use the delivered results. This also does not require researching all schools in a country since most of the questions (of course not all!) will be repetitive and one can generalize those at some point. In that regard, conducting more research with public schools' educators and learning what teachers, principals, superintendents, and other school stakeholders need in terms of using data is a most urgent matter. Bowers, Bang, Pan, and Graves (2019) echo the same emphasizing the "central need of building capacity, tools, datasets, and networks of researchers and practitioners". Unless the schools and teachers are using tailored methods (e.g. assessment that is conducted only in certain districts), the big picture and analysis methodologies will be pretty much the same. Establishing a strong community sharing mutual interests can happen in education as well.

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CHAPTER 15

Direct Data Dashboard

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About the Authors

Melissa O'Geary is the Director of Data, Assessment, and Administrative Services for the Oceanside School District. She has worked in multiple roles including Technology Coordinator, IT Specialist, Supervisor of Learning Teaching and Assessment, and as a Google for Education Trainer. She currently works closely with the Oceanside administration on the data needs of the district. When she is not computing numbers, she is most likely spending time with her family and her King Charles Cavalier dog, Andy. You can visit her on Twitter @mogeary.

Melissa recognized the importance of data in schools while she was working in a small parochial school. At the time, while she was teaching technology, New York State began to require schools to report student demographic information to the state. This soon became Melissa's responsibility. In addition, some software programs began to use data to help inform instruction. Since teachers were not yet comfortable with how to utilize this new information, they looked to her for support and training. As time went on and New York state and other instructional programs required more information from schools, Melissa continued her career with various data analysis positions.

Laura Smith is a Reading Specialist in the Oceanside School District. She has worked in multiple roles including classroom teacher, middle school ELA teacher, and as a special education/IEP teacher. She currently teaches Reading Recovery and AIS reading to students in grades first through sixth at Boardman Elementary School. When she is not in her classroom, you can find Laura spending family time with her husband, two teenagers, and Keys, the dog. You can visit her on Twitter @LSmithOSD.

Her first realization of data-informed instruction was in the late 1990s when she was trained in the Reading Recovery program. In a Reading Recovery lesson, data is continuously collected. The teacher adapts the teaching prompts to build upon what the child already knows to advance his/her learning. It is a constructivist approach to learning. A "Running Record" assessment is given each day and analyzed to decide which teaching decisions will be made for the following lesson. "As children learn to read and write, their processing systems are changing as they make new links and learn more each time they read or write. Close and careful observations inform teachers about changes in a child's literacy behaviors over brief periods. Daily recording of behaviors enables teachers to make helpful teaching moves." ("Early Literacy Learning" 2018)

Laura realized how imperative it is to diagnose and monitor students using various assessments and diagnostic tools to determine eligibility for additional academic support. Identified students require careful and systematic monitoring techniques to determine the effectiveness of any new program. Through her data collection and analysis, she recognized that data was often missing, incomplete, or inconsistent. She realized that for data to be valuable, it must first and foremost be accurate and purposeful. There is much to be learned with careful examination of this data, particularly in informing future decision making and planning for students.

Melissa and Laura met as colleagues at the Oceanside School District. Along with another district administrator, they joined up to work on a common goal to rebuild current data practices. The three came together for the NSF Data Collaborative Workshop at Teachers College, Columbia University eager to hear multiple perspectives on how data is being collected, used, and shared amongst various stakeholders. Upon arrival, all participants were placed in different groups with representatives from various positions. The groups were tasked with creating an answer to a data problem that would be of use to a school district. This mini-chapter focuses on Direct Data Dashboard, which was an idea that one of the groups developed around the question: How can a district connect all shareholders in successful use of data?

Our Goal

The Direct Data Dashboard explores having usable, pertinent student data on a user-friendly platform, which teachers and administrators could easily access remotely. This data would be modified in real-time and used to drive instruction while tracking student growth and progress. School and state assessments would also be analyzed, compared, and measured over time to glean valuable data for all district stakeholders.

When conducted properly, using data to inform teaching practice is one of the most effective ways to help students achieve success. Data-driven instruction involves changing a school's focus from "what was taught" to "what was learned." "Being data-driven is an admirable goal. Just because a school collects data, however, does not mean the data are being used to improve student achievement." (Marzano, 2003, p. 56)

Over the past two decades, districts are extremely concerned with the required data that the State and Federal government are asking for, that the real purpose for data collection is often lost. This is widely due to the amount of publicly available educational data, such as No Child Left Behind (NCLB) and Every Student Succeeds Act (ESSA), that is accessible on state-run data systems on the internet and drives funding and accountability statuses. In addition, all the time that is being spent collecting this information for the State and Federal government, oftentimes school districts do not have the staff or resources to dive into data that may be used to drive student instruction.

From a teacher's standpoint, data analysis began through the use of the Response to Intervention (RTI) process, which was introduced as a method to help identify students with specific learning disabilities. As school districts went to the three-tier model of school support, the need for data to back up the academic and behavioral interventions that were implemented was evident. According to the RTI Action Network (2020), "universal screening and progress monitoring provide information about a student's learning rate and level of achievement, both individually and in comparison with the peer group. These data are then used when determining which students need closer monitoring or intervention. Throughout the RTI process, student progress is monitored frequently to examine student achievement and gauge the effectiveness of the curriculum. Decisions made regarding students' instructional needs are based on multiple data points taken in context over time."

School districts need to recognize the importance of data to drive instructional decisions and have a comprehensive understanding of a district and/or school's progress and growth. This is not an easy task and takes a great deal of work to achieve this goal. When working towards this objective, it is essential to get all stakeholders to understand the importance of data and how it can help within the classroom or the school.

The first, and perhaps the most important group, to whom this message needs to be conveyed, is the teachers. According to Steele and Parker Boudett (2009), "schools that explore data and take action collaboratively provide the most fertile soil in which a culture of improvement can take root and flourish." Teachers must know that administration also realizes that while data is a useful tool, it is not the only element considered when making major decisions. Teachers often fear that assessment data both on an individual and grade level will impact their evaluations, reputations, and the students they teach. Additionally, they do not recognize the value of a complete data set for the purpose of informing instruction and curriculum planning. This concern needs to change and, therefore, school administrators must create a positive school climate through additional professional development.

School district and building administrators must have a clear understanding of what they are looking for and that the data presented is a fair representation of this end goal. For example, if one does not have a large enough sample to study, or if the conditions of the data collected are not standardized, the study is not valid. As mentioned earlier, data is a useful tool; however, it is not the only element considered when making major decisions. Exam scores and standardized test results only tell the knowledge level of the students. It is important to dig deeper to understand the "why" and "how" of the situation. There are extenuating circumstances that may affect a student's ability to perform on these assessments.

Reading is a human activity—the glue, the bridge, the vehicle that connects students to themselves and other worlds, whether formatted digitally or in print (Goodman, Fries, & Strauss, 2016). This is why teachers need to be involved in the process of creating and building a data-driven culture. Another very necessary factor is the parent and teacher buy-in of the particular assessment. Training, support from program developers, support from staff members, administrator buy-in, and control over classroom implementation were stronger and more constant predictors of teacher buy-in to a school reform program (Turnbull, 2002).

Set-up Data Facilitators and Data Teams

To achieve this buy-in, it is critical that more training is available for all stakeholders involved. According to the Center for Teaching Quality, Ferriter (2018) explains that "if you want teachers to invest time and energy and effort into a change initiative, you have to first prove to them that the change you are championing is important — for students and teachers. Teachers buy into change efforts that they believe are doable." Proper training sessions would allow teachers to learn how to analyze data on their school, their grade level, and their students. This, along with discussions about areas of strength and need, and which areas should be focused on will help build a data-driven culture. In addition, this hands-on learning with data about the students helps teachers become interested and invested from the beginning (Ordóñez-Feliciano, 2017).

To facilitate these trainings and as a support system, districts need to implement a data facilitator and data teams. The data facilitator should serve as a liaison between the district office and the schools to use data effectively to make decisions. The Hanover Research (2017) states that a data facilitator should also "organize school-based data teams, lead practitioners in a collaborative inquiry process, help interpret data, and educate staff on using data to improve instructional practices and student achievement."(p.6)

In addition to a data facilitator, districts should establish data teams at each building consisting of leaders who will assist teachers and get them excited about data. Ideally, these leaders need to be comfortable with data and effective in conveying information to other teachers. They need to be skilled collaborators and have a basic knowledge of school data and assessments as well as being able to demonstrate leadership in instructional improvements (Hanover 2017 p. 8).

According to the Massachusetts Department of Elementary and Secondary Education's District Data Team Toolkit (2018), a data team should fulfill five essential functions: Vision and Policy Management; Data Management; Inquiry, Analysis, and Action; Professional Development; and Communication and Monitoring.

- Vision and Policy Management -
    - Create and articulate the vision
    - Set and model expectations through the sharing of successes and challenges from their classroom and/ or at a school level
    - Implement and uphold policies for data use in the district
    - Collaborate to examine data from an equality perspective
    - Consult research to investigate programs, causes, and best practices

- Data Management -
    - Collect and analyze a variety of types of school data
    - Identify student learning problems, variety of causes, generate solutions, and monitor and achieve results for students
    - Engage a broader group of stakeholders to gain their input, involvement, and commitment
    - Manage data infrastructure
    - Access and design meaningful data displays

- Inquiry, Analysis, and Action -
    - Develop focusing questions and analyze data
    - Adapt common assessment instruments
    - Create a data-supported action plan to make district-wide decisions about curriculum, staffing, resources, and professional development
    - Collaborate with other school or district initiatives and leaders

- Professional Development -
    - Provide training to support district personnel to develop their knowledge and skills in data literacy inquiry, pedagogical content knowledge, cultural proficiency, and leadership

- Communication and Monitoring -
    - Communicate with key stakeholders district-level focus questions and findings throughout the district
    - Monitor the school-level use of data, as well as create goals and action plans to identify trends and patterns
    - Oversee the implementation of the plan and/or help implement instructional improvements in a classroom, grade, course, etc.

O'Geary & Smith, 2021

The data team's goal is to build a culture of inquiry to promote systemic data use. This will help lead the rest of the school in data-informed decision-making and establish systems and policies to inventory, collect, and disseminate data. The members will continue to manage ongoing professional development and support of resource needs.

Professional Development

High-quality professional development strategies are essential to schools. Having more effective and more engaging professional development models available is important. All stakeholders should have opportunities that provide them with time for practice, research, and reflection. Unfortunately, most of the staff have little input in this process. In particular, with regard to the data, many of the players have little control over the types of data that are being collected and wish there were other options. By increasing building and district training programs in data literacy, the goal is to create a trusting culture in which teachers can collaborate and use evidence to improve and help to drive instruction (Bowers, et al. 2019 p. 9).

However, there can be many challenges to providing professional development. First and foremost, the people involved must feel that they are respected and that the training is a valuable use of their time. Pressures of daily commitments and responsibilities may limit the time that they are willing to dedicate to learning new tasks (Post 2010 p. 6-7). According to the Data Quality Campaign's (DQC), in a survey of seven hundred and sixty two (762) teachers in grades kindergarten through twelve, fifty-seven percent (57%) of the them responded that time was the biggest roadblock stopping them from studying student data. More than forty percent (40%) of these teachers placed the responsibility of creating this time to analyze student data on principals and other district leaders (Jacobson 2020).

Also, there must be practical opportunities to practice what has been taught and positive affirmations should follow these efforts. If they do not view this information as useful or helpful, it is not likely that it will be used; regardless if it has been learned (Post 2010 p. 8). The Data Quality Campaign's (DQC) survey of more than eight thousand teachers indicated that only about one third reported that they had participated in some type of professional development on how to use this data. Those participants said that learning how to use data to plan for future instruction was most useful to them (Jacobson 2020).

Another challenge that some teachers face is the fact that either there are too little or too much data. For some teachers who work in a grade level or subject area (such as early elementary and advanced high school grades) or teach certain subjects (such as social studies, music, science, or physical education) for which student achievement data are not readily available (Hamilton 2009 p. 16). However, on the contrary, some teachers feel that there was too much data to go through and it was not all useful or relevant; especially if the data needed was not available to them promptly (Jacobson 2020). As Schmoker states, it is important that data analysis not "result in overload and fragmentation; it shouldn't prevent teams of teachers from setting and knowing their own goals and from staying focused on key areas for improvement. Instead of overloading teachers, let's give them the data they need to conduct powerful, focused analyses and to generate a sustained stream of results for students." (Schmoker 2003)

All of these challenges, as well as many others can be addressed by administrators taking the time to understand teachers' hesitations or emotional anxieties around change. They need to work with their staff to find a balance between pushing innovation and getting support. (Chatlani 2017). As Turnbull (2002) indicates, teachers are much more likely to buy-in to school reform when different factors are in place. These include administrator buy-in, adequate training and resources, support from program developers and other staff members, and the ability to decide what (if any) changes are needed.

Data Warehouse

It is interesting to think about student data from different perspectives. A student might be the lowest in a teacher's class, but the highest in another teacher's remedial group for that grade level. That same student may be outperforming his/her grade-level peers from another teacher's class in the same school building. That is why it is so important to have data that is standardized or normed, because, in high achieving districts, a low achieving child in the class may be an average student in another setting. Conversely, in a low achieving school, a high achieving child may only be average, or even behind in another district.

For this reason superintendents and principals have different data needs. They are interested in multiple factors, including teacher and student growth rates, attendance, demographics, etc. They are examining this data for multiple reasons: to keep highly effective teachers, to identify trends in attendance and achievement compared with districts in the region, to determine allocation of budget and finances, and many other factors. Administrators can access data from a variety of sources.

One example of a tremendous data source is Nassau Boces Instructional Data Warehouse (IDW). The IDW gives us a wide variety of reports including NYS assessments, demographic information, teacher reports, etc. It also compares a district's data with others in our region. This data can be downloaded for further disaggregation and can be saved and/or printed as needed (Pratt 2020). Many teachers and administrators use the various features of IDW to study and analyze assessments to help improve pedagogy, but yet many others, unfortunately, do not for many reasons. Some believe that the value and quality of the NYS assessments have diminished since the adoption of Common Core.

Results from a 2015 survey of more than one thousand five hundred National Education Association members teaching the third through twelfth grades in ELA and mathematics, who are required to be tested under No Child Left Behind, indicate that seventy percent of these educators do not believe their primary state assessment is developmentally appropriate for their students (Walker 2016). In addition, in many districts, the data is not a fair representation of the students due to the number of opt-outs. There is very little research or empirical data to explain what motivates parents to opt their children out of assessments, but many feel that it is a statement in opposition to the Common Core State Standards and aligned assessments. The sheer multitude of tests and test prep occurring in schools and a reaction to teachers' concerns about the overreliance of student test scores in their evaluations could be a cause for this concern.

As states rolled out new assessments aligned to college and career readiness standards in Spring 2015, the number of students opting out of the tests was on the rise. Reports indicated that fifty percent of students in New York State opted out of state assessments, with some districts reporting opt-outs as high as seventy to eighty percent. An August 2015 editorial in the *New York Times* reported this amount to quadruple the number from 2014 "and by far the highest opt-out rate for any state." (Opt-Out Policies for Student Participation in Standardized Assessments 2018)

Another issue that arose was the fact that NYS does not release the assessment data promptly. Oftentimes, when teachers were asked to analyze data, it was on the previous year's student, as well as the previous year's state assessment. Some staff did not find it useful to them at that time. However, there are many ways that this information could be very useful for teachers. For example, by studying previous standardized test scores, one can glean valuable information about the level of student proficiency from previous years. This could help inform how the teacher creates groups within the classroom, seating arrangements, and also how instruction can be differentiated. Learning can be adjusted as new information is learned about the child (Alber 2017). Teachers can also reflect upon their current teaching practices and identify learning roadblocks that are affecting the scores of their students. In addition, administrators and teachers can detect what is missing from their current curriculum and must be supplemented through other resources to meet state standards.

One System -Oceanside's Direct Data Dashboard (DDD)

In the Oceanside School District, data study has become the main focus to learn how to use data to inform instruction to best meet students' needs. The district uses various forms of data to inform and make many building and district level decisions, such as its decisions for Response to Intervention, curriculum program adoption, and staffing decisions. Also, in 2019 the district took the steps to invest in a Data Specialist.

Once conversations began, it was evident that Oceanside needed to create meaningful change and appeal to the teachers to get them excited about the proposal. It was clear that teachers wanted more detailed information about the students in their current class. As Brocado, Willis & Dechert (2014 p.5), stated in paper *Longitudinal school data use: Ideas for district, building, and classroom leaders*, ninety-six percent (96%) of teachers were overwhelmingly interested in data that pertained to students in their class. In particular, teachers want their main focus to be on student achievement data not other irrelevant data.

Knowing this demand, at the NSF Data Collaborative Workshop at Teachers College, Columbia University, we came together to create a single system, which we are calling Direct Data Dashboard (DDD), where teachers can access relevant data for their students, which is updated in real-time. Building off the Instructional Data Warehouse system, which was created by Nassau BOCES, we realized that the state assessment data was not enough for teachers, especially with the large opt-out rates on Long Island. The new DDD system will include local testing measures such as Fountas and Pinnell testing, Fundations assessments, and even student portfolios as the system grows. Long term comparisons will be available to analyze data correlations between state testing and reading levels, attendance and performance, effects of intervention and frequency, etc. This will help in determining RTI needs, program effectiveness, and student rate of progress.

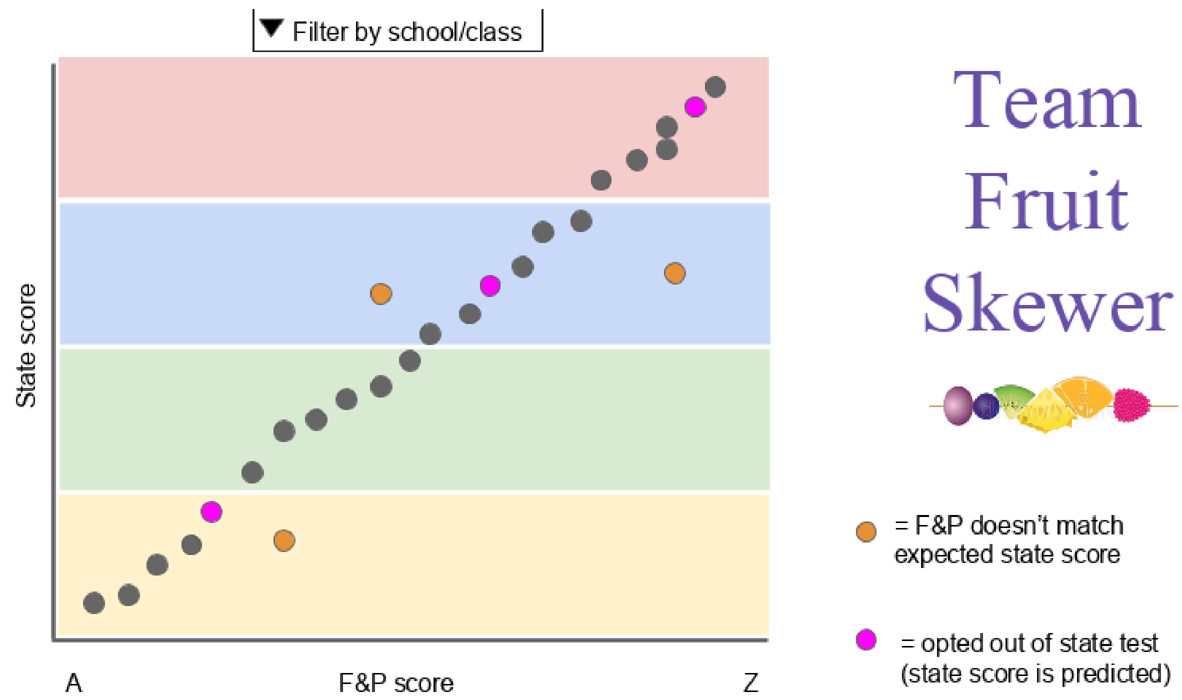

Figure 15.1: *Mock visualization for the new Direct Data Dashboard (DDD)*

As teachers progress and become more proficient in data analysis, the intention is that the new DDD system could be tailored by teachers to include their formative assessments and classroom assignments/projects. This dashboard would offer information necessary to provide high-quality, corrective instruction to remedy any of the learning errors identified. This allows teachers to tweak instruction and develop alternative techniques to present instructional concepts. The dashboard will also offer features that include opportunities to involve students in the process. As students become more involved with personal goal setting and learn how to monitor and track their progress, they develop student agency, which helps to propel their learning forward (Ryerse 2019).

In summary, assessments are a necessary component in any educational program. However, the way we use information from these assessments can transform the way we approach educational practice. An increased focus must be placed on helping teachers understand the reasoning for dissecting the data and learning about how and why their students fall short in particular areas. With purposeful reflection and ongoing professional development and support, instruction can be modified to better meet the needs of all students

(Guskey 2003). The NSF Data Collaborative Workshop reinvigorated our desire to dive deeper into the data needs of our district. We look forward to continuing our work with Nassau BOCES and Teachers College, Columbia University to make the new DDD system come to life.

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CHAPTER 16

Pedagogy-driven Data: Aligning Data Collection, Analysis, and Use with Learning We Value

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Educational data is being collected and used on large scales, for purposes such as data-driven instruction at the classroom level, and data-driven decision making at higher levels. Increasingly, schools are implementing improvement cycles based on that evidence, which is an important practice. But what drives the data collection and analysis in the first place? Who decides what types of data should be collected? How are methods of analysis aligned with what teachers and administrators really value about their students' learning? Pedagogy is at the heart of how we teach, and therefore pedagogy should drive data collection, analysis, and use. Data-driven pedagogy is an important goal, but to get there we need pedagogy-driven data. In this chapter, I will describe the idea of pedagogy-driven data, pointing out disconnects related to current data systems, and how we might move toward closer alignment with pedagogical goals. These ideas have come out of the 2019 Education Data Analytics Collaborative Workshop at Teachers College, and are based on the conversations and collaborative designs created among teachers, administrators, researchers, and data scientists there.

Well-designed technology can support learning that is open-ended and student-centered. One of the affordances of digital learning of course is that

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we have the ability to collect very detailed activity data. But this data is not being collected in ways that provide the most useful insights into student learning, nor is it being taken advantage of in truly meaningful and humanistic ways (Chatti et al., 2014). The data we collect should reflect the pedagogy and the learning objectives we value. To prepare for a rapidly changing future, education will need to move away from rote learning and procedural skills, to value more of the process, as well as a wider variety of human skills (Ouellette et al., 2020). Integrated approaches like project-based learning, inquiry learning, and collaborative learning are often seen as a better fit for preparing students for a rapidly changing future (Parker and Thomsen, 2019). These types of learning activities can also generate data, but don't fit into most of our current assessments and data collection methods, which tend to be multiple choice questions where everyone tries the same set of problems, or written work scored by a strict rubric. If the data we collect isn't generated by the types of learning we care most about, then it won't be able to point us in the direction we want to go.

Similarly, the analysis of the data we collect should be aligned with what we think deep learning looks like. Beyond knowing how many questions a student got right, and how long it took them to complete something, we want learning analytics and data mining results to recognize students' unique ways of thinking, and pull out patterns of progress across skills and standards. The sophisticated methods of analysis available should be able to paint a picture of students as humans, not simply as demographics and statistics. Data analysis should be applied in more creative ways, and those methods need to be designed based on the way we believe learning happens, which is embodied in the pedagogies we use.

Finally, the ways we convey the results of educational data analysis should feed back into the pedagogies driving the data system. If results are communicated once a year, and teachers are planning for each unit based on months old data, that design does not reflect a dynamic process of learning and growth. Similarly, if teachers are inundated with scores and subscores for each student but don't have a way of exploring and making their own meaning out of the data, it's hard for them to curate personalized learning opportunities. The experience of engaging with data must be thoughtfully designed and aligned to pedagogical goals for it to best inform teaching and policy decisions, and to be interpretable and meaningful for users (Jivet et al., 2018). To achieve this, all aspects of the data design process should be aligned with the pedagogy and learning objectives we value, including data generation and collection, data analysis, and communication of insights coming out of the data.

What does current data collection, analysis, and communication look like? First of all, the educational data we collect often doesn't match what we value, or the questions we really want to answer for our students and our schools. A lot of assessment data comes from high-stakes testing, which we know does not measure the human skills that will be necessary for an ever-changing job landscape. At the same time, a lot of rich process data around skills like social interactions and problem solving goes uncollected. As a result, insights from learning analytics often don't align with teachers' needs (Mor, Ferguson, & Wasson, 2015). Second of all, there is a disconnect between data analytics and on-the-ground educators (Piety, 2019). The professional data scientists themselves, as well as the techniques and algorithms they use, struggle to connect with the teachers and coaches who need to make sense of the data to inform their practice on a daily basis (Agasisti and Bowers, 2017). There is a lot of room for improvement when it comes to humanistic uses of learning data for decision-making at the classroom level and evidence-based improvement at the student and teacher levels (Wise and Vytasek, 2017).

These disconnects became evident during the 2019 Education Data Analytics Collaborative Workshop at Teachers College. At this event, data scientists and researchers came together with teachers and administrators from across the Nassau BOCES. In mixed groups participants used the Instructional Data Warehouse (IDW) as a central artifact to discuss purposes of the data and goals for data analysis. They then co-designed and prototyped data visualizations to explore insights coming out of a sample dataset. Educators had a chance to share their ideas about how they wanted the data to work for them, and data scientists got their hands on the data to rapidly prototype actual visualizations. As more of a data designer than a data scientist, I tend to look at the bigger picture, questioning how the data fits into the ecosystem of learners, teachers, and schools, and noticing what's not there as well as what is. This perspective influenced some interesting observations and conversations in my codesign group, which I will share here.

To begin with, the data available in the IDW itself sets the stage for the conversations and data visualizations to be had during the workshop. It contains scores from state ELA and math assessments, Regents exams, and standardized assessments for English language learners. It also includes demographic data and attendance data. There is no doubt that these are valuable data which can be used to understand the progress of a school or district. However, it is quite limiting in conveying many of the important skills students may be building, and in describing their overall learning experience at school. Certainly not everything the Nassau schools are doing in their classrooms are focused on traditional curriculum, or working through problems that have one right answer. In my conversations with educators at the workshop, participants were eager to share about their exciting personalized learning or project-based learning initiatives. These experiences are not reflected in the IDW data, which is no surprise given that we don't yet have scalable assessments for them, and yet the IDW is what school and district-level decisions are based on.

In many cases, educators' requests and perceived needs around data types and data systems seem to amplify this disconnect. Because these are the types of data available, and which educators are asked to work with, their focus on potential improvements still center on standardized test data and technical functionality. At an initial brainstorm session prompted by the question of what schools' needs are in regards to education data, teachers' most immediate issues were around datasets and data systems working together. They wanted to be able to get everything in one place, and to be able to correlate it to get actionable insights. In the post-survey administered to participants after the data workshop event, several comments match these pressing needs. For example, one district administrator said, "A Longitudinal data system would be most effective if the data needed could be pulled from multiple data points." In addition, one of the teachers felt that, "The key issue that needs to be addressed is that the data needs to be brought together in a single place. This has been a serious challenge and will continue to be." The frustration of some of these concrete barriers to use are real, yet at times they also pull focus away from deeper questions about alignment with learning objectives and the need for more diverse types of data.

That deeper thinking about what data is being fed into the system is harder to engage in for educators who have immediate data demands, and who haven't yet seen examples of more diverse types of data. The experience of my own small group during the data sprint activity is an example of this. In the initial brainstorm phase, we had ideas about how data could push pedagogy further. We talked about the types of "human skills" we all value, and what we hope students experience in school—things like creative thinking, problem solving, and taking initiative. One example we brainstormed was around what kinds of data visualizations could map evidence of these skills to the types of teaching going on in a school. With this data, building administrators could better understand the pedagogies that successfully build desired skills in their particular student population, and use that information to support more teachers to shift their practice in more student-centered directions. This blue sky vision is all well and good, but when it came time to create a functional dataviz prototype, the team defaulted back to standardized test data, choosing to focus on literacy skills instead. Tasked with creating a working prototype, we had to base it on the data we had access to. And in the limited time we had, there wasn't enough time to really think through how data about human skills and different types of classroom pedagogy could be collected. In one sense, this situation was circumstantial based on the time and dataset provided during the workshop. However, I would argue that this closely mirrors the real world of education, in which standardized test data is in fact what we have to work with, and in which resources are quite limited and don't often afford the opportunity for big picture thinking and innovation.

Despite these limiting circumstances and a lack of really diverse examples of data use, the survey did surface a few comments from participants starting to think in the direction of more pedagogy-driven data. One teacher responded, "An easily accessed longer term picture would help greatly. Not just results. Teacher comments, attendance, behavior issues would be some types of information that would be helpful." Another suggested, "It would help to have more data representing students that are not meeting standards. We often have standardized test scores and reading levels, but it would be helpful to have other types of data such as demographic information, formative test scores, student & parent input, and information about the teacher and attempts to remediate as well." The idea of including teacher comments and actions, behavior records, formative assessment information, and student and family voices as additional types of data in a repository along with the more standardized results data is an exciting one, as it would provide a more comprehensive picture of student learning based on the pedagogies being utilized. A district administrator commented on timing and the importance of collecting ongoing relevant data, saying, "Our current systems provide responsive results, and in the case of State Assessments, an 'autopsy' approach. We need systems that provide us live daily data to support learners in our current classes. The end of year results help us to inform teacher practice more than they help us to support student learning. The system I envision will do both with fidelity." This call for more of a living data repository makes the point that to support learning goals, data needs to be more closely aligned with the student experience, which is not currently the case. Even with these great ideas about how to get deeper insights from data, there is also a sense of this being an insurmountable undertaking, as one school administrator pointed out that "Seamless integration of a wide range of data sources would be ideal. However, this is a huge, nearly impossible request." This sentiment is completely understandable and also helps explain why there weren't more ideas of this nature coming from educators during the workshop. Teachers and schools are already tasked with too much and when it comes to data, many have to focus on what they can do with what they already have access to. For this reason, researchers and data scientists will play an important role in imagining how pedagogy-driven data can be designed and implemented.

What do we need to do to move in that direction—to explore how education data can be better aligned with pedagogy, and to experiment with how to analyze and convey insights from diverse types of data? Based on conversations and ideas that emerged from the collaborative data workshop, as well as work being done in other research groups and organizations, I suggest the following set of considerations to help us connect data repositories and dashboards with what educators and learners value.

Expand ideas about what data looks like and what it's for. Education data doesn't have to primarily consist of standardized test scores or even other outcomes. It can include information from ongoing classroom assessments, process data from open-ended digital environments, or notes on in-person observations. It can be qualitative, and can come from anyone involved in the learning process. For example the Edsight tool created by Ahn et al. (2019) periodically asks students to reflect on their learning from the day's lesson, generating quantitative information that captures student voice. A variety of types of data together could be used not simply to determine where a student is along a linear path, but to tailor their learning experiences in terms of which pedagogies work best for them.

Codesign with educators and creatives. Interdisciplinary teams are a key ingredient to expanding what education data can do for us (Roschelle, Penuel, and Schectman, 2006). Educators bring the perspective of what information they need and how they make decisions for their students, while education researchers may have a bigger picture vision of the pedagogy and can focus the group's values. Data scientists are essential as they bring the learning analytics methods and tools, while graphic designers or interaction designers can add new perspectives on creating data visualizations that are customizable and interactive. In order to build tools that work with what and how we really want to learn, all of these inputs are needed.

Build systems and methods of analysis that support diverse data types. It's hard to imagine putting weekly classroom assessment data into a system built for yearly testing results, or sticking student reflection data onto numerical test scores. But systems can be designed to be flexible, and data scientists can come up with ways to quantify aspects of the qualitative data and make meaning out of common themes across data types. Creating these systems will require us to envision how we want to use the data before we build the technology, rather than adding new ideas onto tools made for a more conventional purpose.

Increase data literacy for educators. Making sense of complex types of data, and connecting the results to one's own students and teaching methods is no simple task. Interpreting insights from a dataset and applying them to a specific context in order to make decisions requires a certain level of "pedagogical data literacy" (Mandinach, 2012). Looking at process data and aligning it to intended pedagogy is much less straightforward than seeing which students scored below a certain cutoff. To meaningfully engage with these tools, educators will need the opportunity and support to build their data literacy skills.

Combine data with knowledge of personal relationships. Teachers know their students best and can "ground-truth" digital data by combining it with their own observations and what they know about students through personal relationships. For example, game analytics can shed light on the complex behavior patterns of students, but can't reveal for sure what students were thinking as they solved a puzzle. Teachers might probe a student's thinking or ask them to explain their strategy, or they might know something about a student's past experience with the game or concept that affects the interpretation of the data. Personal connections are what make data insights meaningful in the context of a classroom, and good data design can bring the two sources of information closer together.

Empower students and families. Students should be empowered to take charge of their own data, having a say in how they represent their work and how that data is used (Collins and Halverson, 2018). Data that is connected to day to day learning experiences may give students a stronger feeling of agency than once a year testing, and involving them in the interpretation of the data and the setting of learning goals based on it could support their overall learning. With data that tells a story about a learner's experience more holistically, families can also be involved in the meaning making process. This could take the form of collaborative data reviews at student-led conferences, where students pull out salient insights about their data, discuss what they think is accurate and what isn't, and together set goals for their learning that can continue to be monitored and adjusted.

This list is by no means a clear-cut guide to how to build a pedagogy-driven data warehouse solution. I don't believe such a guide can exist, because at the heart of this concept is personalized, context-specific data that describes unique experiences of learning. Rather, this is intended to be the beginning of a set of considerations and approaches that we should use to design data systems that are aligned with pedagogical goals. The intentional design of these systems must apply to all three main components: the data being collected about students and their learning, the methods of analysis that combine diverse types of data and make meaning out of them, and the communication tools such as data visualizations that convey insights to teachers, students, and other stakeholders. The way these systems are currently designed aligns with a more content-focused, teacher-centered pedagogy. As long as that is the case, the insights coming out of the data will not be able to inform student-centered teaching. As schools begin exciting initiatives around project-based learning units, in-school makerspaces, and other student-driven learning modalities, we need data that will support teacher practice by working in concert with data on core math and reading standards. As a field, we will need to get creative about how we collect, analyze, and use education data, and we will have to increase data literacy and collaborate with diverse partners to do it. If we prioritize alignment with pedagogies and learning objectives we really value, we can use data to deepen learning and support teachers and students in the ways each of them needs.

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CHAPTER 17

Collaborative Data Visualization: A Process for Improving Data Use in Schools

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Data Visualization, Dashboards, and Evidence Use in Schools

Adams et al., 2021

Evidence-based improvement cycles that inform instructional practice typically rely on collaboration between leaders of educational systems and data scientists whereby data scientists wrangle data, prepare visualizations, and develop models for leaders and staff to inform the instructional decisions made during improvement cycles (Krumm, Means, & Bienkowski, 2018). Unfortunately, school staff and data scientists typically work in isolation of one another, resulting in disjointed improvement cycles where the visualizations provided to school staff do not always meet their unique and contextualized needs. Without access to wrangling, visualization, and modeling expertise, school staff must develop their own data products, which can take time away from leaders' and staff members' primary responsibilities.

The purpose of this mini-chapter is to describe our experience engaging in a collaborative data visualization process, which we used to propose a three-step iterative process to guide others interested in engaging similar work. Our goal in reflecting on our collective experience is to concretely describe one way in which practitioners and data scientists can come together to jointly analyze and take action on data. During the first step (prework), we identified a focal problem space and specific research question. During the second step (analysis), we collaboratively generated a data visualization related to the specific research question. During the third step (reporting), we collaboratively translated the information presented in the visualization to knowledge through a discussion of next steps and instructional action steps. We outline this process in this chapter. A main goal of this work was to promote community-building and shared ownership of data visualizations in education, with the ultimate goal of promoting equity in schools focused on underserved populations.

Process for Collaborative Data Visualization

Step 1: Prework

A critical first step to engaging in collaborative data analytics and visualization is ensuring that the appropriate voices are part of the process, and that structures are established that clearly define how each voice is needed for success. Our team consisted of seven team members, each of whom brought a unique perspective reflective of the Education Leadership Data Analytics (ELDA) model for quantitative research methods training in education, which includes definitions for the roles of Practicing Administrator, Educational Quantitative Analyst, Research Specialist and

Education Data Scientist (Bowers, 2017). More specifically, our team included:

- Two team members who are administrators at Middle Schools in Nassau County (Amy and Fernando).
- One team member who is an elementary school teacher (AnnMarie).
- One team member who is a school district consultant specializing in continuous improvement in K-12 schools (Leslie).
- One team member who is a data strategist with Nassau BOCES, a public educational organization that provides shared educational programs and services to school districts in Nassau County (Jeff).
- One team member who is a research specialist working in a university setting (Beth).
- One team member who is a data scientist, also working in a university setting (Andy).

The diversity in backgrounds and perspectives represented during discussions allowed for shared understanding of goals and rich discussion focused on the utility of various data visualizations. Though our backgrounds and perspectives were diverse, we learned that our group was established based on similarities in responses to a pre-conference survey. This grouping strategy helped establish instant rapport and a genuine interest in learning more about our teammates in search for common themes in our philosophies, beliefs, and practices related to teaching and learning, instructional leadership, improvement cycles, and data analytics. We engaged in protocols to facilitate discussion, build trust and ultimately develop a shared goal. For example, we engaged in an activity focused on mapping our life trajectory in three main steps using one chart paper. We described our selected three main steps to the group, discussed similarities, and asked questions. Our trajectories intersected in the middle of the chart paper with all of us engaged in the important work of collaborative data visualization.

After engaging in community-building protocols, we spent the largest amount of time (approximately ⅔ of our time together) discussing and identifying a specific focal problem for the next steps, analysis, and reporting. Our team was careful in our identification of the purpose and research questions to ensure that the utility of our work privileged those closest to the work – namely, those who worked directly with students including the teachers and school administrators in our group. We discussed the risks of data visualizations that are beautiful but not actionable and reached collective agreement before moving forward that it was important to us as a group to generate insights that could be directly helpful to teachers in planning instruction, or administrators in creating supportive conditions for teachers to utilize data. We crafted the overarching question "*How can we better know each of our students to help support planning and personalize learning?"* to frame our thinking.

Considering the available data, we agreed to use longitudinal attendance records across school years to plan intervention grouping and additional instruction/home support. Therefore, our initial iteration of our research question was: *How does longitudinal chronic absenteeism influence student performance on assessment data by standard in mathematics?* We believed this research question and the resulting visualization would be actionable because at the beginning of Grade 6, teachers would have an opportunity to review three years of student performance by standards disaggregated by chronic absence in order to predict those who need additional support. We also wanted to link chronic absenteeism and lower performance to create a warning indicator in order to plan student grouping, allocate resources and create a personalized learning experience for students. Our goal was for teachers to be able to link specific interventions by standard based on student needs informed by longitudinal data.

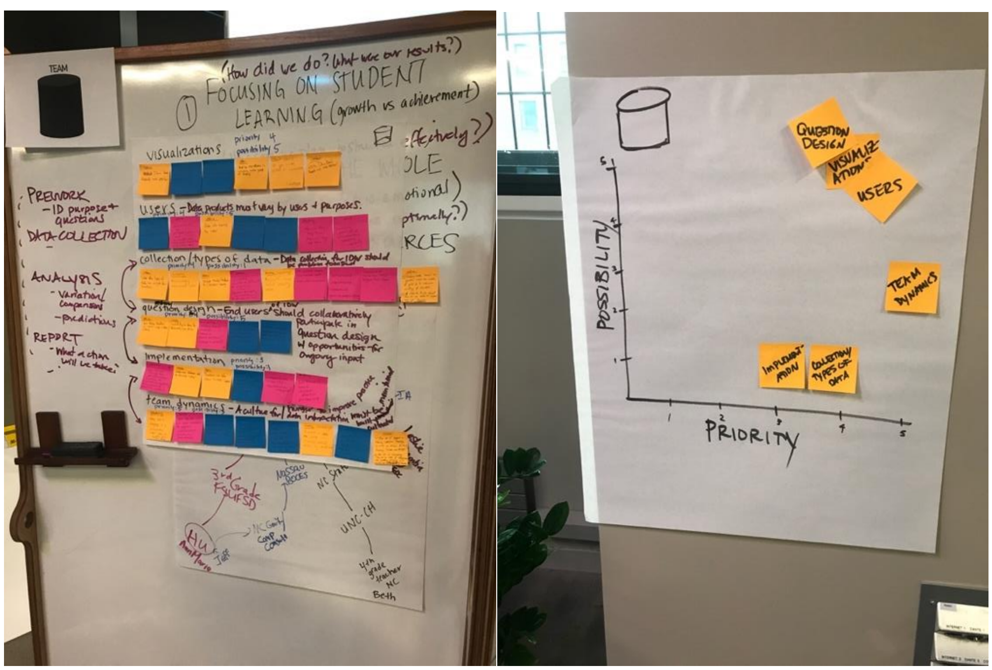

Figure 17.1. *Artifacts highlighting the collaborative process and the consensus prioritization of each focus category determined by the team*

Step 2: Analysis

The second step of the collaborative data visualization process focused on analyzing existing data. During this step, we planned and tested visualizations using existing data to address the target research question. The resulting data visualizations evolved during our time together. This process could have easily continued for another day or two. The first step (pre-work and identification of a research question) was critical; we believe that this step could have only happened collaboratively after establishing trust. However, we also believe that data analysis could have occurred without all team members at the table at the same time. We took advantage of the fact that we were together. One way that we did this was several team members brainstormed visualizations that would appropriately address the research question. The data scientist simultaneously and rapidly wrote code to analyze the data and propose visualizations. The process of writing code and generating visualizations during the workshop was quick and not polished. For this reason, the visualizations included in this chapter are the actual draft visualizations developed during our group work and are not final products.

The data scientist spent considerable time prior to the workshop cleaning and organizing these data, as well as testing visualizations in a freely and publicly available statistical package called R. This was critically important to our work, as without a deep understanding of the data structure, writing code for cleaning and analysis requires extensive time. As one example of how we could explore these data, the data scientist created a heat map visualization that clustered students (rows) and standards (columns) based on the whether a student got 100% of the items associated with that standard correct across 3rd, 4th, and 5th grades. This visual illustrated where students demonstrated gaps in performance (i.e., signified by predominantly gray columns) and whether there were patterns, by student, in terms of standards that clusters of students struggled with. To provide a different view on students' performances by standard, we plotted student percent of items correct for each standard across Grades 3 through 5. This figure did not account for absences, which was central to our research question, yet these two figures helped us in developing a better mental model of students' academic performance over time and how we might later tie missing school with missing instruction related to specific standards. In addition, we determined that given the number of standards and the fact that standards changed across grade levels, we wanted to focus on the content domain in mathematics rather than at the standard level (i.e., geometry, measurement and data, numbers base ten, numbers fractions, and operations and algebra).

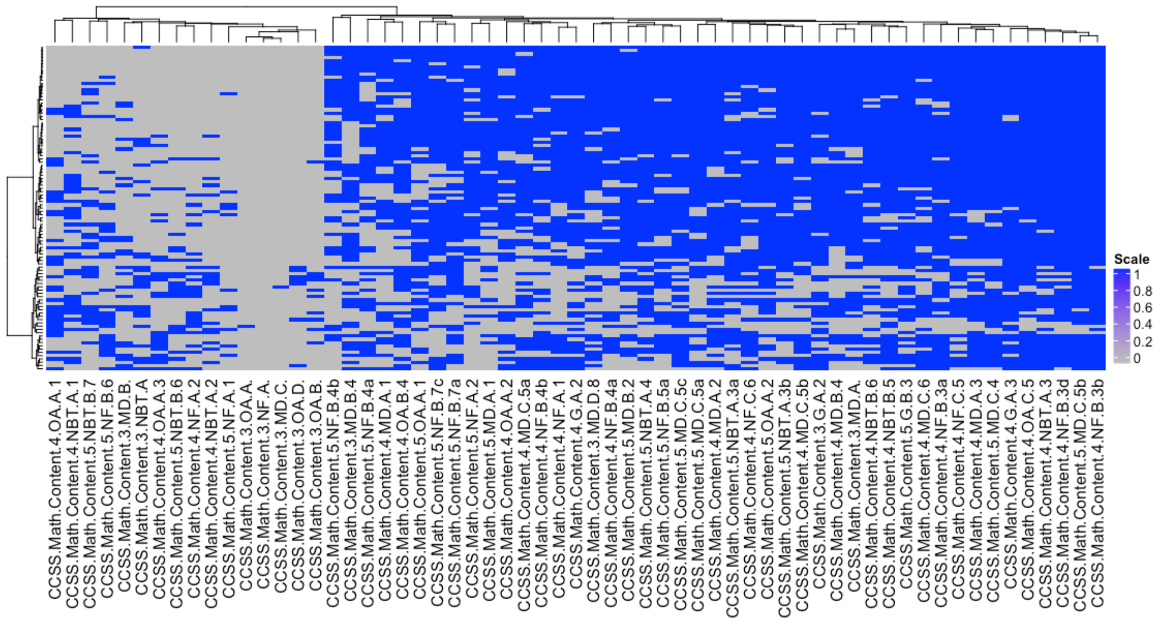

Figure 17.2. *Cluster Analysis and Heatmap of Performances by Standard in Grades 3 through 5*

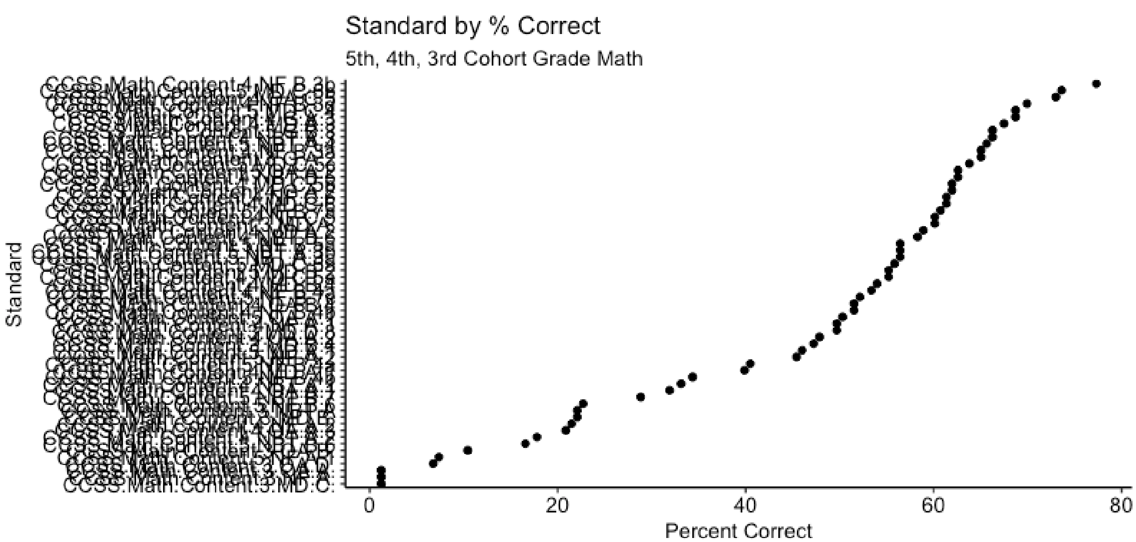

Figure 17.3. *Percent of Items Correct by Standard in Grades 3 through 5*

Going back to our original idea, we wanted to understand how we could better identify the needs of each student to help support planning and personalize learning. We refined our research question to: *How does longitudinal chronic absenteeism influence students' performance on assessment data by mathematics standards across Grades 3 through 5?* Because our intervention would be at the student level, we decided to examine individual students' chronic absence pattern. We defined chronic absence as missing 10 or more days of school. The third chart in Figure 17.4 represents a single student across three years, mapping their performance (% correct) on specific domains. This specific student was not chronically absent in Grades 3 or 5, but was chronically absent in Grade 4 (0=not chronically absent and 1=chronically absent under student identification number). The resulting figure shows that this student may have some gaps from Grade 4 in their understanding of Measurement and Data as well as Numbers Base-Ten. This example student might benefit from interventions focused on these areas if gaps are identified using a universal screener or progress monitoring tool. Despite the fact that it appears this student achieved proficiency in these domains in Grade 5, Grade 4 standards emphasize critical foundational knowledge related to these domains that this student may have missed.

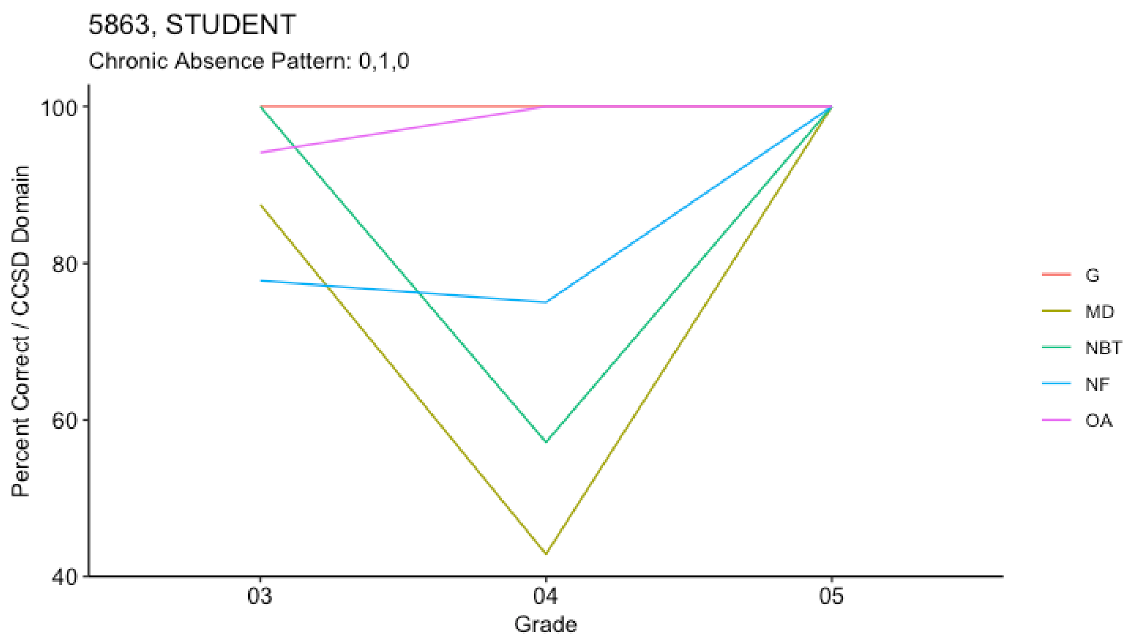

Figure 17.4. *Percent Correct by Domain and Chronic Absence Pattern for a Student in Grades 3 through 5*

Note: G: Geometry, MD: Measurement and Data, NBT: Numbers Base Ten, NF: Numbers Fractions, and OA: Operations and Algebra
Following the third visualization, in part because time was running short, we moved on the third and final step, reporting.

Step 3: Reporting
One of the main goals of this work was to promote equity in education. From a district administrative perspective, we wanted to inform laser-like allocation of resources where the stakes were highest and the resources were scarcest.

The chart above indicates that this student's chronic absenteeism had the greatest influence on their learning and retention of three math content domains: measurement and data, numbers base ten, numbers fractions. The value to instructional leaders will come from matching student attendance data to the course pacing guide. If the content domains where the student struggled were taught during the times when they were absent, then we can identify a direct correlation between their poor performance on the aforementioned domains and their chronic absenteeism. However, if an analysis of the course pacing guide compared to when this child was absent do not align with the areas where they struggled, then poor performance cannot be attributed to chronic absenteeism and a deeper dive into the instructional and assessment practices of the critical skills emphasized in this grade would be necessary. The goal would be to identify areas where we can allocate additional resources in order to build capacity and support student learning. Ultimately, this could be used by classroom teachers to inform the instructional strategies that would best meet the needs of their students. This could be reviewed at the individual, class or grade level to reveal patterns, effectively group students and allocate funding to additional targeted interventions in efforts to promote student growth and achievement. We discussed the possibilities for the visualization to inform an early warning system that would use real time data to identify students who were absent and in which mathematical domains they needed support.

What We Learned

Through collaborative visualization involving both school staff and analysts, visualization of unknown patterns serves as a community-building tool that encourages engagement in improvement cycles. Through this process, analysts are empowered to see how their work immediately informs practice and student outcomes. School staff are empowered through their involvement in the data visualization process with access to the visualizations they need. In addition, data literacy capacity is cultivated for educators and administrators, contributing to a recognition of the affordances and limitations of data. This brand of analytics focused on collaboration and community-building contributes to shared goals and mutual trust across groups who usually work in isolation of one another. Researchers typically involve end users (i.e., school staff) at the back end of this process after generating example visualizations based on what they believe school staff need to know. Researchers usually collect feedback on the visualization and reporting tools through cognitive interviews or other forms of systematic feedback like surveys (Huff & Goodman, 2007). Recent frameworks for score reporting encourage analysts to engage end users early and often in the process of developing and interpreting visualizations (MacIver, Anderson, Costa, & Evers, 2014). This type of collaboration is important for several reasons. Involving end users early in the process of visualization promotes shared meaning and ownership of visualizations. In addition, the needs of school staff are often highly contextualized based on their unique settings. District and school administration, as well as teachers, have specific, important research questions about their students. For example, teachers might wonder if a specific intervention is more or less effective than another form of instruction. To address this, an analyst might add a student grouping feature within the visualization interface so teachers can group students and compare progress across time. When analysts develop visualizations with school staff's feedback and needs at the forefront, the resulting visualizations have vast application for improving instructional outcomes.

Incorporating Multiple Sources of Evidence

Community-building is critically important to ensuring successful integration of improvement cycles and collaborative data visualization. If school staff are not part of the data visualization process on the front end, then visualizations that challenge current practices may be dismissed. During our discussions, we frequently encountered situations where we wanted to collect or integrate additional data sources (e.g., focused on socio-emotional learning or progress monitoring). One way to build a culture around data literacy is to integrate additional data that teachers or schools collect into the data visualizations. This integration of additional sources of evidence is only possible when school staff are involved on the front end of data visualization. The analyst or data scientist should work with school staff to support systematic data collection efforts that: (a) minimize bias in those data, and (b) integrate easily into existing databases (e.g., formatted as an Excel or .csv file with students' unique ID).

The incorporation of teacher-collected data with state and local assessment data recognizes teachers' current efforts and instructional practices, increasing shared ownership and applicability of the visualizations. This extension of the work described in this chapter builds data capacity within schools and supports a culture of continuous improvement. Once a culture of continuous improvement exists and teachers view data and the resulting visualizations as valuable, we can safely introduce in-depth data analytics and mitigate the risk that end users will reject analytics that challenge long held beliefs about instructional practices.

Changing the Status Quo in Data Visualization

This brand of "messy" collaborative analytic work is not always comfortable or typical for data scientists. Similarly, it is not always typical or comfortable for school staff to engage in collaborative data visualization as described in this mini-chapter. We need structures and systems in place to support those who engage in this work. This mini-chapter offers one such structure. In addition, we need systems to support collaboration around data visualization. For example, how do schools get access to a data scientist? We were afforded two days in the Data Collaborative Workshop to engage in this work without interruption. However, this is far from typical from how we engage in our work outside of the collaborative workshop. There is a need to move the status quo toward collaboration that is reflective of the Data Collaborative Workshop. To encourage this process, we recommend encouraging data scientists to engage in this work through competitive grants and calls from top-tier journals highlighting this brand of collaboration. Another idea is to encourage competitive conferences and consortiums where teams of analysts and school staff can present their collaborative data visualizations. These types of opportunities allow data scientists and educators to share resources, ideas, and information.

Transparency in Analysis

During data analysis, data scientists make several decisions about criteria for inclusion in visualizations. Educators need to be a part of these discussions or at the very least have access to the interpretable code or decision rules about who is included and why. This type of open-source access to visualizations and their code further builds trust and increases the likelihood that visualizations will meet the needs of educators. This necessitates a transition from a focus on data visualization for accountability purposes to an emphasis on data visualization for instructional improvement. For example, during our process, we collaboratively determined a cut point for chronic absenteeism. Making this decision rule with the individuals who would be using the data contributed to the applicability for informing meaningful instructional change.

Limitations

One of the challenges we had with identifying a specific focal problem was the limited dataset we had available to us. In order to protect personally identifiable information (PII), we could not use live district data. Instead, we had access to a restricted data set containing predominantly New York State assessment data for an anonymized sample of students. This limited dataset not only constrained what questions we could pose, but what data we had available to report.

In addition, time constraints also made it more difficult to quickly code and re-organize the data for meaningful analysis. For example, as we began analyzing the item analysis data, we realized that test items across grades did not belong to the same learning standards. What we needed was a field that grouped standards across grades into a higher-level domain, which was not available. Fortunately, the data scientist on our team quickly authored code to address this limitation.

There were other issues, however, that just could not be addressed in such a short amount of time. One major issue was the lack of an item difficulty benchmark in our dataset. NYS Assessments are standards-referenced tests where students are classified into one of five performance levels for high school Regents examinations in English and Math, or one of four performance levels for all other assessments. It is important to note that not all questions are designed to be of the same difficulty, since they are meant to differentiate students at each performance level. Assessment questions that are meant to distinguish mastery level are naturally more difficult than those meant to identify basic knowledge of a specific learning standard. As such, it is important to not simply compare the percentage of correct responses among each question without first creating a "difficulty index" for each question based on a larger population of test-takers. Due to time restraints, the reports that we began to design at the NSF Data Collaborative did not take question difficulty into consideration.

Considerations for sharing reports among many districts

One major question was how would we be able to deliver these reports to a wider audience? In Nassau County, we have fifty-six individual districts, often with fifty-six individual wants and needs. How can we be sure that our designs will work for most, if not all of our districts? In addition, Nassau County public school districts do not store data in a unified student information system (SIS). Districts are free to use any SIS they choose, and currently have chosen products from five different vendors. Multiple SISs can mean that we don't always get the same data from all districts. For example, will all districts report attendance data, and in the same way?

Other questions we had regarding the delivery of reports to a wider audience:

- How do we enforce security so that an individual school or district only has access to their data?
- How do we provide comparisons to other districts while still maintaining confidentiality?
- Will static "one-size-fits-all" charts be sufficient, or should we look into creating more interactive "one-size-fits-many" visualizations?
- How do we roll out R-coded reports when local expertise in R does not presently exist in districts?
- How do we create reports that are both eye-catching reports and easy for users to understand?
- What skills and competencies do district and school leaders need to facilitate generative dialog that informs practice?
- In what ways can data visualizations be leveraged differently from other data forms to build psychological safety among teachers and school leaders, instead of the common use of data to blame or shame teachers?

Next Steps

Leveraging the Nassau BOCES Instructional Data Warehouse

Nassau County public school districts already have access to an existing shared reporting system that can address some of these needs. The Nassau BOCES Instructional Data Warehouse (IDW) provides users with reports and dashboards designed in IBM's Cognos Analytics business intelligence platform. The reporting model maintains both role-level security (superintendent access vs. principal access vs. teacher access) and row-level security (making sure each district only sees their student data). This allows districts to work with data that are directly relevant to them, while protecting PII by limiting data access to authorized personnel only.

Although data security is essential, districts still need a way to compare their data to others. As mentioned earlier, not all test questions are created equally in terms of difficulty. How can we tell from the graphs we created which questions/standards students really struggled with if some are much more difficult than others? While we can't directly compare multiple districts, we can create benchmarks based on all Nassau County districts combined. Because the IDW houses data for all fifty-six districts, we can provide aggregate, comparative analysis in our reports while still maintaining district confidentiality.

Nassau BOCES also employs staff who are proficient in data modeling and report/dashboard design using Cognos. We thought it would make more sense to convert the algorithms and reports that were designed in R Studio into Cognos and leverage the resources we already have in-house. Not only can we create static "one-click" reports for novice users, but we can also take advantage of Cognos' interactive features (sorting, filtering, grouping, summarizing) that will allow more advanced users to customize their data exploration.

Conclusion

Stay Out of Silos

We have all attended many workshops. We make connections with incredible people, discuss great ideas, and learn about new tools and techniques only to go back to doing the same things we've always done once we get back to face the immediate reality of our everyday responsibilities. Often, we get so busy that we move on to other projects and these reports never get to see the light of day. If we are lucky the reports do get written, but we miss the mark due to our tendencies to code independently (sometimes at 3am) without any further collaboration. We need to ensure that the feedback-loop remains intact.

Continue the Momentum Generated by the NSF Data Collaborative

Nassau BOCES will be scheduling future working group sessions modeled after the NSF Data Collaborative. These sessions will bring together various district stakeholders and data strategists where we can spend additional time making sure that we:

- Pose the right questions
- Have access to the right data
- Produce visualizations that are user friendly
- Increase the data literacy of educators at different levels
- Expand the technical skills of end users and coders alike.

Nassau BOCES will provide training to end users to help them become more comfortable with available visualizations and data analysis tools. It is important that we help our most novice users become more comfortable with our Cognos reporting environment and data analysis in general. A greater comfort level will hopefully encourage further engagement. We also want to help our more seasoned district users become “power users” by introducing advanced techniques such as the ability to analyze their own data. Lastly, we need to help our data strategists increase their proficiency in other coding platforms such as R and Python. This will increase the ability to collaborate and share code with other data scientists. In addition, Nassau BOCES can take advantage of Jupyter Notebooks, which integrate R and Python code with Cognos Analytics.

Invest in Building Social-Emotional Competencies of School and District Leaders

While it may seem disconnected from the technical analysis of data to develop stronger social-emotional competencies of school leaders, it is a critical precursor if our ultimate end is for data usage to translate into experimentation with new action in the classroom or schoolhouse. Even with clear data that point to clear implications for action, it is possible – even probable – that teachers will not take the quantum leap in implementing something different outside of a school culture of belonging and learning. Patti, Senge, Madrazo & Stern (2015) identified four critical leader social-emotional competencies that leaders can exercise and practice to create ripe conditions for data analysis to seamlessly translate into cycles of trial, error, adaptation, refinement and ultimately, student success. Specifically, leaders’ skill in engaging in meaningful conversations, building generative relationships, crafting open questions, and systems thinking that helps build connections between data insights and broader purposes of the school are vital companions to the technical skills needed to collect and analyze data.

Invest in Building Capacity of Data Literacy of Educators

With emphasis placed on the integration of instructional technologies, educators have access to more data than ever before. This includes but is not limited to IDW, NYS mandated assessments, locally determined measures, teacher administered tasks and data generated from applications/ web-based platforms. While this affords increased opportunities for personalized learning experiences for students and provides information to impact systemic change through inquiry based improvement cycles, it also requires a commitment to building capacity for data literacy of educators at all levels. District Level

Administrators must seek out partnerships with developers, data scientists and universities in efforts to prioritize data into actionable visualizations housed within a user-friendly data management system. Building Level Administrators must create structures such as Professional Learning Communities (PLCs) where teachers assume leadership roles to guide subject matter and grade level teams through evidence-based inquiry cycles using protocols that promote observation, application and revision. Classroom teachers must be trained to identify bias, communicate the relationship between variables and interpret visualizations in efforts to predict trends and influence instructional decisions. Our experience engaging in collaborative data analytics and visualization further revealed the need for and the importance of educator input. Next steps require that the educator is provided a platform upon which to contribute and that educational leadership invests in the technical development of this voice.

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CHAPTER 18

An Open-Ended Data Collaborative (Imagined)

Fred Cohen
Nassau BOCES

Introduction and Background

The Columbia University Teachers College Data Collaborative offered a hands-on experience for teams of professionals who regularly gather, process, present, and analyze school data. What a unique experience! As a former high school principal and Deputy Superintendent of schools, I never before had the opportunity to see a talented coder turn my crude chart drawings and explanations into a visual reality. Even better was the opportunity to have a team from the ranks of teachers, administrators, researchers and "techies" critique and improve that visual presentation.

My own background began as a high school English and reading teacher. Later, as a department chairperson and high school principal, I became eager to show teachers how their classroom teaching related to test results and school grades. Then, as a district administrator responsible for five secondary schools, I began to develop data analytics to improve instructional practices. Finally, in my final year as Deputy Superintendent, Nassau BOCES

Cohen, 2021

began to create a data warehouse which housed test data and presented its data in a format called cubes.

In practice, the cubes were intriguing but not helpful in my role as a central office administrator. I was about to retire and accept a position at a local college, and I advised BOCES that my district would likely not participate in the data warehouse service in the future. They suggested, instead, that I work as a consultant to the warehouse for the following year and help turn the data gathered into productive teaching tools. I am now in the middle of my 18th one-year contract, serving BOCES as a consultant.

What I have learned (and I hope to portray in BOCES reports and dashboards) is that by tracking longitudinal progress, comparing results to Nassau County benchmarks, and disaggregating results to the teacher level, teachers can gain insight into improving their practice. Nassau BOCES was among the first to produce “gap” reports at the question level and companion wrong answer analyses. And, to this day, Nassau BOCES is the only data resource that provides districts and teachers with comparative results on Advanced Placement participation and performance, with a detailed test by test analysis.

So, it was with eager anticipation that I attended this collaborative workshop at Columbia’s Teachers College. As impressed as I was, I was oddly disappointed. Why did the collaboration have to end? **So, I engaged in a thought experiment.** Imagine the entire Nassau County professional staff (teachers, administrators, and support personnel in all 56 districts), as a single entity, collaborating without any time limitation. And then, why not add the Teachers College Collaborative experts to the mix! The following is what might occur in the immediate, short-term, and long-term future. Before presenting these three imagined scenarios, let me help set the stage by offering a brief and hopefully instructive diversion about the “I notice, I wonder” protocol.

Using the “I Notice, I wonder” Protocol as an Operational Device

The “I notice, I wonder” protocol is an effective exercise in citing important data points (“I notice”) and then postulating conjectures (“I wonder”) concerning those data points. A basic but highly imaginative (and exaggerated) example might look like this. You “notice” an odd light in the night sky approaching rapidly in an unusual manner. You then “wonder,” what might that light be? Your “wonderings” range from the mundane—your neighbor’s son playing with his drone, to the far more expansive—a space ship from a distant world with benign creatures looking to question you in detail about important details of your home planet.

Why not apply the same expansive and optimistic vision to some of the intriguing presentations and scenarios exhibited at the NSF Data Collaborative Workshop! What if, in fact, the workshop was not a two-day workshop but an unlimited one where participants had full and open-ended access to the talents, abilities, and data resources present at the Thursday and Friday sessions. What might occur if we could have an open-ended chat with experts who could answer our questions or even write code at our behest! And how responsive might we be to district needs if we could get instant feedback from all districts present at the collaborative and even from others in those districts not present so we might thereby survey their needs and desires concerning data!

In this manner, my "what-ifs," might be turned into full-fledged programs, reports, and actions instead of just wonderings. Before flying to the moon, someone had to imagine it, then envision it, then plan it in detail, and finally build a working model. For these wonderings, I simply skip the middle steps and turn some of the imaginings into three fully realized products—one short term, one intermediate-term, and, for the last one, clearly a dream for the distant future.

"What-if" Scenario Number 1—I noticed the elegant redesign of the Nassau BOCES **Wrong Answer Summary report**. I wondered if that initial prototype presented could be improved to display all the information shown in BOCES' original table while still exhibiting the elegant visuals of the clever prototype. Shown below is a segment of the original BOCES table.

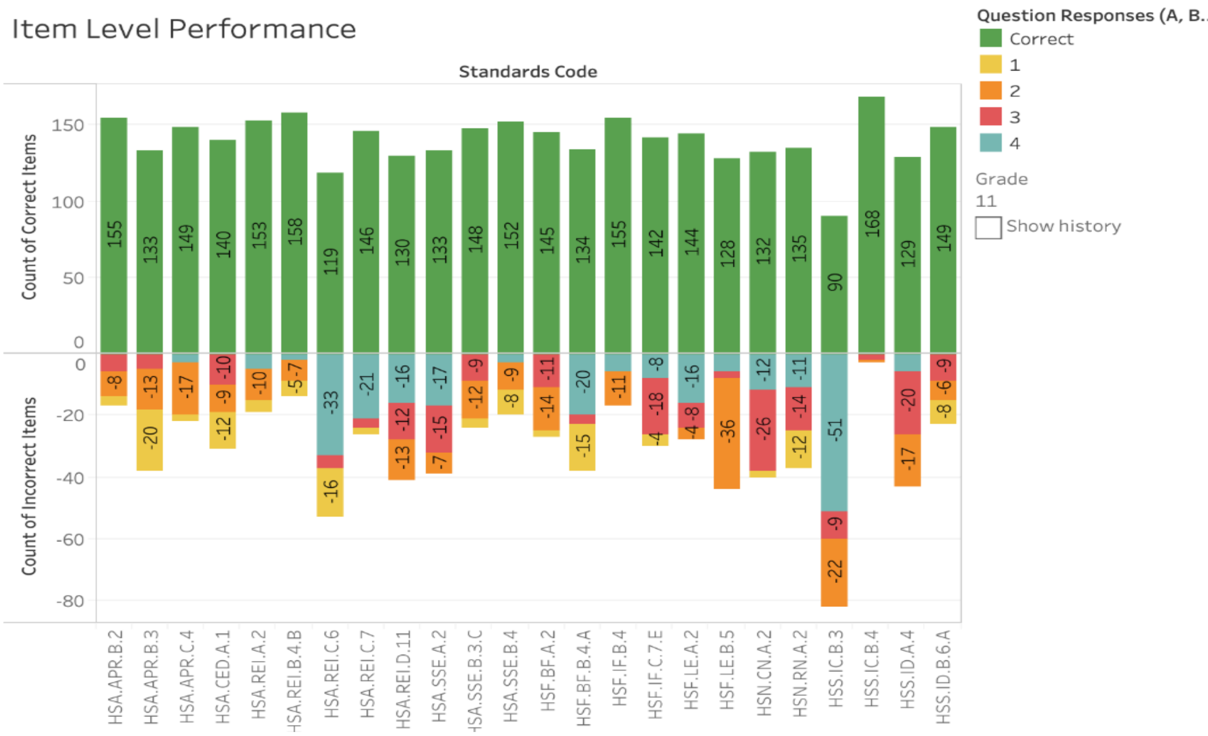
Sort Report By: Skill Tested

Q#	Skill Tested	Region %	Correct Resp	Blank #	Blank %	Resp 1 #	Resp 1 %	Resp 2 #	Resp 2 %	Resp 3 #	Resp 3 %	Resp 4 #	Resp 4 %
I-07	Arithmetic with Polynomials & Rational Expressions: A.APR.2---Know and apply the Remainder Theorem: For a polynomial p(x) and a number a, the remainder on division by x - a is p(a), so p(a) = 0 if and only if (x - a) is a factor of p(x). --| HSA.APR.B.2	79.7%	4			8	2%	32	7%	25	6%	370	85%
I-21	Arithmetic with Polynomials & Rational Expressions: A.APR.3---Identify zeros of polynomials when suitable factorizations are available, and use the zeros to construct a rough graph of the function defined by the polynomial. --| HSA.APR.B.3	70.0%	4	1	0%	62	14%	9	2%	7	2%	356	82%
I-02	Arithmetic with Polynomials & Rational Expressions: A.APR.4---Prove polynomial identities and use them to describe numerical relationships. For example, the polynomial identity (x^2 + y^2)^2 = (x^2 - y^2)^2 + (2xy)^2 can be used to generate Pythagorean tr	80.8%	4			31	7%	34	8%	10	2%	360	83%
I-10	Building Functions: F.BF.2---Write arithmetic and geometric sequences both recursively and with an explicit formula, use them to model situations, and translate between the two forms. --| HSF.BF.A.2	79.6%	3			35	8%	30	7%	352	81%	18	4%

The strength of this report is that it clearly displays, for each multiple-choice question, the correct answer, the number and percent of students who chose each incorrect answer, an extended description of the skill tested, and the percent correct for the Nassau County region. Finally, the user can click on each question number to see the printed question.

Now view the prototype proposed at the Collaborative.

Its visual appeal is obvious as is the incorporation of most of the data on the original table. What is missing, however, is the regional benchmark for Nassau County which shows whether the district underperformed or excelled on that test item. Also missing is a full description of the skill tested, and, finally, the prototype lists only the number of students not the percentage.



Imagine what could be done if the collaboration continued. First, we could change each column on the chart to indicate **"percent correct"** and allow the user to hover over the bar to see **"number."** Then, we could **add a colored dot** on (or beyond) the green columns to indicate the **percent correct for the region**. We could allow hovering over the abbreviation of the Skill Tested to reveal the **full skill description**. And, since the collaboration is open-ended, we could then test the efficacy of the report by releasing a beta version and soliciting comments from users. In the final stage, county, district, school, and teacher level versions would be available so all users could compare their own results to the other benchmarks.

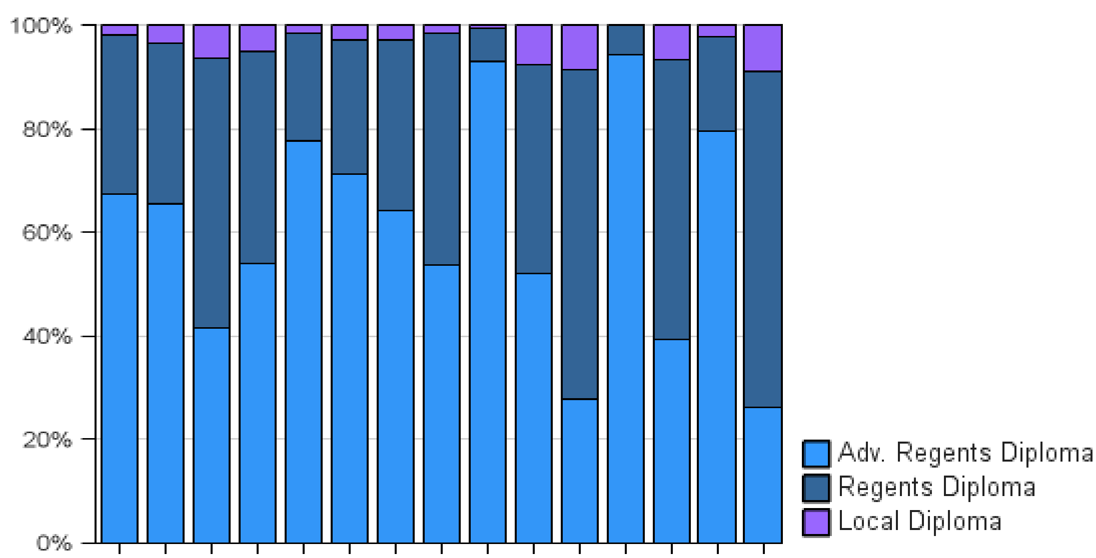
In this "What-if" Scenario, the prototype visual above is so fully realized that some could likely complete the project without benefit of the original creative team from the Collaborative. The result might be somewhat different from the originators' intent, but it might be equally effective. So, in the end, these wonderings could have been converted to reality without much of a stretch. "What-if" Scenario Number 2, however, requires us to stretch our imagination somewhat further.

"What-if" Scenario Number 2—One of the hopes and dreams expressed at the Data Collaborative is that some of the data available in the Nassau BOCES Instructional Data Warehouse (called the "IDW") are not sufficiently current. There are actually two currency issues. The first, **which will not be addressed**

here, is that the IDW includes mainly yearly test data and does not include ongoing daily or interim testing, homework, or attendance.

But for the data already included in the IDW, some say that users still must wait too long before seeing test data. Oddly, the reason for the delay is rarely Nassau BOCES turnaround time. Rather, it is the lag time in NYSED releasing key data fields or the result of districts delaying the upload of their own data. The IDW is always prepared to turn out reports almost immediately after data is received. Other factors can also affect reporting turnaround time such as the format of the data that is made available by NYSED. Once these data are made available, however, the IDW produces reports that typically add a county benchmark which is the key comparison needed to add context to district, school, and teacher level data.

A powerful example of data currency occurs with high school graduation data. What could be more important to a district than comparing graduation rates for the types of diplomas earned? How does my district compare to other districts in the county? The IDW developed a dramatic graph (and accompanying table not shown) allowing comparisons to Nassau County and NY State benchmarks and encouraging, as well, comparisons to any district in the county. Look at the visual below.



The graph lists the home district first, then compares county and state averages in the second and third columns. But the graph also offers the inclusion of any (or all) districts in Nassau County allowing for a quick comparison to any district chosen, thereby allowing the user to view “like” districts or even “reach” districts.

Unfortunately, the data shown is not for the most recent graduating class. As of this writing (December 2019) New York State Ed is not expected to release June 2019 graduation results until January 2020 at the earliest. How can districts plan, or even measure their progress compared to other districts, when comparative graduation data is not released until the second semester of the following school year?

Is it not appropriate to wonder how much more effective it would be to share **more current** data? If our Data Collaborative were both ongoing and universal in scope (**all districts included**), we could share **unofficial, preliminary, June graduation rates** as soon as we calculate them and apply any insights gleaned by September instead of waiting for the following January when the year is half over. Oddly enough, there is another high school graduation report which NYSED uses for accountability. This report can be quite punitive if drop-out rates are high, yet the accountability data published in January 2020 is actually for the 2018 graduating class, and accountability data for the 2019 graduating class will not be published until 2021.

BOCES, in theory, gathers data from districts and uploads such data to the state for processing and distribution to the public. But an ongoing Data Collaborative could short-circuit this process and get preliminary data to districts with the immediacy needed to be truly useful. Responding to district needs in timely fashion is essential for real improvement to occur. It is fully recognized that accountability data must be checked and verified if it is to serve its intended purpose, but the immediacy of an instant feedback loop would be helpful to many analysts.

<u>"What-if" Scenario Number 3</u>—The greatest frustration, by far, in attending the collaborative was to see how magnificently some of our users have utilized the IDW while surveys show (and experience proves) that many others use the IDW with only varied and limited levels of frequency and effectiveness. So, I wonder how a universal (all districts included) and ongoing Data Cooperative might be utilized to push relevant data to the right users and ensure their timely use.

I wonder what would happen if **every teacher woke up one day and found a corresponding Gap, Item Analysis, and Wrong Answer report, with subgroup disaggregations included, in his or her mailbox** (whether literal or electronic). Does anyone doubt that classroom instruction would be improved? Although this may seem like a distant dream, the IDW currently does offer Gap reports, Wrong Answer reports, Item Analysis reports and more to every teacher giving a state test. We also can provide the subgroup make-up of every classroom and the subgroup components for Nassau County benchmarks too. Currently, though, we fear that some **mailboxes are not being checked, and mail is left unopened** despite the fact that the data are available and delivery is possible through the IDW.

And I wonder how much more effective **guidance counselors could be if they reviewed the available college tracking reports** which show the success rates of their students (disaggregated by college). Who received a four-year degree, who received a two-year degree, and who did not? How did district college graduation rates compare to Nassau County graduation rates over the past decade and beyond? Which colleges provided the highest success rates for our students? **All these data (and far more) are in the IDW now, if only all counselors would simply "pick up their mail"** and review all reports currently available.

Finally, I wonder what my own contribution to my students' instructional welfare might have been if I had access to the teacher reports described and to the Advanced Placement and graduation reports noted when I was a central Office administrator. At every level of instruction, a universal ongoing Data Cooperative would allow and encourage responses and collaborations never before imagined.

Summary

Alas, these are just the musings of an aging educator in the middle of the 54th year of a varied career in education. When I look at the difference between today's reality and my wonderings, I feel a sense of disappointment. But when I reflect on what the Nassau BOCES IDW has accomplished since its inception in 2001, and especially the innovations displayed by the Teachers College Data Cooperative, I am more than encouraged. The flying saucer hasn't landed yet, but I can see that odd flashing light just above the horizon.

CHAPTER 19

Let Data Work

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Abstract

How will education reinvest itself to respond to the megatrends (e.g., Artificial Intelligence and Big Data) that are shaping the future of our society and educate learners (especially, K-12 students) in Generation Z? Attempts to understand, apply, and develop data science techniques in education has a long history, but practical efforts to reduce the disconnectedness between educators and data scientists are limited. On the one hand, educators rely more on the information from data for more evidence-based, adaptive, and accurate decision-making. On the other hand, new technologies that data science per se are not "silver bullets" to addressing long-standing dilemmas in school. Consequently, there is a strong need for bridge this gap and help the educational data practitioners to build the evidence-based improvement cycles in reality. To illustrate, I will present my experience during the NSF collaborative workshop from a data scientist perspective. The purpose of this chapter is to provide a summary of the outcomes from the group collaboration in this workshop.

Keywords: Educational Data Science, Evidence-based Improvement Cycles, Data-driven Decision Making.

Data Visualization, Dashboards, and Evidence Use in Schools

Chen, 2021

The NSF data collaborative workshop is a two-day event, which aims at exploring the opportunities in building community and capacity for data-intensive evidence-based decision making in schools and districts. The event is held at Teachers College Columbia University with the support from the Nassau Board of Cooperative Education Services (BOCES) as part of the National Science Foundation (NSF DGE # 1560720). I participated in this event as an educational data scientist and researcher. My previous educational projects involve the recommendation system on higher education digital learning platforms, educational and psychological measurement of large-scale assessment data, and social network analysis of digital learning platforms.

In general, this event benefited me in terms of a) learning how the data are used across districts and schools in Nasus County as a real case, and b) collaborating with the educators, data scientists, and researchers from to explore the innovation of data analysis techniques and, in particular, visualization tools to improve instructions. In this mini-chapter, present my experience during the NSF collaborative workshop. In the next section, I will introduce our team members and identify the distinct perspectives that educators and data scientists have when looking at educational data science. Then, I will summarize what we think useful data science should be in education and what is limited in reality. Finally, I will introduce the two data visualization examples that we explore during the event as a possible innovation for the instruments.

Who are we?

During the event, I was a member of team Hexagon in the NSF collaborative workshop, which is made up of educators (teachers and principals) from Nassau County Long Island New York, education researchers, and data scientists. All of us, to some extent, do data science for daily decision-making and expect to improve educational data science in reality. At the same time, the interdisciplinary backgrounds of our team members make us think about educational data analysis from a different perspective.

Educators pay attention to the practical usefulness of school data. They ask: what data should we collect and use (in particular, beyond the cognitive assessment records)? What information should principals, teachers, and other stack-holders receive? And whether they will use these data differently? They all appreciate the importance of data use while disagreeing on what data should be most accessible, useful, and informative. They all willing to see more comprehensive and dynamic data sets available in the future while feel stressed of analyzing these data set.

For data science and researchers, we focus on demand and problem-solving. We ask: what is the structure of the data we have (longitudinal or cross-sectional, single-level, or hierarchical)? What information can be collected and saved in reality (e.g., school climate, students' emotional education, and community culture)? Can the system be "gamed"? How much do we know about the validity and reliability of these data and analyses? How can we avoid psychological safety and privacy issues? Do we ask the right questions when we use the data? We care about the potentials and risks when we apply data science to education and desire feedback from practitioners.

What is the educational data science we need?

The field of education is already in the midst of data transformation, and schools are inundated with an increasing amount of both qualitative (e.g., course evaluation survey) and quantitative (e.g., standardized tests assessment like SAT) data (Bowers, Shoho, & Barnett, 2014). These data include but are not limited to the assessment data (e.g., traditional teacher-assigned course grade), multidimensional performance measurement (e.g., the quick course feedback data in edsight.io), demographic and health information of students, staff, and faculties. With the development of data collection and data storage technology, we can access even more data in education than ever before.

However, data in education also bring more challenges. All the data we are collecting from school and students comes from different platforms, under different data manipulation processes, and be measured using different methodologies. Most of the counties in the United States do not have a standardized, dynamic, and user-friendly database system until today. Consequently, it comes difficult to set up a standard in terms of data use and even to combine the data from different sources together for a specific research purpose.

Meanwhile, the information that we can get from data is not ideal to fulfill our expectations. Many useful data (in particular daily data at the classroom level) in practice are missing or hard to collect. For example, teachers need the data about the students' emotional or psychological status to help the individual students in learning. Similarly, teachers and parents are disconnected so that students' data beyond the classroom are still limited. Consequently, any decision-making based on these data is prone to bias in data collection, analysis algorithms, and interpretations.

Last but not least, other issues like privacy and security are also becoming nonignorable. For example, the FBI found that schools across the country lack funding to provide and maintain adequate security, and most student data disclosures are caused by human errors. Even though, "data for good" is becoming one of the most fundamental consensuses among data scientists (in particular in the field of education), we lack precision from the perspectives of technical practitioners and other participants involved to identify where we can do better and how.

Fortunately, BOCES already provides the teachers and administrates in Nassau County with a longitudinal database, which incorporated a wide range of information related to students, teachers, and schools. The data that makes me most surprised is the students' item response (both the key and the alternatives students select in reality) are each exam. Detailed information like this opens the opportunities for many advanced psychometric analyses (e.g., cognitive diagnostics modeling and item response theory). Except for the educational researchers and data scientists, these data may also be beneficial for educators for evidence-based improvement cycles.

However, there are still many unsolved issues. The problems educational data practitioners in Nassau County are facing can be summarized as three main points. Firstly, the data dashboard cannot support more personalized data analysis purposes. For example, the teacher pays more attention to the individual summary. At the same time, the principal may care more about the longitudinal improvement of the overall performance for a class or a grade. Since educators may lack the skills to manipulate the data quickly, this vital information is hard to access for them. Second, there are limited visualization tools available in the system. Educators are not sensitive to the raw numbers showing in the table. Instead, they rely on visualization to reduce the unnecessary load of understanding. All educators in my team are very willing to learn the logic and skill of display. At the same time, I also feel that these analyses will be too time-consuming. Finally, the summary and report are basic. Most teachers and principals know about their students and schools. If the system can only provide basic a data summary, they cannot get extra insights from the database, which could have an immediate impact on their daily practice. In review, how to make the data quickly to use and access is the most critical "late mile" problem.

Let data work

During the whole workshop, our team explores two primary data set: given data set which extracts were downloaded directly from the Nassau BOCES Instructional Data Warehouse, and the real classroom data from one of my team members. In this section, I will work the reader through the process of how we manipulate, analyze, and visualize the data in R.

During the NSF workshop, we are provided with a sample of real data from the Nassau County system without students' indicators. Three types of data are offers: item analysis data (which incorporated all question and answer choices made by individual students on a single assessment as well as some student demographical data), item map data (which contains the information about learning standards for each question on a single evaluation), and student assessment summary data (contains total scores on specific assessments for an individual student). Except for the student assessment summary data, all the other data are saved separately in a different year and different tests.

```
regression_example <- lm(`MC Total` ~ Gender + Ethnicity + Teacher, data)
summary(regression_example)
Coefficients:
                                                  Estimate Std. Error t value Pr(>|t|)
(Intercept)                                       30.14512   12.11527   2.488   0.0129 *
data$GenderMale                                    0.04353    0.30082   0.145   0.8849
data$EthnicityAsian                               -2.47996   12.03523  -0.206   0.8368
data$EthnicityBlack or African American           -8.02112   12.04373  -0.666   0.5054
data$EthnicityHispanic or Latino                  -8.89244   12.03153  -0.739   0.4599
data$EthnicityMultiracial                         -2.88616   12.19012  -0.237   0.8128
data$EthnicityNative Hawaiian/Other Pacific Islander -2.37542 12.35689 -0.192  0.8476
data$EthnicityWhite                               -4.99619   12.03000  -0.415   0.6779
data$TeacherB, TEACHER                            -1.18866    2.01262  -0.591   0.5548
data$TeacherC, TEACHER                            -0.10843    2.04338  -0.053   0.9577
data$TeacherD, TEACHER                             2.84712    1.99880   1.424   0.1544
data$TeacherE, TEACHER                             1.80783    2.03525   0.888   0.3744
data$TeacherF, TEACHER                             1.18668    1.99872   0.594   0.5527
data$TeacherG, TEACHER                            -0.58634    2.02104  -0.290   0.7717
data$TeacherH, TEACHER                             0.48106    1.97781   0.243   0.8078
data$TeacherI, TEACHER                             0.52568    1.96599   0.267   0.7892
data$TeacherJ, TEACHER                             8.38598    1.64084   5.111 3.30e-07 ***
data$TeacherK, TEACHER                             9.11244    1.60479   5.678 1.42e-08 ***
data$TeacherL, TEACHER                             8.07123    1.65154   4.887 1.05e-06 ***
data$TeacherM, TEACHER                             3.78622    1.44905   2.613   0.0090 **
data$TeacherN, TEACHER                             3.60132    1.44793   2.487   0.0129 *
data$TeacherO, TEACHER                             3.28424    1.44902   2.267   0.0235 *
```

Figure 19.1

Item analysis data provides opportunities for psychometrics analysis of assessment. The most straightforward usage of these data set for teachers could identify the total score distribution of examinees and find the most difficult items for each student. However, many other more advanced techniques are also available for item analysis. For example, item response theory (IRT) can be used for identifying the latent students' ability, item difficulty, and item discrimination. The scale measured by IRT also provides a more robust analysis than the single test score. In terms of student assessment summary data, principals may want to identify the most influential background variables for students' performance. Consequently, regression analysis can be used. For example, when we set the total score as the dependent variable and make students' gender, ethnicity, and teacher independent variables. The code is showing in the first two lines in Plot 1. Based on the coefficient, we can see some teachers have a significantly positive effect, which indicates the importance of teachers in their performance.

Another issue that is frequently mentioned by my team members is the difficulty of manipulating data set by themselves. Most of the time, they rely on the summary report automatically created in the system. However, they cannot easily map, combine, and transfer the data set. As an example, I will illustrate how I combine the data from a different data file in item analysis under a separate folder together to create a summary of all students and all exams into one table. The basic idea is to create an empty data frame (named "year_data"), go through all folders named by the year, get all the file names under each folder (list.files), open these files one by one, select the variables (e.g., demographic information and total score), and finally merge these data into the data frame we created.

```
library(readxl)

year_data <- data.frame()
for (y in c("2017","2018","2019")){
  element <- c('Files/Item Analysis/', y , '/')
  folder_name <- gsub(", ","",toString(element))
  file_name <- list.files(folder_name)
  for (file in file_name){
    filename <- paste0(folder_name,file,sep = "")
    temp <- read_excel(filename)
    temp <- temp[temp$Score!=999,]
    year_data <- rbind(year_data,temp[,1:17])  }  }
```

Similarly, I also showed my team members how to use the R package `dplyr` for manipulating the data set. For example, we can use the following code to identify the student with ID equals 000001055 and list all the formation about how many total scores it makes in which assessment in which year.

```
year_data %>% filter (`Student ID`=="000001055") %>%
select(c(`Assessment`,`School Year`,`MC Total`))
```

I recognize that the data analysis R needs practice, even though it seems to be straightforward. Many educators without coding skills are not able to spend too much time coding and debugging every day. Consequently, the data dashboard could and should be more flexible and user-friendly to them with the only simple so that users only need to click and drag to get all the data and analysis they need. However, there are many data manipulation, analyses, and visualization we can apply to the same data set. The question is, what is the analysis that is most useful and important? Facing these issues, we decide to narrow down our discussion into two practical use cases, when teachers and principals benefit more if we can visualize it. The two questions are: 1) how can we identify the struggling students in the assessment quickly? 2) how can we see the longitudinal improvement of students across different grades?

My team members shared two real datasets in one class with me for visualization. These two datasets are the assessment scores of students from the same class in two consecutive school years (Grade 3 and Grade 4). For each year, the students' ID, score, and level are provided. To solve the first questions, we use the single scatter plot with the following code. We add three threshold scoreline in dark green (score = 629, level 3 and level 4), green (score = 602, level 2 and level 3), and red (score = 582, level 1 and level 2).

```
ggplot(data=Student_Assessment_Scores_Teacher_Interface) +
geom_point(aes(x=`Performance Level` ,y=Score)) +
geom_hline(yintercept=582, linetype="dashed", color = "red") +
geom_hline(yintercept=602, linetype="dashed", color = "green") +
geom_hline(yintercept=629, linetype="dashed", color = "green4") +
geom_text(aes(x=`Performance        Level`        ,y=Score,label=`Student
ID`),hjust=0, vjust=0)+
theme(axis.text=element_text(size=10, face="bold"),
axis.title=element_text(size=10,face="bold"),
legend.text =element_text(size=1),
legend.title =element_text(size=10),
legend.key.size = unit(1, "cm"))+
labs(x ="Score", y = "Level")
```

Figure 19.2 shows the result of this code. Based on the feedback from my team members, they think this visualization is helpful since they can easily focus their attention on the students right below the threshold line. The students above the dark green line (level 4) are good students who are expected to perform well in the future. The students below the green line are the students who may perform badly all the time. However, the student with ID 4260460 is right on the green line is the student that teachers may need to pay more attention. Perhaps with more support, this student can move into higher scores under level 3. Similarly, student with ID 4280392 is also the student that teacher can help most in level 3 since it has the highest possibility to move into level 4. We can also think about map the student in level 4 together with the student in level 2 to make a study group, so that good performance students can share their learning strategies and help the student with low performance. In this example, we can clearly see how the visualization of scores can help the teachers make the decision about how to allocate their support in the limited school time. However, the conventional score destruction plot does not indicate the threshold score across different levels. Consequently, teachers cannot identify the struggling student directly.

To solve the second question, we need a longitudinal visualization of students' improvement. The most straightforward plot that is widely used in data science for this purpose is called an alluvial plot. There are many tools to make this plot. In this example, we use the R package ggalluvial.

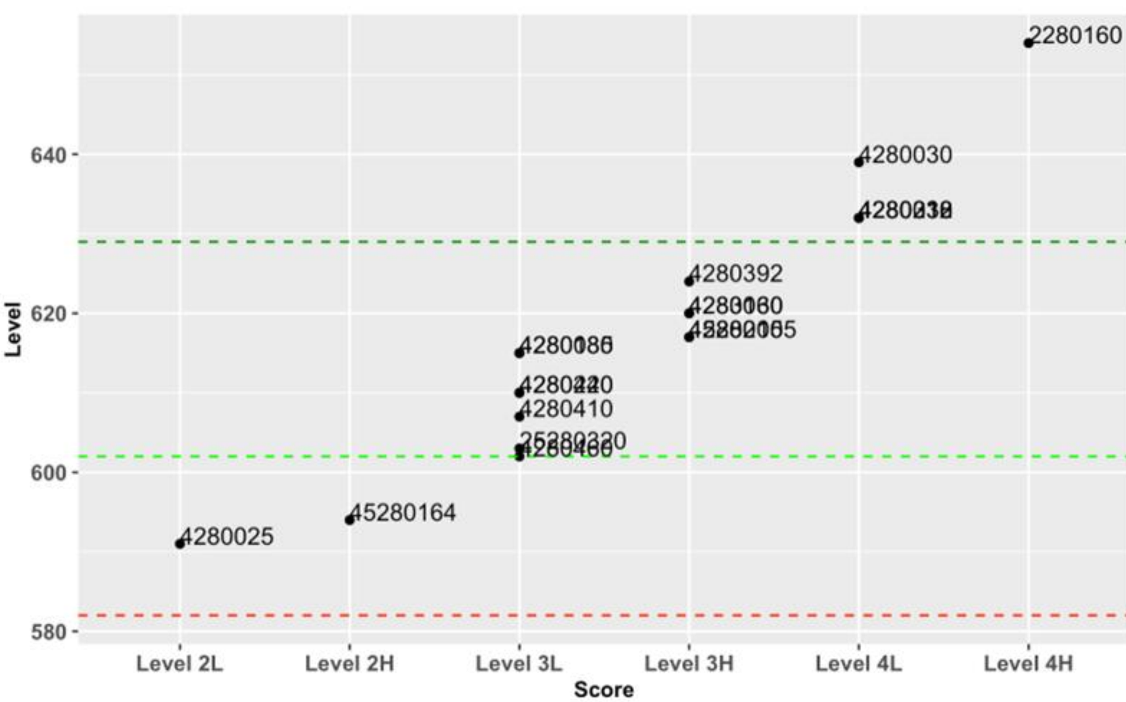

Figure 19.2. Visualization of Score on each Level

```
library(ggalluvial)
#install.packages('ggalluvial')
ggplot(new,aes(x = Grade, stratum = Level, alluvium = StudentID,
           fill = Level, label = Grade)) +
```

```
scale_fill_brewer(type = "qual", palette = "Set2") +
geom_flow(stat = "alluvium", lode.guidance = "frontback",
          color = "darkgray") +geom_stratum() +
theme(legend.position = "bottom") +
ggtitle("student performance level from one grade to another")  +
geom_text(x=1, y=30, label="Scatter plot")+
annotate("text", x = 1.9, y = 4.75, label = "004270025")
```

As we can see from Figure 19.3, most students improved to a higher level from Grade 3 to Grade 4. This plot can give a direct insight into the overall change of student performance in a class for principals. There is one student who used to be located in level 4L became level 4H now. Teachers may want to know how this student keeps improving its performance consistently and what is the excellent experience it can share with other students. We also can quickly see the first-year English language learning student adjusted to the new environment and get level 4 in the next year. However, there is one student with ID 004270025 whose performance moved down from level 4L into 3H when all the other students are improving or at least staying at the same level. Teachers may need to figure out why this student did not perform well and pay more attention to this student before it is too late. Longitudinal data perhaps is the most critical data in K12 education, which helps us to track the development of kids. However, most data set does not provide the visualization or analysis for this type of data since it is much more complicated than the cross-sectional data.

We have to recognize that R is not the only tool for visualization and data analysis. Probably, even not the best. During the event, we also tried Tableau, which is an interactive and straightforward visualization tool without requiring users to code. However, this tool is not free and had a limitation in data manipulation. Python is another popular choice for many data scientists, which is dominant in terms of statistical machine learning and data manipulation. However, it may be harder for educators to use. Consequently, data scientists need to provide a more interactive, user-friendly, and dynamic data dashboard to the practitioners for personalized use, so that data that we collect in education can play a much more powerful impact.

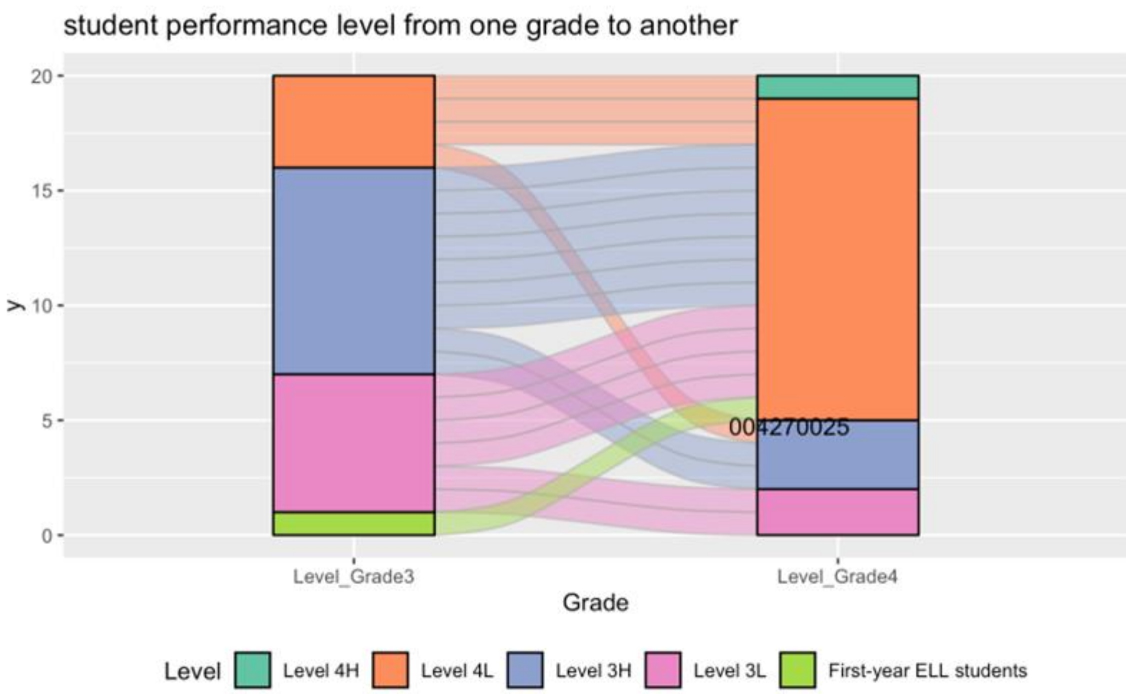

Figure 19.3. Longitudinal visualization of student performance

Summary

It is always helpful for educational practitioners to master some core skills in data science and apply them to their work. On the other hand, data scientists and data system providers should also pay more attention to the data users and give them more options and guidance. "Simply inserting technology into classrooms and schools without considering how the contexts for learning need to change will likely fail" (Collins &Halverson 2018; p. 140). The fundamental problems practitioners in education face are nothing new: they may still lack the background, ability, and support to make use of data. Consequently, data scientists and educators should work collaboratively to develop the techniques that, indeed, in the end, benefit the students. We need more collaborative learning opportunities like this NSF workshop.

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Collins, A., & Halverson, R. (2018). *Rethinking Education in the Age of Technology: The Digital Revolution and Schooling in America.* New York and London: Teachers College Press.

CHAPTER 20

When in Rome…

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All roads lead to Rome; in a school, Rome is in the Principal's Office. From the HVAC system to security, budget, transportation, community relations and accountability reports, the Principalship is a smorgasbord of responsibility, and each day the list grows. Yet, the Principal is ultimately the principal teacher in a school (as it was originally defined in the 1800s) as well as the leader relative to the success of school and its students. As such, he/she is charged with managing both the plant and its people, but also cultivating culture, celebrating strengths, diagnosing weaknesses, ionizing a vision, paving the path for progress and providing the professional development necessary for charting a course in the right direction. In the sea of mandates, changing demographics, turbulent economics, strained family situations, learned pessimism and a mental health crisis, positively impacting the life trajectory of children who are counting on us to do so is truly daunting. So what do you do? With whom? When? Why? How?

Data has some answers. (*I've heard ShopRite does too, but I cannot confirm that ☺)*

[1]*Data Visualization, Dashboards, and Evidence Use in Schools*

Dunne, 2021

Said the Home Depot to do-it-yourselfers, “You can do it, we can help. In “Rome” that translates to, “You *must* do it, **data** can help.” Credible data and the effective use of such is tantamount to the efficient use of myriad resources, most notably time; it sheds light on best practices and reduces the anguish of ambiguity. Thus seizing any chance to grow as a data consumer represents an imperative investment of time in that it stands to exponentially save same futuristically. So, an invitation to turn in the circles of impassioned data scientists, researchers, professors, fellow educators and assorted professionals spanning the globe while immersed in collegial discovery could equate with a utopian opportunity.

Enter the NSF Data Collaborative Fellowship.

And so it goes…..when a collection of brilliant minds comes together, expect a masterpiece. The NSF Data Collaborative at Columbia University was evidence of such, as the aforementioned utopian opportunity came to fruition therein. As a Principal, time away from my school can increase stress by at least a factor of 2 upon return, so choosing to be out of school is a rarity and two consecutive days, unheard of. Participating in this 2-day workshop however, was one of those extraordinary events that warranted roaming outside of Rome and proved to be both humbling and prolific. Rather than compounding stress, it provided instant return on the investment, paying off in dividends upon completion. The coagulation of the multifaceted realm of educational data that took place at this summit of sorts, was not only inspiring, but potentially groundbreaking. It changed mindsets and started conversations (which are ongoing). The “datasprint teams” brainstormed and revolutionized. Their results: masterpieces in promulgating brilliance pertaining to educational data in both theory and practice. Now, when in Rome, the Romans can do more.

The following is the story of how an elementary school has formidably embraced data as told from my perspective, the Principal of said school. It seeks to identify we what have done, how we have done it and how the NSF Data Collaborative has already improved the lives of almost 800 children in the suburbs of Long Island.

The McVey Way

Rome for me is in McVey Elementary School of the East Meadow Union Free School District. McVey is home to approximately 770 children in grades Kindergarten through fifth. We also offer a modified Pre-Kindergarten program, which serves scores of additional children. McVey is a true melting pot of youngsters from twenty-six different countries spanning four continents speaking seventeen different languages. Approximately 50 % of the student body is bilingual and 30% come from poverty. Since 2012, McVey's enrollment has increased by 21% and students of poverty by 70%, but so has the school's performance:

	ELA		Math	
	2013	2019	2013	2019
Proficiency	56%	83%	77%	95%
Level 4	17%	41%	34%	72%

The following is a partial summary of "The McVey Way" of employing instructional data in the most efficient and effective manner. The underlying assumptions inherent in the following approaches are that in every classroom, the teachers are the "main event" and that the quality of any school is only equal to the quality of instruction for all children in all arenas, collective responsibility/teamwork is the norm and that our ultimate goal is virtuosity, that if we do the common uncommonly well, our children will make the uncommon, common. That is to say that we believe that if we understand the simple nature of excellence (that it has no finish line and does not discriminate) we can defy the normative correlation of socioeconomics and academic achievement and that our school will function as a microcosm of the distal portion of the bell curve defining academic achievement.

But it certainly is a jungle out there!

1. **Lions, Tigers and *Hares?***

In gazing out in great wisdom, mindful of the tigers lurking in their solitary demesne, but as a streak, seemingly overwhelming if not insurmountable with a multitude of cubs relying on their lead, what is a lion to do? Such is the scene in our classrooms. Curriculum, technology, mandates, standards, achievement, growth, data, etc. all provide separate but equal stressors that intermingle and coalesce while students' life trajectories at stake. What's a teacher to do? Answer: *spare a hare.*

2. The Power of Rabbits

If you chase two rabbits, both will escape, adage that both clarifies and accelerates progress. At McVey, we think in terms of rabbits. We pick a rabbit and chase it until we catch it. Then we pick the next one, etc. while spiraling back to their predecessors. The mandates and standards dictate the habitat, the data identifies the rabbit, the curriculum creates a geo-fence and the teacher navigates the strategic course. It is that simple.

When looking at a data set, it is easy to get caught up in any number of points it may illustrate or attempt to identify. In fact, doing so can cause analysis paralysis, which is contrary to progress and may completely hinder growth, especially if it is contradictory to itself or specifically leads to ambiguity. For example, proficiency in a single standard in third grade ELA requires a wealth of skills. Take ELA standard 3R3, "In literary texts, describe character traits, motivations or feelings, drawing on specific details from the text" OR, "In informational texts, describe the relationship among series of events, ideas, concepts or steps in a text, using language that pertains to time, sequence and cause/effect." So, if the data suggests a weakness in 3R3, what's the plan? Should you tackle cause/effect as it relates to a timeline or study the development of grit in a protagonist? Maybe both. Perhaps neither. Was either of those the cause of the weakness or was it rooted elsewhere. Since the standards build on themselves, they assume a level of competence in those that underpin them. Perhaps the youngsters did not understand the way that the question was asked or the vocabulary contained therein, or, just could not decode with fluency. Thus, proficiency in standard 3R3 assumes proficiency in the RF (Reading Foundational Skills) L (Language Standards) and both 3R1 ("develop and answer questions to locate relevant and specific details in a text to support an answer or inference") and 3R2 ("Determine a theme or central idea and explain how it is supported by key details; summarize the text"). In order to understand the relationship of a series of events in text, you need to be able to make an inference, which requires that you locate…..which all began with successful decoding. Where do you start and how do you know if you are in the right race? Answer: Chase a bare hare.

3. <u>Bare Hares</u>

So much to cover, so little time, the battle cry of many a teacher. And it is true! So what do you do? Let's take a look at 3R3 again. With a modicum of effort, we tease out the hare; just a few exit tickets later and the chase is on for our first rabbit. After discerning whether the weakness is pertaining to an understanding of a particular genre, which can be quickly determined based upon other similar tasks, we start simple.

Let's play it out. Ask yourself:

1. Did they understand the question?
    a. Find out – ask the same question about a topic they are familiar with.
        i. If they can answer it, great, it is not the question, perhaps the skill - move to next exit ticket
            1. What skill (not standard) is this question assessing?
            2. Have they performed similarly on other such assessments of this skill?
                a. If yes, great…..what are the requirements for success in this skill?
                b. Are they proficient at those?
                    i. ***<u>Stop at the most concrete deficit, the bare hare ….that is your rabbit….chase it….catch it….repeat.</u>***
        ii. If they cannot answer it, great, catch that rabbit…
            1. What did they not understand?
                a. Find out – use the same question stem or question word for a topic they are familiar with? For example, do they understand the difference between why and how questions? (A why question should have a because-style answer, whereas a how question should have a process-based answer).
                b. Are they proficient at those?........
                    i. ***<u>Stop at the most concrete deficit, the bare hare ….that is your</u>***

rabbit….chase it….catch it….repeat.

The growth process has commenced; the chase is on.

4. **Bright Spots**

The first step to solving a problem is admitting you have one. The second step, find your bright spots. What does that mean? Contrary to convention, catching a rabbit does not mean studying its nuances and features, but rather those of the chaser. Focusing on the rabbit is a problems based approach…..the rabbit is fast and agile…... Focusing on the chaser is solutions based…I am stronger to my left than my right, I am a better sprinter than distance runner, etc. Find what you are good at and grow those attributes. It is that simple. Grow your bright spots. Positive Psychology yields positive results. Likewise, find what your students are good at and build on that strength.

Let's play it out.

Students do poorly on a math assessment, in fact, the results are abysmal on most test items, but they are all showing their work. What do you do? Where do you start? The bright spot here is their effort. It indicates that they want to work hard and are putting forth a strong effort. Great! Select 2 -3 problems from the assessment and study their work. Is it their computation or process that derails them? Was it a reading issue? Vocabulary? Grow their strength:

1. They can compute, but the process is marred.
    a. Potential courses of action
        i. Use their strength in computation to solidify the process.
            1. Student as Teacher. Give them an assessment addressing the skill with the teacher's answers provided wherein the students are tasked with proving correctness, or, finding errors in the process.

2. Magic Boards – Next Step Diagnostics (a quick way to glean the necessary data):
    a. The teacher begins a problem filling in some information
    b. The students complete the next step as a diagnostic (all students write on their magic board and on the command, display for the teacher by holding it up.)
    c. Continue until misconception or misunderstanding is revealed

5. <u>Catch of the Day</u>

Again, if you chase two rabbits, both will escape, but, the opportunity of catching one, is losing the other. Alas, everything that we do is an opportunity cost. If we are teaching sentence structure in ELA on Tuesday, we are not teaching a multitude of other skills in ELA that day. Thus, it is imperative that the rabbits we chase are those that have the greatest overall return on investment. Connected learning is a potential avenue for getting the best "bang for your buck" in each lesson ensuring that the catch of the day is more of an octopus rather than a trout. In this way, the impact of the conquest is multifaceted; catching rabbits that are in a hole is helpful, but not nearly as efficient as those that serve to clarify the jungle.

The NSF Data Collaborative

At McVey, these strategies and others like them have helped us "cut to the chase", pun intended, and realize growth at accelerated rates. We are able to problem solve and make the instructional modifications in real time, based on daily student performance. However, larger data sets and spiraled assessments often take longer to evaluate. Likewise, assessments that address a multitude of skills, can require much greater analysis. Moreover, when attempting to triangulate, compare cohort to cohort on a particular assessment or looking at a growth trajectory of a particular cohort over time, the data can be not only cumbersome, but the variety of visual representations that they exist within, can significantly hinder progress and as mentioned earlier, even cause analysis paralysis. And so we dream of better ways and better days of chasing rabbits. In short, the experience with my Datasprint team added dimension to this rabbit economy in both more efficiently identifying and chasing the grandest rabbits.

PC (Post-Collaborative)

…..Imagine a platform in which any data set can be exported to and instantaneously converted into a visual that is familiar, user friendly and universally applicable. Now imagine a data set that speaks to metacognition too. What if the data included qualitative measures relative to student perceptions? It's the equivalent of metacognitive Amazon Prime of "one stop shopping." If a tool fabricated by Team Pentagon during our sessions could be accessible to schools at the teacher level, the speed at which progress is realized could be increased exponentially. Any data set could be uploaded and converted into a visually pleasing diagram for growth-minded next steps. Teachers would be able to instantly chunk their results and chase a rabbit. Furthermore, if data relative to metacognition, in other words, what students perceived as "sticky" (those things that had the greatest impact on their learning during the lesson) was combined with the numbers related to achievement, the growth potential in each lesson could be further maximized. Greater efficiency helps everyone, most importantly, the students. Henceforth, until such time that a perfect platform exists, PC we have been working on streamlining our data sets to look as similar to each other as is possible.

Feature's Features

In addition to the data representation, the team at Columbia University in concert with the wizards at Nassau BOCES started conversations that have sparked greater conversations by presenting data through a metacognitive lens and taking it a step beyond triangulation in an integrated, connected fashion. Thus, they ignited inquiry in areas previously dormant. That has played out at McVey. For example, the youngsters at McVey are ostensibly adept at using text features in informational text (85% accurate overall in the standard that addresses this skill). However, their results relative to character traits is more scattered; they tend to understand such, but recently tanked on a question in this area asking them to identify the "features" of a particular character. Upon further metacognitive style inquiry, we discovered their prowess in using features in informational text was a relative strength as it exists in a bubble; "feature" as a word was learned in a tunnel, as a single concept - text features in informational text.

Prior to the NSF Data Collaborative, an anomaly such as this would have been addressed by adding this word to our Tier 2 Academic Vocabulary list and started using the word as often as possible in a multitude of venues and subject areas. This strategy has been effective with other similar examples of this kind of abberation such as words like context as it relates to the use of context clues in ELA or “the difference” in math pertaining to subtraction. PC, we have a new perspective. Rather than being reactive to the data that exposes issues and attempting to generalize the word or concept, we are seeking metacognitive data to clarify our data, AND, being proactive by searching for other such perhaps tunnel taught “rabbits” (skills, concepts or even words) to chase. The unique thing about a rabbit of this nature is that it can be very elusive requiring constant patrol as in one venue he/she may have been caught, but it may hop freely elsewhere in the jungle. Consistent with the McVey Way, we’ve given this rabbit a snazzy name, Feature Rabbit (a play on Peter Rabbit with the anomaly that describes its characteristics) to make it more fun. We look for Feature Rabbit and we seek each Feature Rabbit’s features (we just say Feature’s features….corny but fun.) The NSF Data Collaborative sparked this “Feature” hunt as it put metacognition in a whole new spotlight for us.

Let’s play it out:

When learning new concepts in math, we try to move our children from the concrete, to a pictorial representation and finally the numerical (abstract). As such, primary classrooms are equipped with counting cubes, rekenreks, ten frames, etc. Daily diagnostic data suggests the youngsters can use these tools effectively, can draw pictures of circles to represent numbers and solve basic number sentences. Great! But, as they continue to soar in mathematics, in the fifth grade, they struggle immensely with understanding fractions as they relate to decimals. Not great! BC (before the NSF Collaborative), we would have worked the problem in 5th grade and likely mitigated it (which may not have included garnering conceptual understanding, but nonetheless fostered correctness). This year we have tried something else as follows:

1. We asked ourselves, what are Feature’s features?
    a. What is the concrete of this?
    b. What are the underpinning skills?
        i. What is their success rate therein?

   c. Could they identify with ten frames that 6 full frames of 100 is 60/100? **(Yes.)**
      i. Could that be reduced to 6/10 using the ten frame? (They had a difficult time with this, but eventually saw it.)
      ii. And then converted to .6? (**NO)**
         - *(As described earlier, when chasing a rabbit when a "No" is realized, we stop and chase…..this time, PC, through metacognition.)*
2. We investigated the manifestation of Feature Rabbit's features (the disconnect between fractions, decimals and now in light of how it applies to something they've seemingly mastered, and the basis of an understanding of base ten, the ten frame by asking more questions:
   a. Do they understand that if they got 6 out of 10 questions correct on a test that the number 60% at the top represents the fraction 6/10? **(YES)**
   b. Do they understand that a food advertised as 100% Natural means that it is all natural? What about 75% less fat? **(YES)**
   c. Can they convert either? **(NO)**
3. We thought about it.
4. We asked ourselves more questions.
   a. If they understand the 6/10 is .6 and 60%, why can't they work backward with 75%?
      i. Can a first grader reverse the process – see an equation represented in a ten frame and create a word problem from it? **Yes and No.** Yes with numbers to ten, **NO** with numbers greater than ten. (**And,** in general, they selected items that were round. The "number one answer on the board" was followed by cupcakes and munchkins.)
   b. Why can they create problems to 10, but not beyond?
   c. ***<u>Is our concrete, concrete or concrete enough?</u>***
      i. Is the ten frame concrete?
      ii. Are the counting cubes concrete?
      iii. Where else in the universe do ten frames exist?
      iv. ***If not, what is?***

v. Where else in the universe do counting cubes exist? (Unlike most Legos, counting cubes can be added to on all 6 sides.)
vi. ***What would be more efficient?***

We are in the process of modifying the concrete starting with kindergarten and seeking new ways to create concrete learning in fractions.

Thus, PC, we may prevent the decimal/fraction gap and other gaps from developing through proaction. If we catch this Feature Rabbit, now defined as the concrete portion of our math lessons, and grow that as a bright spot, we may be able to avoid several rabbit chases in the future, which really means creating more efficient and meaningful learning experiences for our children.

Conclusion

The NSF Data Collaborative was a monumental event. There is a reason for the debate of whether a degree in education should be a BA or a BS; it is both. Thus, combining art and science in favor of student growth through its measure of such, data, makes sense. The NSF Data Collaborative did just that and will hopefully cause the genesis of many a rabbit farm. For us, using analogies helps eliminate the emotional baggage or feelings of professional inadequacy or competition that can erupt when analyzing data, and conversely, works to stimulate both empathic comradery and commonality of purpose. In this way, we can maximize objectivity, collegiality and teamwork. Plus, it's fun to talk about rabbits, cerebral to strategize their capture and rewarding to conquer them. PC, we are taking our process to a new level, enhancing The McVey Way and hopefully making Rome feel less like a rabbit hole.

CHAPTER 21

Responding Positively to Creative Packaging of Information

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Nassau BOCES Regional Information Center

Selling Information

Teaching is selling information. No matter who the audience, from children to adults, the process of teaching is really packaging information into interesting units that are more than informational; they must compel the student to want and look for more. We often remember our best teachers as storytellers who would draw us into their lessons. In reality, the teacher was the package. In today's world, especially as we experience the online presentations forced on us by this virus situation, the packaging become even more important. I think you will see from my reflections on this study that teachers are also students that respond positively to creative packaging of information, and in this case digital information.

My most recent career experience was selling technology. Without minimizing the importance of teacher training, I hope you will see that the skills and tools used in several other professions in which I participated are quite applicable to teaching and to the packaging of information. Fundamentally, I believe that simplicity and graphical communication is key to effective learning and the “package” that is either embraced or rejected. In addition, I believe multiple sources of feedback: digital, written, or even verbal are the keys to constant improvement, just as good teachers hone their lessons with experience in front of a class. Finally, the equation is all about “time.” Our whole society is driven to delivering our messages in the shortest slivers of time. It frowns on using extensive amounts of it for anything, and reinforces the view using ever-smaller sound bites. Hence, our patience and attention spans are diminishing from this relentless, fever-pitched communication we receive each day. This further emphasizes the importance of packaging information to meet the almost hyperactive characteristics of the student.

I had the fortunate opportunity to play a role in the development of Alex Bowers’ National Science Foundation program, researching the role of data in the design and delivery of classroom curriculum. I have to believe the results of this study were less about understanding how teachers use data, and more about how they want to receive it; neatly, graphically packaged in convenient forms they can use to better understand their students’ progress. The second lesson demonstrated by this study was the use of feedback, the importance of closing the loop on a process to improve the quality of the product being delivered.

The first basic lesson reinforced by Alex’s study is to believe my intuition and be willing to share and collaborate. My years of experience in previous roles have provided extensive, empirical knowledge that enhance intuition, and have provided me with extensive understanding of peoples’ behavior interacting with technology. It is my objective to take this opportunity to share some of the interrelated experiences from my careers, along with the experiences from our data sprint meeting in NYC to offer some insights into how they influenced the results of my group’s collaboration.

My perspective on the National Science Foundation study is significantly different than most of the participants, since my career background is very different. My training is in electrical engineering, and began with software development for automotive test equipment utilizing previous experience as a technician in a General Motors dealership.

My unique knowledge of the two disciplines drew me into a short career in teaching automotive electronics and finally participating on a curriculum development team for the New York State Department of Motor Vehicles in which we developed training programs and documentation addressing the role electronics plays in reducing exhaust emissions. The ultimate goal being to reduce vehicle related air pollution initially in the New York metropolitan area, and subsequently to states throughout New England.

Ultimately, my career morphed into supporting the sales of computer systems and applications to various industries from automotive to banking in which I provided training to customers prior to, and after the sale. Technical sales training with larger, successful technology vendors includes a variety of disciplines ranging from basic presentation skills to classes bordering on behavioral psychology. It often focuses on how customers relate to salespeople, their peers, technology and software. It encourages observation of peoples' learning process, how they accept new ideas, and how they change their work behavior to adapt technology in their daily routine. In many ways it incorporates the skills of a diplomat and a lobbyist as decisions to incorporate new data systems and their associated new procedures can meet with great resistance. They have to be gracefully introduced to the workplace to get acceptance and support.

I joined Nassau BOCES five years ago after leaving a career in technical sales with what is now Dell Corporation. My role with Dell, and several software and hardware vendors before that, was in presales technical support as a Systems Engineer. Presales engineers are typically paired up with account executives who work together to develop new business. Dependent upon the nature of the product, the position is often focused on introducing new technology and business methods to the workplace. The skills needed to be successful are teaching, lobbying, project management and, most importantly, listening. The foundation of knowledge for this position is broad, yet requires detailed knowledge of digital computers, networking and application software including database technology.

In sales, communication is the key skill for success. Potential purchasers can have extremely different levels of understanding. In addition, they often speak very different technical languages depending on their areas of expertise. This is a crucial lesson for teaching, knowing and being able to speak to the audience at multiple levels. Often, all of these different skillsets and personalities have to come together to decide on a purchase. The ability to communicate at all levels and to have each member understand the technical lingo unique to them is crucial to success. You have to draw them into conversation, learn about their businesses quickly and identify the problems important to them that your product can solve. You have to deliver your targeted, "packaged" message expediently and confidently to make them feel you have the knowledge and resources to fix their problems. Finally, you have to teach them how to use your product to achieve the results they expect. Delivering data to educators is no different. It is exactly what was demonstrated by this study with the teachers doing the package designs.

Nassau BOCES hired me due directly to my presales experience. The position was opened to bridge a communication gap between hardware/network technicians and the instructional data warehouse software developers. My job is to understand the needs of the development team and communicate them properly to the hardware team, along with helping the developers understand the functional limitations of the systems they use. This communication between the two departments was very strained, primarily due to the vernacular of the two disciplines, hence a good reason to open the position to a person of my experience.

Since starting with BOCES, I chose not to interject my ideas into the plans and designs of the development team. I have been invited to nearly every department meeting, not so much as a contributor, but as an observer to learn their needs and direction so that I can plan for their technical support. Initially, I provided system documentation, then operating system support expanding finally into application support. Having limited experience with the numerous acronyms, testing programs, demographic classifications and reports, along with virtually no academic training in delivering lessons, I believed that I really had nothing to contribute beyond that.

My Role

Nassau BOCES primary information delivery system is a web-based product called Cognos provided by IBM. It had been in use for several years before I joined and was as much a mystery to the people using it as it was to me. Unless changes were introduced, the product was extremely stable. It was for this reason the product had not been upgraded in years, which is also a reason why its presentation features were quite limited. As I developed plans to perform up-grades, I had to learn all its underlying components and configuration information of the product. I was actually quite surprised to find out how sophisticated the product actually was. Most importantly, I found it had an accounting system that, when switched on, would write a database entry every time a report was used. The basic entry included the name of the report being called, a session number and a time stamp. As I explored this database further, I found a wealth of additional metadata pertaining to login accounts that allowed me to make school district identifications when joined with the user directory system.

The data in its raw form didn't have a lot of meaning. However, it contained information that allowed me to link, group and sort it into reports that could help me determine reporting patterns and application usage, such as how often a report is used and when. When I was invited to Alex's first meeting with the IDW team, assuming my standard role of "fly on the wall," I realized this might be of value to him and offered it. It took me several weeks to get all the proper linking in place but in the end, I managed to identify complete sessions with all their related transactions in sequence. This data turned out to be the basis for the click-stream study the results of which were presented at subsequent meetings. The only additional information added was to categorize the reports using meaningful labels to provide more insight into the nature of the activity. The four significant categories were: Assessment Aggregate, Assessment Fact, Assessment Response and College Tracking. These categories could be associated with the actual report names for more detail. This initial role in the project was my entry point, and the reason I continued to play a role in the program.

Feedback

My perception of the study is based on the concept of feed-back. That is creating a product (or process), running it to see initial results, then using various forms of return information to improve it. Feedback is crucial to improvement and is used extensively in automotive applications. It is the constant feedback supplied by the sensors in our vehicles that is allowing vehicles to make huge leaps in functionality, from better gas mileage to self-driving.

It is extremely important to collect metadata associated with a system's usage to see how changes in design and placement of information affect the behavior of its users. Passively collected data is a truthful source of information about a system's use. Simple stats can help put into perspective the popularity, and to some extent the behavior, of the user population. It can help prioritize development projects, determine the value of certain content to different levels of educators and the role they play in acquiring information about their teaching environment. The metadata from the instructional data warehouse was the primary source for behavioral data that was analyzed to help determine and verify the perceptions and misconceptions conveyed in the surveys used for NSF study.

Passively collected feedback is certainly helpful to understand users' areas of interest and to some extent their needs. However, we can see from my earlier discussion the design of the information system may be influencing their activity, and if they can't find what they want, we never learn their actual needs at all.

The data sprint meeting was truly a breakthrough in this area for two reasons. The first is, it helped identify the specific wishes of the educators themselves. Second, it emphasized the importance of packaging graphical representations to our development team. Graphics have the ability to help users evaluate relationships more easily and quickly. With the activity filled schedules of most educators, the ability to evaluate "properly represented" information quickly is crucial to its adoption.

The reason I call out "properly represented" is because there are so many places where valid information can be misleading, even to the person developing the presentation. It is extremely important that developer know the nature and history of the data on which they are reporting. In the collaboration, the knowledge came from the educators, while the presentation form came from the data scientist.

Collaboration is the key to evaluating actively collected feedback. Numerous individual requests will come from districts for reports they will tell you are crucial to their operation. However, after many hours of development time, the reports may be used by one person, or extremely infrequently or not at all, wasting resources that could have been put to better use. This study did a good job of seeding ideas with educators and developing a collaborative environment that produced valuable visualizations concisely communicating summarizations, comparisons and anomalies. The following discussion should shed some light on how this process developed, and things that can be done to ensure its value is not lost.

First observations

Going back to the mid 1980's business software applications did not use graphics. All data acquisition and presentation were done using the equivalent of black and white text. Often, companies like IBM would design and program a single function key to display a form on the screen to receive information from the operator. One of the most popular applications of this technology was used by the airline industry. If you can imagine the screen was a big index card that displayed traveler information, and the only method of entering information was to use arrow keys to move around the screen where the operator would type over the existing information in the designated field. Imagine an index card that could be repeatedly changed. Once the form was updated pressing the enter key would return the whole form to electronic storage.

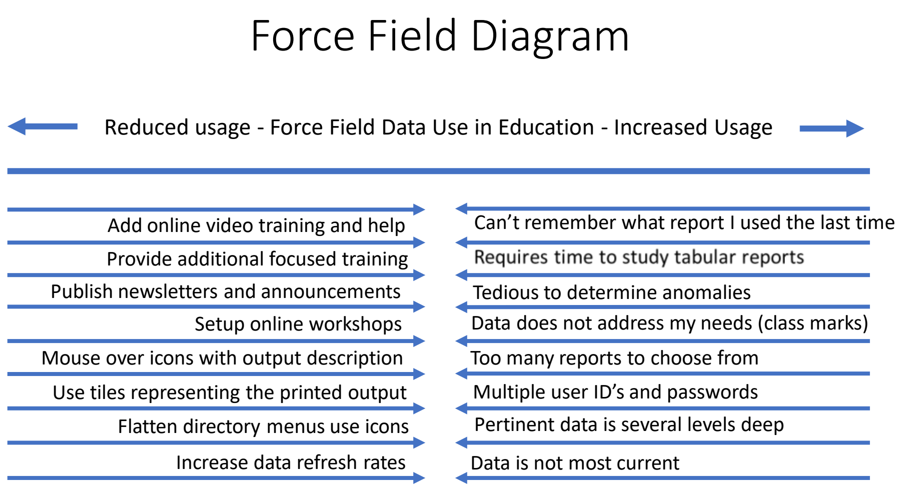
The industry matured. More manufacturers entered the market and new strategies were implemented for data entry. One in particular comes to mind with an operating system developed by AT&T in conjunction with UC Berkley called Unix. Unix was designed to work across slower speed wide area networks and much of what they developed is still in use today. It had a mature history but, was only being introduced for commercial use since it became stable and at a much lower cost. It also allowed the use of multiple vendors' hardware.

To access a desired function, the operator would enter the number of a desired menu selection and may even be dropped into multiple submenus. Operators would become extremely proficient at navigating these menus, often not looking at the machine, but simply hitting the sequence of numbered menu selections to get to their desired function. However, on occasion, a missed key would send them off to some completely unexplored location forcing them to carefully read the menu selections until they found where they went astray. This would cause frustration and needless to say, would add to the fatigue of the day.

A simple fix was introduced to assist in the navigation process. That was to make the menus appear significantly different on the screen by changing their position and/or size. This was the first step toward using graphics to ease access. The operators could quickly identify their locations and navigate appropriately without reading a word on the screen. They could simply glance at the visual pattern on the screen and make a selection from rote.

This was the first place I noticed changes in design would make interaction more expedient and less frustrating. By making distinct changes between menus the operator could more quickly identify the desired menu and return to it quickly without resorting to the "start over" method. In this case, displaying each menu on different areas of the screen was enough. The lesson learned: people rely more on visual patterns to identify virtual locations than they do on reading text. What's more, reading though lists of textual menu entries for infrequently used reports was reason enough to put off the task in many cases. In presales training, there was a theory that was curiously "promoted" and sometimes practiced that said: to influence a behavior it was more effective to eliminate all obstacles to its use than to promote it through advertising and training. It was the called force-field theory.

The whole force-field theory could be applied again as desktop PC's started to displace centralized systems during that same time period. The ease of windows graphical displays and the ability to run applications locally eliminated begging datacenter personnel to provide needed business information. The downside of this strategy was the limited storage capacity of the desktop machines. The result was the loss of access to the larger datasets that, when analyzed, could provide better insight into user behavior. In addition, all the locally stored data presented extreme security risks. Sample force-field diagram:



Changing user behavior

Since the development of graphical interfaces and supporting technology, such as websites and browsers, users have become to completely dependent on graphics and icons to navigate to desired applications. And, if applying force-field theory is valid, it becomes obvious that users' behavior can be easily manipulated by changing graphical design. Add to this another marketing lesson gleaned from graphics training, users' eyes follow typical patterns as they scan written pages, generally stopping or veering from lines demarking separate areas of text, in addition to trailing off for a final look on the lower right corner of the page. In printed material this is considered to be the most valuable advertising location on the written page. While I have less recent information about how users scan web pages, I do know that some industry trends have been impacted by the placement of articles on a popular web-based, technical publication. One publisher actually claimed they had no standard order for article placement, but when an article was placed at the beginning of the list on their monthly newsletter, they found a noticeable influence in technical trends and discussions reflected in other data sources.

So, what does this all mean to the process of educational data presentation and analysis? Reporting systems need to consider that they can change the behavior of the end user by adjusting their design. They can increase or decrease usage by reducing obstacles and providing designs that convey greater amounts of pertinent information in a single presentation. They should utilize the computational power of the system to analyze and display the parameters of normal ranges and other useful information that helps reduce the study time needed to evaluate a report and determine which students need attention.

The NYC meeting

The final meeting is the focus of my interest. The truth is, there was so much information exchanged, it could have run another half a day to digest, but only after the real work was done. The process of forming, storming, norming, and performing could have used a follow-up for refining and evaluation.

To begin, the meeting opened with what I would describe as a seeding and orientation operation. It was the process of communicating the work already done, introducing creative ideas and setting goals for the event. I believe this is an important step but, strangely the one least consciously retained. Key presentations and phrases that had significant meaning to me could be easily recalled but, overall it was necessary to review the pictures of the event and presentations to recall. I don't think this diminishes its value, however. It was the foundation for what was to come, a key to the forming process and probably a good lead into the storming process, that awkward time when you are getting to know your team and build trust. I associate the storming process with the initial exchange of experience after the introduction process. For me, I took this opportunity to affirm my intentions and expectations for the meeting and emphasize my limited experience as an educator. I found myself starting to play a "project manager" role, working to identify a goal and a strategy for our task. We verbally explored options based on the information available to us.

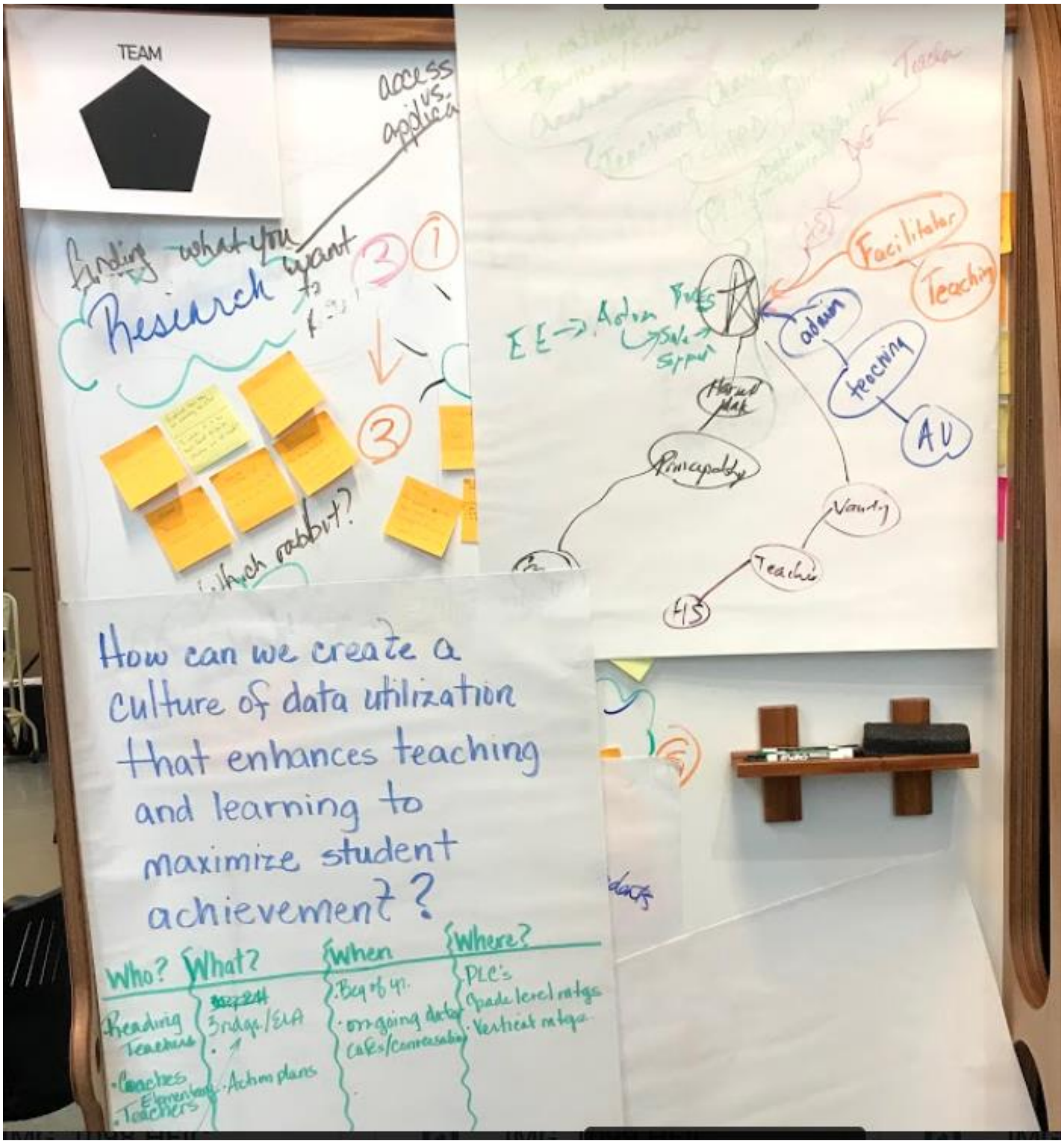
The storming process included another interesting phenomenon. It provided time to discuss daily and weekly needs, things like reports that could be shared at multiple levels from superintendents to students and parents. These points were reinforced by one keynote presentation exploring the concept of a grassroots distribution of information to students to generate more interest at all levels. This concept helped us to set a goal of creating a culture of using data to enhance classroom results at all levels of the process from superintendent to the individual student. This goal set the standard for the graphic we designed for our “Wrong answer analysis.”

Our Data Sprint Team – Pentagon

Our group, named Pentagon, consisted of a graduate student, a teacher, an ELA chairperson, an assistant principal and a principal, as well as me and a data scientist named Josh. I introduced myself as a project manager representing the IDW development team with the intention of listening to and learning from them in an effort understand what information they find important to effectively deliver classroom training.

Consistent with my earlier point of view, I did not believe at the time of the NYC meeting that I had anything to contribute. I was a bit apprehensive about the role I was expected to play. I assumed that I was invited somewhat out of courtesy or simply in case questions came up about the data collection process-- I would be available to respond. I also thought there would be more discussion of the results of the survey and the actual use of the IDW. I could not see myself playing a role until I actually attended and saw the focus of the whole event, the graphical representation of instructional data.

I have played no role in the design of existing IDW presentations since the system had been in place for several years before I joined the Nassau BOCES team. In addition, the subject matter was not my bailiwick, and the people that developed the system were highly trained professionals, many with years of teaching experience. I accepted the existing system as the industry standard and made no attempt to inject my opinions. I find the numerous tables of detailed information, along with the constantly changing acronyms tedious and time consuming to review and understand. And it appears I was not alone. BOCES in-house instructors began to hear the same general message from the districts that are their primary end users. Pressure was starting to mount to modernize the system with a “Teacher Interface” or “Teacher dashboard.”



As a project manager one of my roles is to conduct brainstorming sessions with the intention of extracting ideas from participants in a group. We had done this internally with our IDW instructors and the development team a couple of years ago, but I had never done it with actual frontline educators. I decided to assume this role at the NYC meeting. I stated to the team that they are the experts, I was here to as an observer and I intended to take their suggestions back to be considered for use. As a general rule, the project manager is not supposed to actually participate in the brainstorming process in order to avoid creating biases or missing key inputs. As software designer, I could not help breaking the rules.

In the IDW internal meetings, BOCES IDW instructors provided detailed feedback from their training sessions about the requests they would hear from the districts. The general messages included ease of navigation, more up-to-date information (real-time), and better ways to quickly analyze performance and troubleshoot anonymities. I heard the very same requests from my team at the NYC meeting. In addition, a discussion with a key district administrator prior to the start of the meeting, and a message in the keynote presentation about creating a more grassroots strategy as an incentive for teachers to use data, or at least be more aware of the power of this information, contributed to a team-goal of producing a presentation format that could be shared (considering appropriate filters), from the superintendent all the way down to the class or even at the student level. Prior to the official event, in a conversation with a principal, it was explained to me that he would run IDW reports and summarize the reports to be shared and discussed with his teachers. The teachers were always receptive to the information, but would generally not make much effort to retrieve them on their own. The conversation actually ended with the final, unanswered question: "what if the reports were available to the students?"

Expectations Seeds and Results

Seeding can be an important tool to spurring new ideas. In sales we often found that customers could not describe what they wanted. The term we applied to this was: "I will know it when I see it." For the original inhouse BOCES meetings, I put together a few slides to get some feedback from the IDW team as part of the brainstorming session. I had reviewed the ideas with the department director in advance to test their validity before I suggested them to the group. Her positive feedback encouraged me to follow through. That first meeting took place more than two years ago. The results had only a very small influence on the IDW where they placed some large icons on a home page they called a "teacher-dashboard" that represented some of the more popular reports. It became a key component and starting point of the IDW reporting system. It became known as the "teacher interface" and much effort has been made to maintain and update it, even as new versions of the development system reduce its original value.

My seed ideas were introduced only to the IDW team at our internal brain-storming session trying to graphically represent the relative performance of a class or cohort compared to county benchmarks. Growth is an important area of interest at two levels, one for the individual students, to see that each is progressing according to expectations. The second is the general performance of teachers. Single reports should never be used as conclusive proof of performance, but administrators familiar with the actual environment may be able to evaluate patterns or anomalies that can be emulated by others to improve methods or identify individuals that need assistance. We are currently doing extensive work with third party data sources, particularly NWEA to present this information on the IDW with the added value of regents-grades, other New York State test results and county benchmarks. This was an area of particular interest to the Pentagon group. However, understanding the nature of the sample data available to us, we chose to focus on question evaluation.

Limitations in the currently used development tools make it difficult to produce many of the presentations proposed, although plans are in the works to upgrade development tools that utilize the new designs. One of the key values of the seed design, which was not commonly available, is presenting a third dimension on a single x/y graph representing that dimension with various size diameters of circles. The newest version of our development system is incorporating these capabilities and can even use auxiliary servers to develop portions of more complicated presentations not supported by the native software.

I did not bring my designs to the NYC meeting. However, I began to describe from memory the general concept I had put together for the IDW development team, and did a couple paper sketches, which had mixed reviews until we came across item analysis. Keeping in mind that our available randomized data set was very limited, and we had no growth information at all, a logical choice for our visualization was “Item Analysis.” In fact, as I mentioned earlier, the item analysis data contained the only unaltered content in the sample data set that could reflect actual, real-world results since all the other sources were an extraction of multiple districts and anonymized to prevent any possibility of identification. Because of this, any patterns or correlations in the other datasets might have less real-world value.

This is where the collaboration took off and the experience of the team really demonstrated its value. A rudimentary sketch of the ball distribution exploded into a discussion with contributions from every team member. One team member in particular, penciled a sketch of the basic bi-directional (negative & positive data divided by the X axis). The team added new ideas to provide a more detailed summary on a single visual presentation, and excitement about the visualization began to mount. Josh struggled to find a tool that would deliver the requested results. The limits of more than one software development system were thoroughly tested. I have to congratulate

Josh for the skill he demonstrated adding new attributes and labels as the ideas popped.

As the team's development process progressed, we continued to remind ourselves of the goal to produce a visual presentation that would have value at all levels and become the standard reference tool for quickly identifying anomalies in test responses. The product could effectively identify teaching strengths, weaknesses and trends. It singled out questions that needed evaluation for poor wording, vocabulary or even exclusion from lesson plans.

I think our focus helped significantly to refine the final product and was consistent with establishing a visual presentation of data as a communication device, which underlines our goal of establishing a data culture. The IDW development team has embraced the design and is currently working to publish it on the data warehouse.

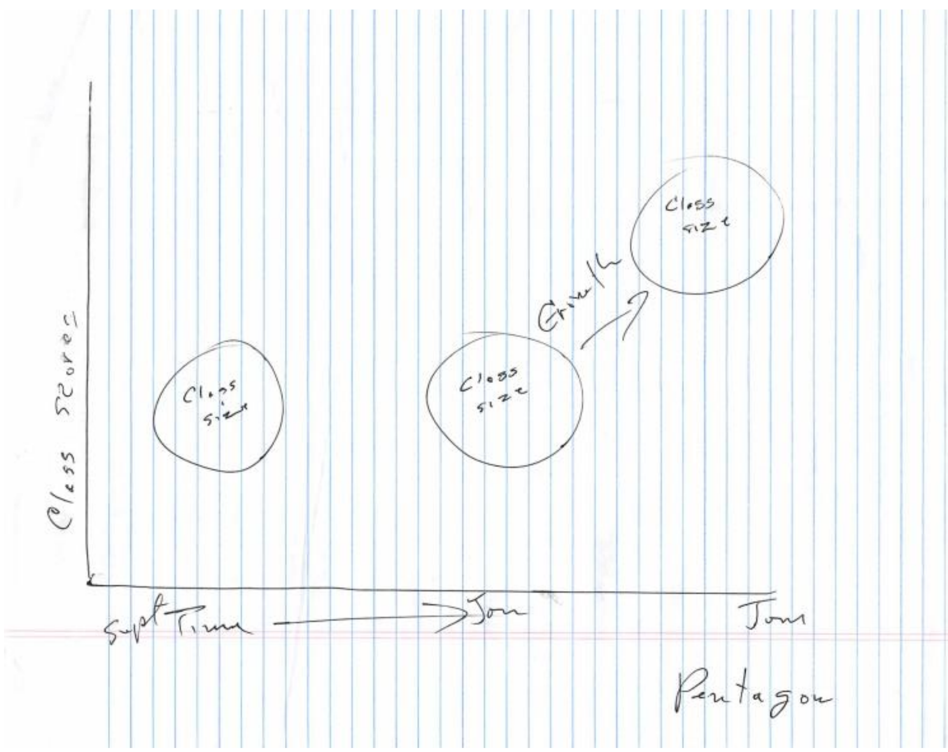
The final graphic had a bit of special meaning to me. In some ways it was a validation of my original ideas, even though it was significantly enhanced with the knowledge and experience of our team members. It was so well received that it was like getting a new product to sell, which I did, to everyone who would listen. I am so pleased to see that the IDW development team came back and immediately started work on its development. I feel a bit proud that I played a role in the contribution.

In my opinion we are just scratching the surface. I believe that reporting systems need to do more than just regurgitate facts. Using the enormous amounts of raw data available, these systems should provide guidelines projecting levels of variance based on the larger population (i.e. "80% of the population missed by 3%", etc.). In addition, my experience indicates that wording and selection of vocabulary words in test questions is a crucial element in understanding if students are truly knowledgeable of the subject. Written math questions can just as easily be a test of language skills as they are of math. I would like to see a correlation report based on the number of times certain vocabulary words show up in highly missed questions. This is where more work can and should be done to assist educators by uncovering less intuitive information.

The seeding slides follow with the final result of the team's collaboration. I am still in awe of the creativity and detail my team incorporated into the single final slide "Item Level Performance".

Feihel, 2021


Domain & Correct answer
% by selection or percent correct
Question #
1 2 3 4 5 6 7 8 9 10 11 12
Pentagon


Class Scores
Class size
Class size
Class size
Growth
Sept Time
Jan
June
Pentagon

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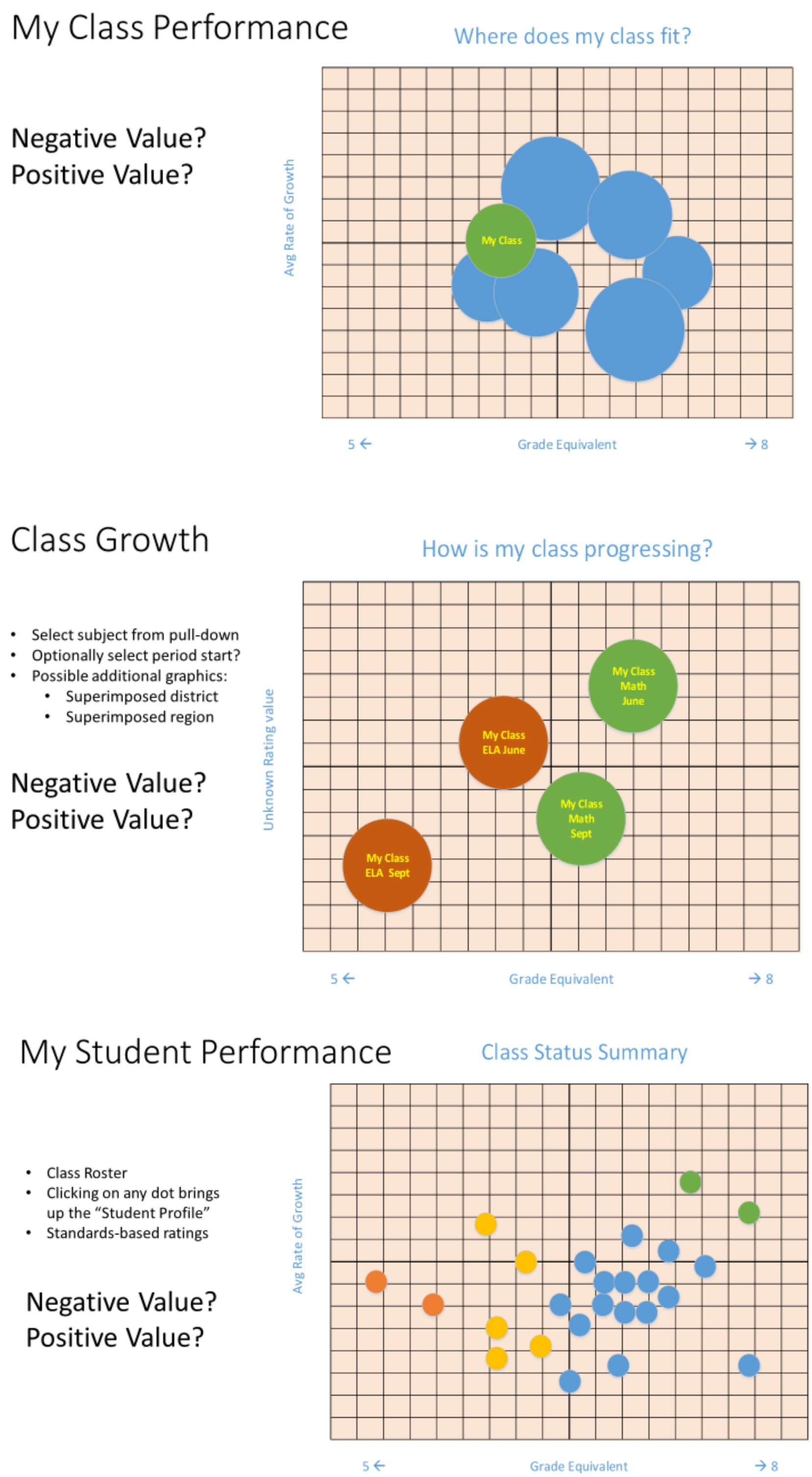
My Class Performance
Negative Value?
Positive Value?
Where does my class fit?
Avg Rate of Growth
My Class
5 ←
Grade Equivalent
→ 8
Class Growth
Select subject from pull-down
Optionally select period start?
Possible additional graphics:
Superimposed district
Superimposed region
Negative Value?
Positive Value?
How is my class progressing?
Unknown Rating value
My Class Math June
My Class ELA June
My Class Math Sept
My Class ELA Sept
5 ←
Grade Equivalent
→ 8
My Student Performance
Class Roster
Clicking on any dot brings up the “Student Profile”
Standards-based ratings
Negative Value?
Positive Value?
Class Status Summary
Avg Rate of Growth
5 ←
Grade Equivalent
→ 8

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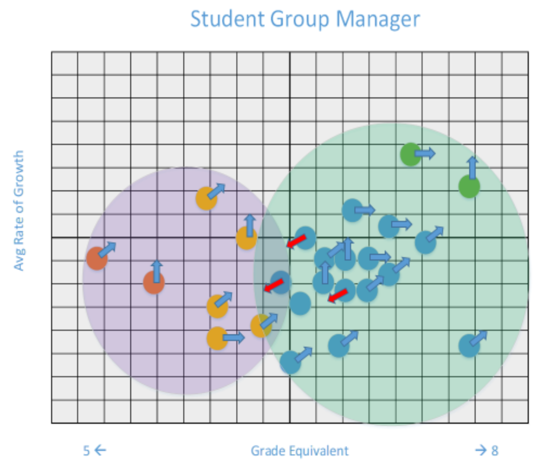
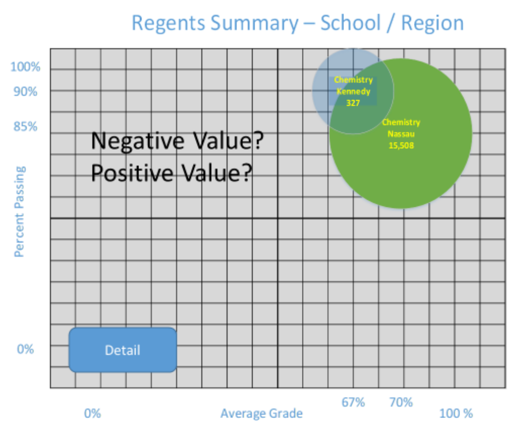
Individual Tracking

- Optional arrow indicators to identify movement



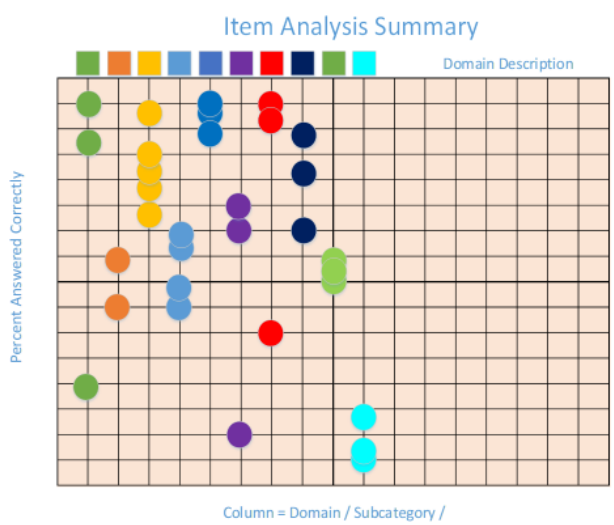
Relative Performance

- The logic behind connecting to benchmark information is to see how the class and the region performed on the same test
- Poor benchmark ratings could indicate an excessively difficult test, not objectively, reflective of the individual's ability
- Optionally, the individual's performance could be added to this graphic



Item Analysis

- Squares identify the domain
- Clicking displays the description
- Balls represent the questions and percent accurate answers
- Mouse-over the ball displays the actual question
- Clicking on the ball displays a pop-up report of the question and the students who missed



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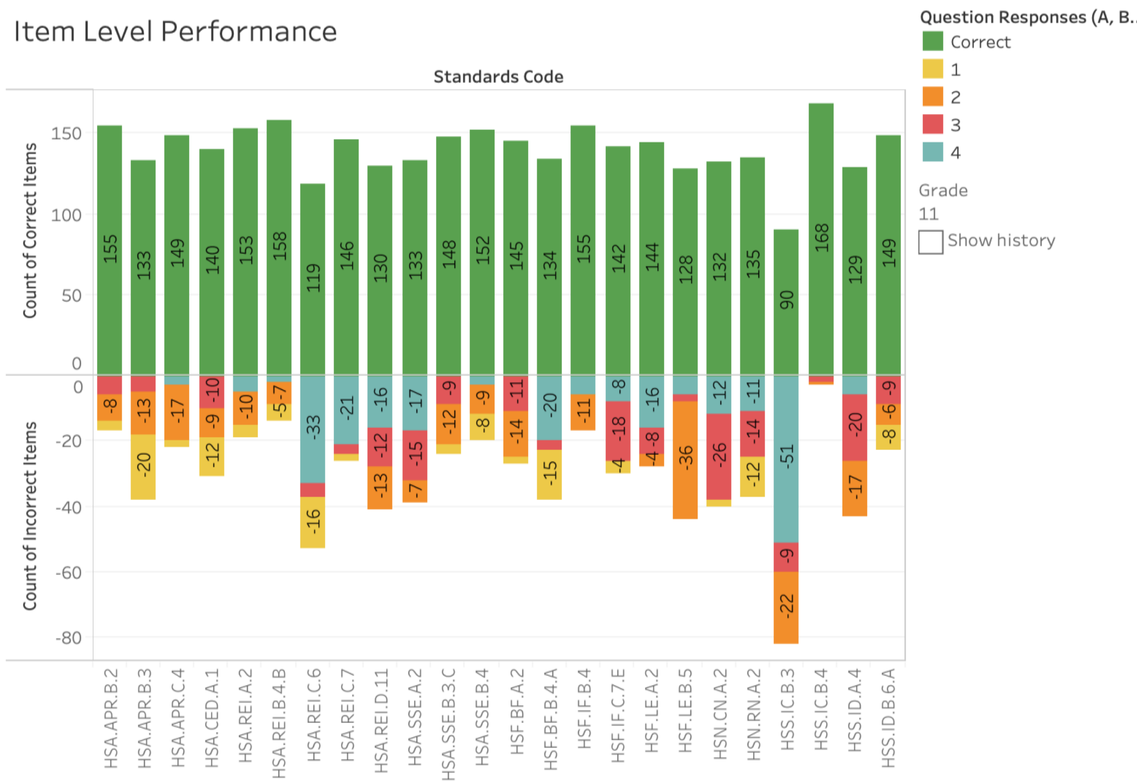


The result of the collaboration, “Item Level Performance” (above), has the capacity to convey an enormous amount of information concisely, without having to hunt through tables of numbers. It is a single graphic presentation, in which the reader can quickly see the distribution of results for a given population. With currently available presentation tools, the population can be easily modified to meet the reader’s level of interest—student to superintendent. It meets the goal of quickly identifying patterns that can provide insight into characteristics, such as particularly difficult questions, areas of teaching strength or weakness, or even skipped or missing teaching material. Most importantly, the emphasis placed on representing data graphically is key to promoting its use, which is the single greatest contributor to providing feedback for improvement.

Final Comments

All teams need coaches. Coaches provide the feedback that is crucial to not only improvement, but also the maintenance of procedure. From golf pro to football coach, the information provided about our performance and suggestions for improvement is essential to every process in which we participate. What is more, the more forms of feedback we receive, the more influence it has on results. Coaches can verbally guide us, but a video of our performance can have much greater impact. Vendors we deal with today have implemented rating systems for their products and services to improve performance in an effort to set themselves apart from their competition; it appears they work, or they would likely be abandoned very quickly. Many of us use them religiously to help us choose products on a regular basis. Surveys are vendor's coaches and provide the information they need to improve. Needless to say they would be foolish to ignore them.

Education should be no different. Educators need coaches as well. We all hope to be the best at what we do and provide the best product in our power. The key is knowing when we are attaining our goal and making it as easy as possible to maintain that goal. This is what this Nation Science Foundation study accomplished. First, it took the crucial steps to collect and organize the information needed to support its mission. Secondly, it provided an initial coaching in the form of feedback from its surveys and studies that helped educators recognize areas in need of improvement and uncovered some misconceptions. Then, it released its first valuable product in the form of a workshop, a process that has already been adopted into Nassau BOCES instruction and development process.

So, what are the valuable features of this product? Two things that are crucial to success: simplicity and feedback. The need for simplicity was echoed by every member of our team. Simplicity and packaging of the product is crucial to its adoption, since our behavior is often based on limited time and "the path of least resistance." The meeting procedures coached the participants about the options available to them for presenting data important to achieving their goals. It demonstrated the power of graphics in presentation of data. It enlightened everyone as to the interest of educators in receiving their information in forms that are easily digestible, and that provide greater insight into the actual meaning of results. More importantly, it provided feedback to the information providers. Providers learned what information is really important to educators to help them do their best. It emphasized the value of keeping things simple, as well as highly informative. It was not limiting the amount of data presented, only the clarity of its graphical presentation. There can be no doubt that this meeting provided valuable coaching to the information providers that was quickly adopted and is currently being refined. However, this should not be the end. This should be a lesson that continues into the future providing instruction to newcomers and veterans a like. Admittedly, the study's value and success greatly exceeded my expectations.

I have to congratulate the team on an outstanding job of communication and cooperation. I have to say I came away from the experience proud to say that I contributed to a project that was almost completely outside the realm of my experience and provided me with a sense of commitment to delivering the enhancements that came to light in this session.

Thank you, Alex Bowers, for the opportunity. It was truly enlightening.

Feihel, 2021

CHAPTER 22

Say Farewell to Dusty Data!

Josh McPherson
Principal
WS Boardman Elementary School
Oceanside School District

Introduction

As a proponent and practitioner of effective data usage in the field of education, I have strived throughout my career to help my colleagues harness the potential of meaningful student assessment data. I've devoted countless hours to taking raw data, often in the form of monochromatic Excel spreadsheets, and transforming them into user-friendly visualizations that help the data come to life. This has been my self-assigned charge since I was a classroom teacher, back when I also wore the hat of a school data specialist. Now, as an administrator, I've continued to help my colleagues access and understand data in a way that promotes collaboration and progressive change. My credentials in this field consist of a handful of graduate level courses related to the subject and the opportunity to work with several skilled Excel wizards early in my teaching career. Beyond those experiences, my expanding knowledge base has been driven by the guiding belief that success in any field cannot be met without an understanding of key data. And yet, although I am a cheerleader, practitioner and believer in the field of educational data science, I resolutely identify as a novice and a perpetual learner. This self-categorization was pleasantly reinforced recently when I was given the opportunity to attend the NSF Education Data Analytics Collaborative Workshop in December of 2019. As I write this chapter six month later, the multitude of ideas, wonderings and questions sparked by that workshop continue to maintain their original vibrance and relevance. Most of us are familiar with the old adage, “You don’t know what you don’t know.” Having this opportunity to pull back the curtain surrounding the arguably nascent field of educational data science, I now have a much better understanding of what I don’t know. This unique opportunity provided an unprecedented context in which to share ideas and learn from a diverse collection of data practitioners, including other educators and data scientists. This confluence of stakeholders was no doubt a rare occurrence. Prior to participating in this two-day think tank, I had already embraced the belief that data visualizations hold untapped potential for teacher efficacy, efficiency and effectiveness in the classroom. However, this event broadened my understanding of what meaningful visualizations in the world of education could look like, and subsequently, their potential impact on student achievement. I commend Dr. Bowers and his team for organizing and executing such a memorable event. The format and focus of this event signified a critical ingredient to the successful understanding and application of data in the field of education. That ingredient is collaboration.

The Parlance of Our Times

As I write this paper, I realize the importance of establishing a glossary that provides further clarity and nuance regarding seemingly generic terms. I hope that by taking the time up front to elaborate on each of these terms, I am able to establish a common vernacular between myself and you, the reader.

The Workshop - the NSF Education two-day workshop that took place on December 5-6, 2019 at Columbia University’s Teachers College. It is important to note that even though the term “the workshop” connotes a brief interactive professional experience, this two-day metacognitive expedition into the current theories, practices and innovations in the field of educational data science was no perfunctory exercise. Rather, it was the kind of experience that left me cognitively exhausted, and at the same time, professionally inspired to steward change in my school, district and beyond. There were approximately 70 participants in the workshop. The list of participants included, but was not limited to, teachers, instructional coaches, principals, superintendents and data scientists.

The Space - As an educator, I never underestimate the importance of physical space. The way a classroom is organized plays a critical role in student engagement, productivity and class climate. The workshop took place in the Smith Learning Theater at Teachers College. This space was quite unique. Whiteboards, SmartBoards, interactive televisions, wireless microphones, sticky notes, open-concept seating, beacons that projected real-time location mapping; these became much more than the sum of their parts over the course of the workshop. They became tools to foster creativity, collaboration, inquisitiveness and more. Ideas were immediately transported out of the ether, into reality. Data and feedback were generated fluidly, unfettered by typical constraints. This was my first introduction to the Smith Learning Theater. As a Teachers College alumnus, I was quite perplexed when I stepped off the elevator on the top floor of the library and was confronted by such an awe-inspiring space, the existence of which was previously unknown to me. I was only slightly crestfallen when I learned that it was created several years after my matriculation. At the same time, I was slightly relieved that its existence had not been an oblivious oversight on my part.

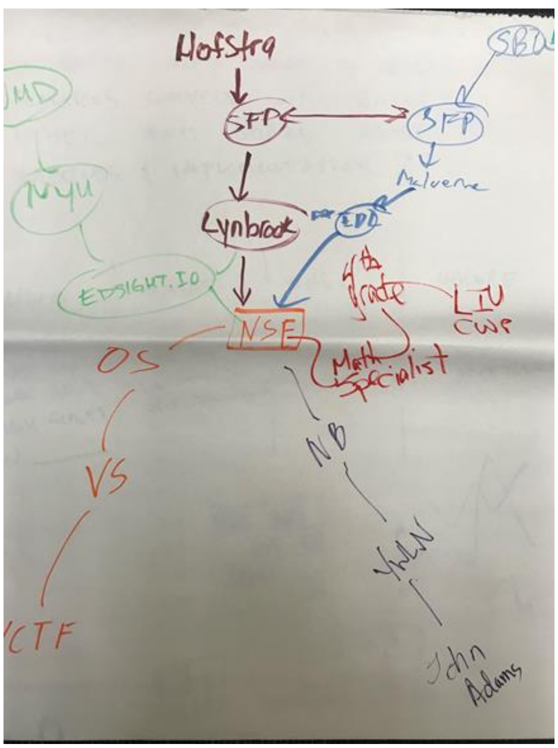
Team Square - At the beginning of the workshop, participants were assigned to specific “datasprint” teams, each represented by a randomly chosen shape. Our team’s logo was the square, undoubtedly a coveted identifier in a room of data practitioners. In the true spirit of the workshop, the composition of each group was not determined at random. Rather, pre-event survey results were used to group individuals based on their interests. Based on our team’s shared vision and general productivity, it is safe to say that a great deal of data mining went into the creation of these groups. The data worked. Each team included one data scientist, tasked with helping to bring ideas to life through the magic of R-coding.

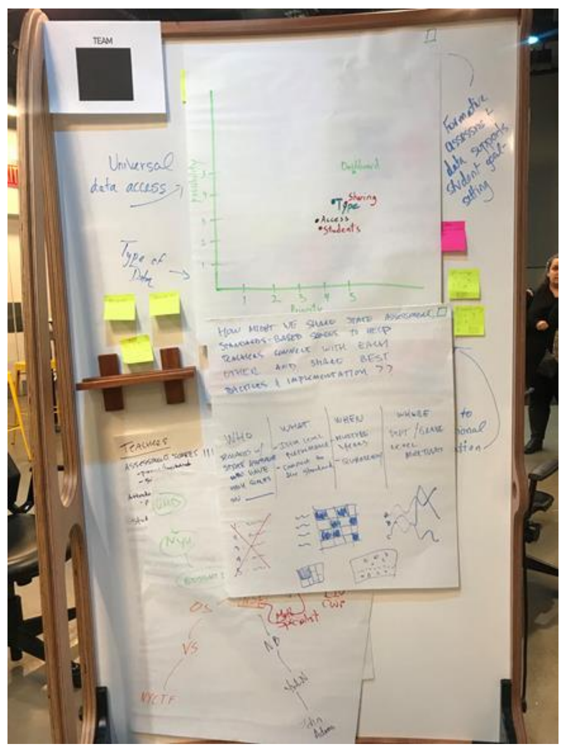
Team Projects - All groups were asked to create a visualization to represent a given data set. This data set was anonymized NYS assessment results. The collection of projects created during this workshop was vast. Some groups honed in on dashboards aimed toward helping district-level administrators support schools. Still, others developed visualizations that reimagined standard item analysis reports. These projects were as varied as the diverse cross-section of individuals attending the workshop.

The Given Assessment/Data Set - As stated, during the NSF workshop, our data set was anonymized NYS assessment results. This data was compiled by

Nassau BOCES. As a Nassau-based educator, I have been a user of the Nassau BOCES Instructional Data Warehouse for many years. This vast collection of data dashboards and visualizations has played a critical role in informing my understanding of NYS assessment results for my school and district. For the purposes of our project, Team Square operated from the standpoint that our work could be applied to any given standards-based assessment. It could also apply to composite performance data from multiple standards-based assessments.

The Process: This was the trajectory of our team's work. Rather than belabor this topic with words that will inevitably fall short of the actual experience, I feel it best to show how our collaborative efforts progressed from an ice-breaker activity to our ground-breaking visualization and teacher-collaboration interface.





Additional Context

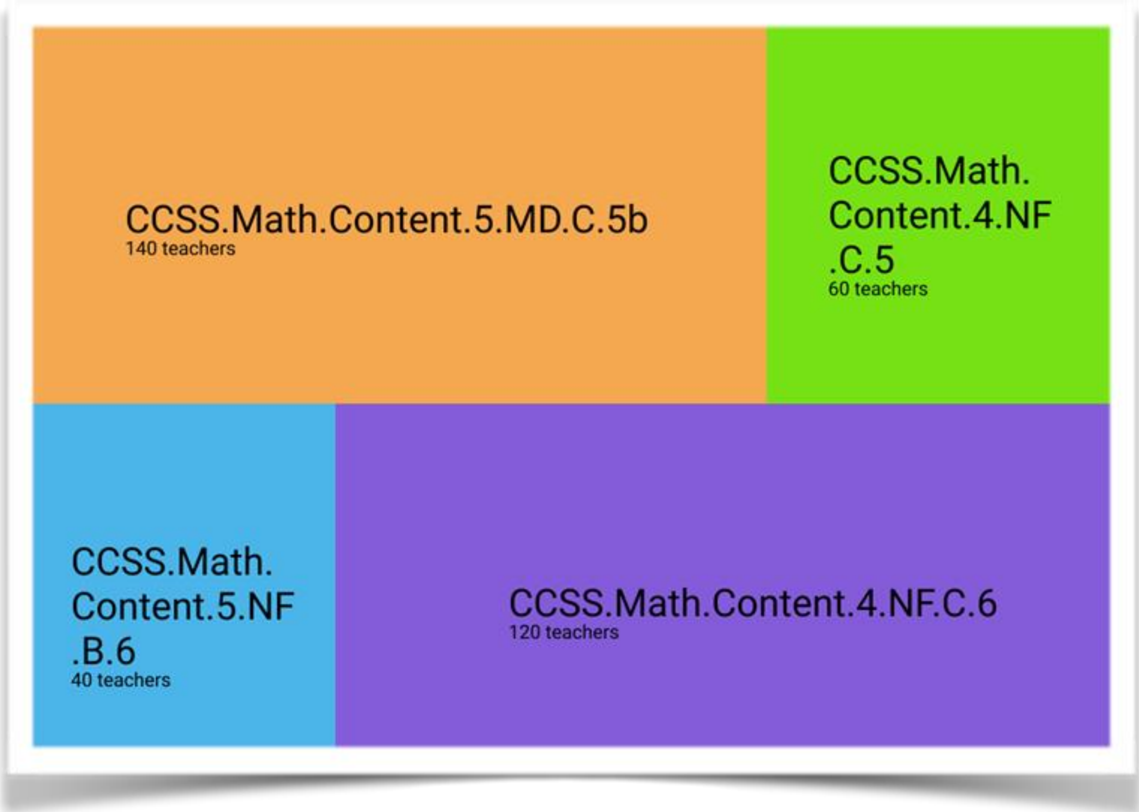
I find myself typing these words during the 8th week of a stay-at-home order issued by New York State governor Andrew Cuomo, in response to the COVID-19 global pandemic. Although my perspective remains consistent and aligned to my original thinking immediately following the NSF workshop in December, it has been further sharpened by the current unpredictable landscape of education. This bears no tangible weight on the content of my words, but rather the tone of voice they emulate. Currently, education in my state and many others, has shifted entirely to an online interface. The remaining weeks of the school year will conclude in the same fashion. It is hard to predict what September will look like. Effective use of data is arguably more important than ever. Time is limited for students and their families as they work to complete assignments at home. When we return to the classroom, time will continue to be a limited resource as we strive to reduce the gaps in education that have occurred due to the challenges and limitations of at-home instruction.

Team Square: Part 1

The work of my group, Team Square, centered around the notion of collaboration. In my professional practice, I've strived to establish systems and norms to bring data out of the shadows of solitary classrooms, where they often reside. In each school I've worked in, there have been different challenges that have impacted the pace of progress towards the optimization of these systems and norms. Regardless of challenges that have inevitably arisen when promoting the sharing of data amongst colleagues, I've always viewed this plight as a prerequisite for success. Without question, I brought this perspective to the table from the first moment our team sat down to share ideas and brainstorm a direction for our culminating project. I was pleasantly surprised to see that my new teammates immediately shared this outlook, despite our varied backgrounds and professional roles. Our team was comprised of teachers from varied grade levels, a data scientist and myself, an administrator. Despite our diverse backgrounds and educational experiences, our conversation quickly centered around the value of connecting educators, as a means to transform data into action.

Our collective experiences guided our conversation toward a phenomenon we had all seen play out all too often. This phenomenon was one in which the elaborate spreadsheets, graphs, charts and tables summarizing student assessment data were relegated to dusty binders and equally dusty desktop folders, rarely seeing the light-of-day. The prevalence of this phenomenon varied amongst classrooms, schools and districts. In some settings, where data-based decision-making was valued, this dusty data phenomenon was the exception. However, in too many educational settings, it was the norm. The question of why this phenomenon exists in so many schools became an essential beacon that guided our work. One theory was that time is a limited commodity for all educators. If data are not represented in a user-friendly format, they are swiftly shuttled to the aforementioned dusty realms. Another theory to explain unused data, arguably a precursor to all others, is a lack of confidence in the initial data source. This could be a result of many different factors, including but not limited to obsolete data or inaccurate testing measures and more. Adaptive testing is one method for counteracting this type of distrust for data. Anchoring assessments in standards and including qualified educators in the assessment development process are also effectives ways to instill trust in data. Even though all assessments are not created equal, for the purposes of our endeavor, Team Square consciously embraced the assumption that the data sources for our project were relevant and valid. This is sometimes necessary for academic endeavors that aim to pinpoint specific variables.

In alignment with the focus of the two-day workshop, we thoroughly discussed the types of visualizations we were most familiar with and their accompanying shortcomings. As a data practitioner, conditional formatting in Excel and Google Sheets, along with various basic statistical functions, have been my primary means of representing data for myself and my colleagues. It was at this time that our team's data scientist's contributions became invaluable. He quickly educated the rest of the team about the apparently limitless compendium of data visualizations. Our team ultimately decided that a tree map would be a simple visualization that could be used to represent state assessment data. The space allocated to each section of a tree map corresponds to its relative value. Below is our visualization.

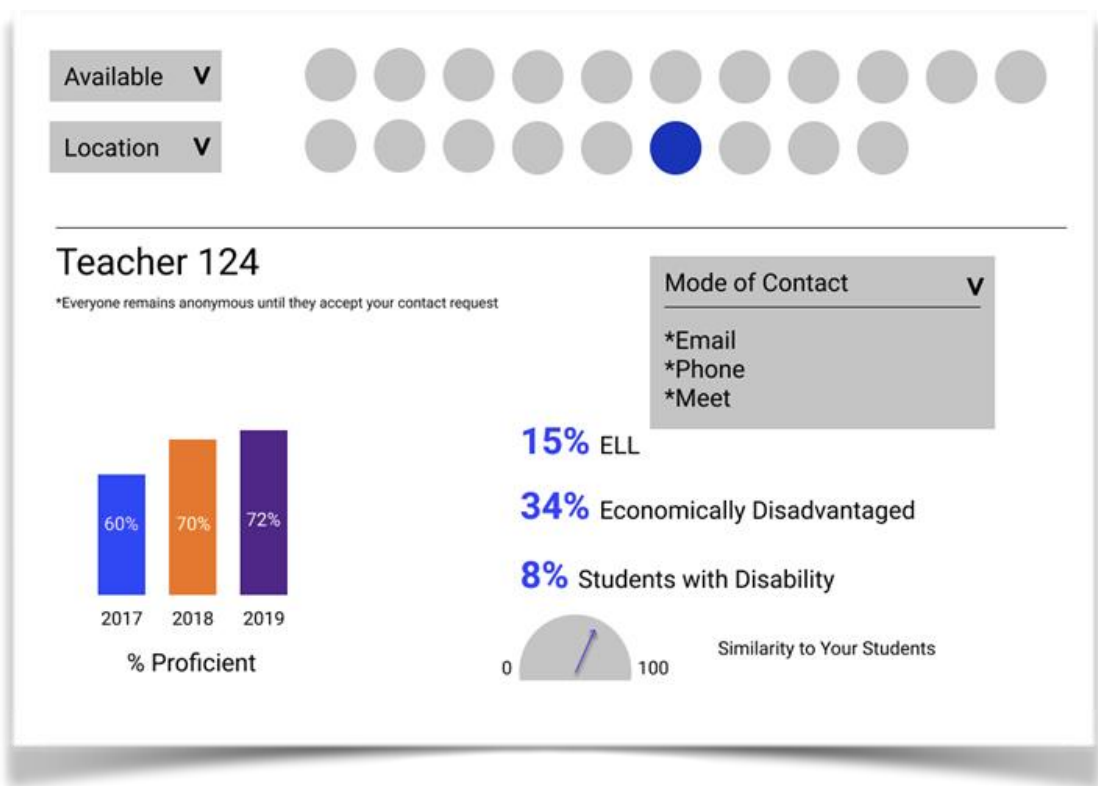


Included in each rectangle is a learning standard and the number of possible teacher connections. These standards represent the weakest areas of performance for a teacher on a given assessment. It is important to note that the ideal, real-world version of this tool would not only compile the weakest standards. It would allow an educator to also toggle to view the highest performing standards. In this way, the tree map becomes an "at-a-glance" teacher profile. An essential disclaimer to mention is that no solitary assessment can or should be used to determine teacher effectiveness. It is also important to note that this particular tool was designed for teachers, not administrators. However, it could be easily scaled up to present building and district-level data for administrators.

Team Square: Part 2

The first goal of our tree map was to streamline the data analysis process. We aimed to provide teachers with a clear representation of the most relevant data points for the given assessment. This spacial representation can quickly be analyzed to identify essential information. In the example above, math standards 4.NF.C.6 and 5.MD.C.5b would be the lowest-performing standards for this class. An exploration into the source of this deficiency could reveal some innocuous rationale that requires no further investigation. For example, these standards could be two that are scheduled to be taught during the 6 weeks remaining in the school year, after the administration of this, the given exam. However, if in fact these standards were taught with the goal of mastery, time must be devoted to further understanding this deficiency. This at-a-glance visual representation of standards-based performance becomes a springboard for next steps. For our team, the most logical next step was collaboration. Without it, the potential for this data to remain inert and unused is too great. There is no doubt that some educators could take this dashboard and make meaningful revisions to daily instruction, without being given the chance to collaborate with others. However, most teachers would benefit from the opportunity to tap into the broader pedagogical knowledge base when developing action plans to improve student performance in these target standards. The next stage of our project speaks to the benefits of collaboration and collegial inquiry when turning this data into action.

Team Square: Part 3



McPherson, 2021

Above is the second stage of our visualization. Although it is a shell, absent of code and authentic user data, we feel is still conveys a clear vision. In practice, once a teacher identifies a target standard in their personalized tree map, they would be transported to this screen. This is a connection dashboard. The circles at the top represent teachers who have demonstrated proficiency in teaching the selected standard. These featured educators would have previously opted into this data sharing system. With a click, the user would have access to mentors beyond their school and district. Teachers would not be limited to learning just from the colleague teaching in the classroom next door. Once the user selects a potential mentor, that individual's profile would populate the bottom half of the screen. This profile includes a longitudinal summary of that potential mentor/collaborator's performance over multiple years. Class demographics, along with a compatibility rating, would also optimize the matching process. In addition, contact information would be readily available. This dashboard would aim to combat the "accident of geography" and connect teachers throughout a region, state, country and beyond. Of course, norms and protocols would have to be developed to ensure that participants on both ends of this interface understand how best to maximize the potential for a successful outcome. This project represents the precipice of meaningful professional discourse that is unbound by the limitations of physical space. Once again, as I write this in the current educational, health and political contexts, I realize the indelible relevance and need for such a tool.

When creating this hypothetical tool, we thoroughly discussed many of the logistical challenges that would come about when launching such a lofty dashboard. However, at its core, it speaks to the value of using data to connect educators. It represents an archetypal climate in which teachers feel comfortable reaching out to colleagues to ask questions, share best practices and acknowledge what they don't know.

Project Summary

At the core of our project is our collective effort to combat some of the aforementioned challenges that impact data usage in schools. Dusty data does not have to be the norm. To accomplish such a shift, we aimed to first represent data in a user-friendly format that promoted teacher efficacy while removing initial barriers to the data analysis process. In my experience, teacher buy-in relies on a delicate balance. At one end of the spectrum is simply telling teachers the conclusions that have been drawn about their student assessment data. In this scenario, an administrator, coach or teacher leader would have previously done the heavy lifting needed to analyze the data. This approach places teachers in the passenger seat. Although this may seem enticing to some educators, a top down-approach can drastically affect teacher efficacy. By being passive participants in the data analysis process, teachers would miss the opportunity to internalize the skills needed to manage data and truly understand the needs of their students. When this task is outsourced, it no longer becomes a teacher's responsibility. Relinquishing this key stage of the data analysis process can have detrimental effects on all other stages, including the development and implementation of action plans. At the other end of the spectrum is burdening teachers with raw data that requires them to spend hours and hours just trying to transform it into a usable format. It takes years to develop the skills needed to manipulate data in this raw format. We must find a balance in between these two extremes to truly impact teacher efficacy in the field of data usage. Keeping this in mind, our team selected a visualization that simplifies the space between viewing and understanding data. It is important that this space exist to empower teachers to own their data. However, we shouldn't try eliminate this space entirely in an effort to help teachers. The correct balance for any teacher or teacher team will vary. Selecting the best visualization to represent the given data is a critical way to empower teachers. Once data is represented in a way that can spark discourse and inquiry, collaboration ensures that the best possible theories and action plans can be developed to promote student achievement. For teachers who are not fortunate enough to be part of strong professional learning communities, our project could be used to drastically expand their professional sphere to include colleagues from distant locales. It could also be used to help existing professional learning communities evolve in their practices surrounding data usage.

A multitude of arguments can be made regarding challenges that may arise if a project like ours actually came to fruition in the real world. Regardless of these potential hurdles, our work as a team and our broader participation in the workshop is living proof of the type of ideas and solutions that can arise when time and space are provided for professionals in the field of education to collaborate.

Data in the Days of Covid-19

My current reality consists of students learning solely at home. In my district, our teachers use Google Classroom to organize instructional materials and communicate with students. Google Meet sessions simulate in-person class discussions. Although this format presents a slew of logistical challenges, teachers have accelerated their own learning in the field of online instruction. They continue to deliver targeted lessons and provide an invaluable forum for students to connect with our school community. In this new and likely temporary paradigm, data matters. For online instruction to be relevant and engaging to students, it must be informed by standards, students' academic needs and their interests. Otherwise, we run the risk of stunting students' academic, social and emotional growth. Our current instructional format will no doubt give way to some iteration that more clearly mimics our traditional system for education. I cannot predict exactly what that will look like or when it will manifest, especially since education policy makers and elected officials express their own uncertainty on this subject. Some proposed models include a hybrid approach that consists of learning at home for some and traditional, in-person learning for others. Truncated school days have also come up as a possibility. Variance in instructional formats may even exist in the the same school or district, depending on how public safety protocols unfold throughout the next year. Whether the current learning at home model endures or evolves into something else, teachers must use data more effectively than ever before. The opportunity gaps that existed for some of our learners prior to this crisis will widen during this period of learning at home. Socioeconomic disparities, along with the new demands on families struggling to make a living while still supporting students at home will create new challenges that can only be solved by intentional instructional decisions that are informed by data. This has always been the case. However, in our current context, our acceptable margin for error has been reduced drastically. Objective data and collaboration are prerequisites for success.

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CHAPTER 23

Linking Data to Empower Meaningful Action

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Baldwin Union Free School District

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The cost of dropping out of high school continues to be a concern for school districts across the nation. As we know, adults who dropped out are more likely to be unemployed, have poor health, live in poverty, and be on public assistance. This strain affects their health and social relations, leading to lower life expectancies and higher family dissolution rates, as well as incarceration rates many times higher than those of graduates. In contrast, high school graduates earn 50 to 100 percent more in lifetime income, providing additional revenues to communities and government. Why is this still the case when across school districts in the US and globally, schools are inundated with increasing amounts of data (Bowers, Shoho, & Barnett, 2014; Halverson, 2014; Mandinach, Friedman, & Gummer, 2015; Wayman, Shaw, & Cho, 2017).

This chapter will explore how a school district can use data to empower meaningful actions and increase the graduation rates of all students.

Demographics

Baldwin USFD is a community which celebrates its diversity! According to suburbanstats.org, 48% of community is Caucasian, 34% is Black or African American, 20% is Hispanic or Latino, 4% are Asian, 3% are two or more races, and 8% are some other race other than those previously listed. As you can see from the diagram 1 below, Baldwin High School is a majority minority school comprised of 50% African American students, 27% Hispanic students, 17% Caucasian students, 4% Asian students, 3% two or more races. Over the past 5 years, we have seen a growth in Hispanic students and an increase in economically disadvantaged students.

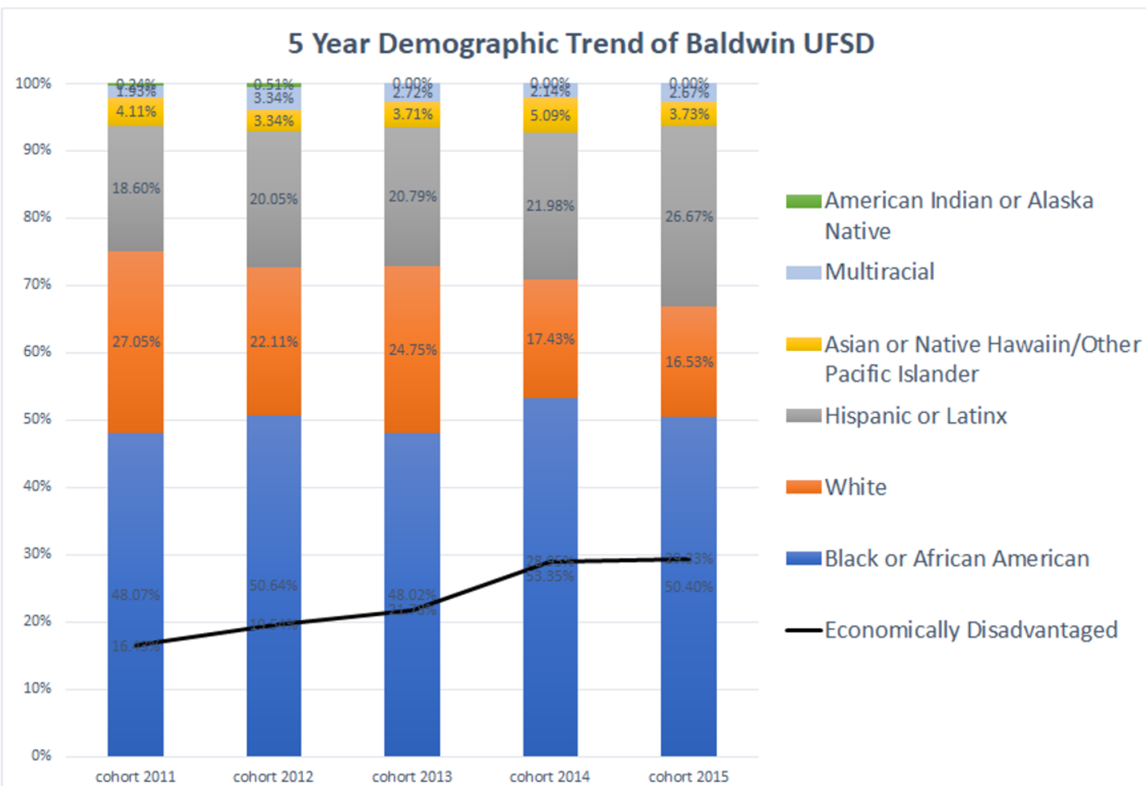

Figure 23.1: *Demographics*

Methods

To ensure success of all subgroups, we actively monitor trends in student enrollment, demographics, and numerous indicators such as academic trends, attendance trends, and discipline trends by subgroup.

The continual process of running, exporting and analyzing reports from several different data sources is both time and labor intensive and often completed in isolation and primarily for State Reporting purposes (ESSA) by the person responsible for state reporting. The leadership team at Baldwin UFSD has recognized that in order to ensure equity, success, and inclusiveness for all student subgroups, critical and current data needs to be brought together and reviewed regularly by building and district stakeholders. Data is actionable when it is current, insightful, visual and easy to access by the end user.

Thus, the district has made a commitment to maximize the data reporting tools of our SIS and explore the use of innovative data analytics and data visualization applications.

In addition, we have strategically built time into staff members schedule to regularly review the data and use it to inform and empower decision making.

As noted in the EDLA Summit Report 2018 Report (Bowers, Bang, Pan, & Graves, 2019), through these evidence- based improvement cycles, teachers and leaders can work together to build capacity throughout their organization to leverage these new types of data and analytics as a means to build collaboration, trust, and capacity to improve instruction for each student, and across the organization. This is the methodology used by the Baldwin UFSD leadership team and has helped Baldwin High School to be named as a Recognition School by New York State in 2018-2019 and in 2019-2020 under ESSA accountability measures.

Several years ago, the district activated the Performance Map module offered in our Student Information System (SIS). A performance map provides a HS Guidance counselor with a visual on students' course, credit and assessment progress towards graduation. Before turning on the Performance Maps, all courses in the SIS had to be verified against the current and historical high school course catalogs. Additionally, in order for the performance map module to work, all courses needed to be aligned to the appropriate subject, department and correct state course code. Implementing Performance Maps right through the SIS, was a low-cost way to empower counselors with current and important student information through a easy to use data visualization (Figure 23.2). Counselors now rely on various Performance Maps to easily monitor student progress and quickly take action as necessary. Our work on implementing Performance Maps has been extremely helpful and has since inspired the creation of an Early Warning System (EWS). Another live data visualization used to help identify and take action on at-risk students (Figure 23.3). Example of the Performance Map and EWS are below.

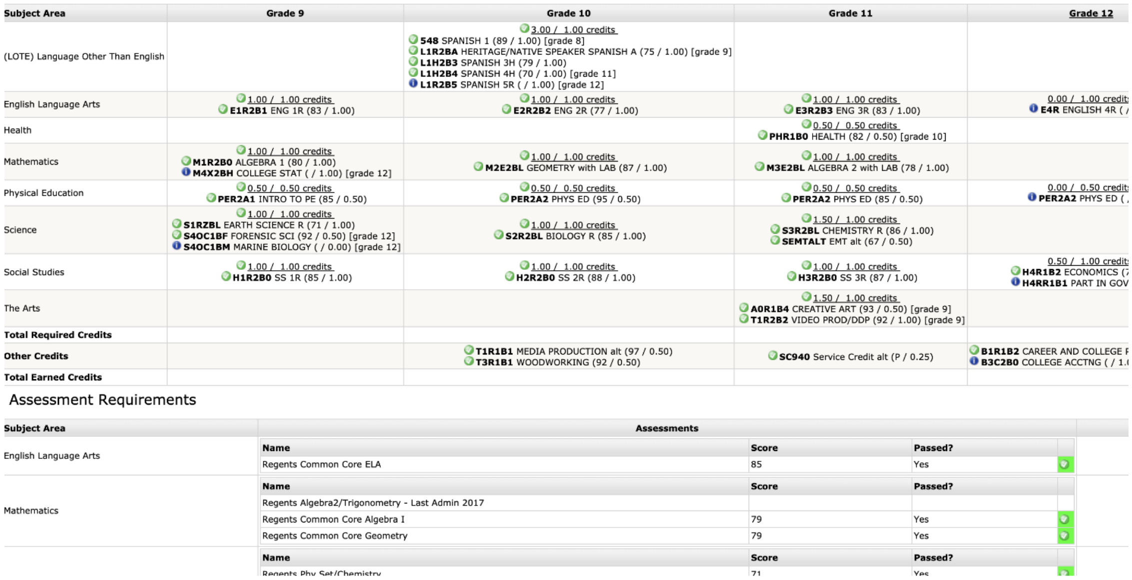

Figure 23.2: *Performance Map*

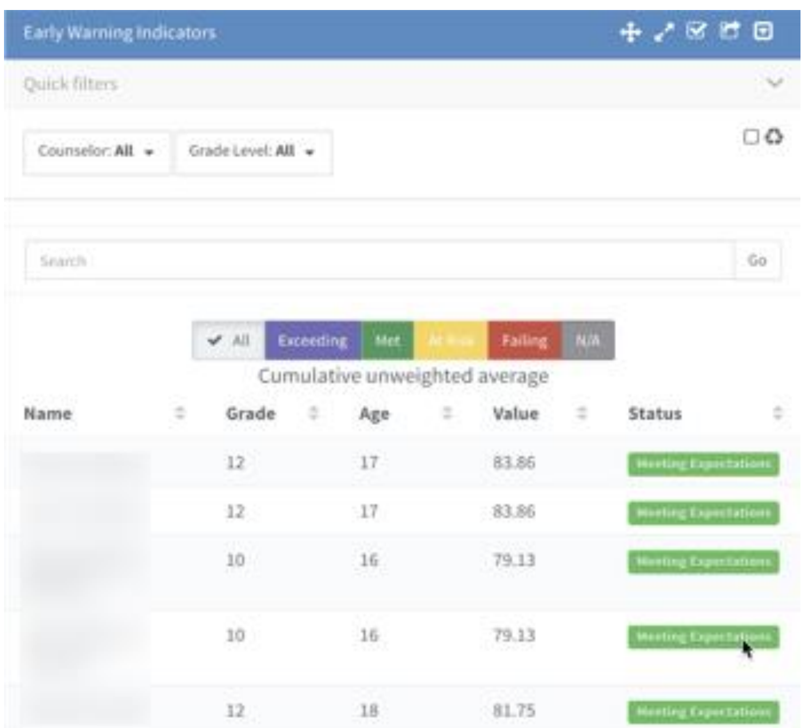

Figure 23.3: *EWS in SIS*

In addition, we continuously upload all static student assessment records into our SIS. These data sets include all administrations of PSAT and SAT, all annual State Assessment scores along with Advance Placement results. Putting all student assessment data in one location gives servicing staff a complete picture of a student's performance. During the aforementioned data meetings with staff members, we are able to create low cost programs and immediately offer appropriate interventions to support all students and ultimately have them graduate with their cohort.

Included in our data discussions is analyzing the various reports offered Nassau BOCES Instructional Data Warehouse (IDW). We are fortunate to have a plethora of reports developed by the data scientists at Nassau BOCES to examine and empower our decision making. We also are extremely fortunate to have the ability to collaborate with the Nassau BOCES IDW team and create new reports such as a Multi-Year Teacher Gap Report (diagram 4), Subgroup Analysis Report and the Regents Maximum Achieved reports. Access to these reports and more have allowed us to evaluate our curricula and make informed decisions to make adjustment in curriculum, design and implement professional development for teachers. The IDW is an important district resource used to meet the challenge of ensuring equity, access, and success for all subgroups.

Multi-Year Gap Report

Building/ District	Standard Category	Standard Description	Year	Question #	Item Detail
Baldwin UFSD	4.NF.C.7	their size. Recognize that comparisons are valid only when the two decimals refer to the same whole. Record the results of comparisons with the symbols >;, =, or <;, and justify the conclusions, e.	30, 2016		
	CCSS.Math.Content.4.NF.C.7 - Average				
	CCSS.Math.Content. 5.G.B.3	Understand that attributes belonging to a category of two-dimensional figures also belong to all subcategories of that category. For example, all rectangles have four right angles and squares are rectangles, so all squares have four right angles.	Jun 30, 2016	36-MC	MC (NR)
			Jun 30, 2017	25-MC	MC
				39-MC	MC (NR)
			Jun 30, 2019	31-MC	MC
	CCSS.Math.Content.5.G.B.3 - Average				
	CCSS.Math.Content. 5.G.B.4	Classify two-dimensional figures in a hierarchy based on properties.	Jun 30, 2016	05-MC	MC
				24-MC	MC
			Jun 30, 2018	13-MC	MC
				37-MC	MC

Figure 23.4: *Multi-year Teacher Gap Report from IDW*

Data discussions have become part of the culture in Baldwin UFSD. Each building/department has established embedded time to review data during their meetings to make informed decisions to better support students.

The school year started with building administration presenting their building goals to the Superintendent and each goal is justified with data (S.M.A.R.T Goals). The building administration also present the goals to their faculties. Each department established their departmental specific goals which supports the building goals. The teachers also reflect and craft their own goals which are aligned and support the department goals as well as their own areas desired or needed growth. The goals are revisited throughout the school year during reflection meetings and data is used during these conversations to make informed decisions/adjustments so as a district, we meet our goals.

Another example of the data discussions in our schools can be seen in the secondary level. In the secondary schools, teachers are asked to keep their gradebooks updated weekly and provide either a progress report or report card every five weeks. The administration, counselors and teachers review the academic performance reports from the gradebook and Projected Final Average (PFAs) calculations every five weeks. Intervention plans are then put into place for students with a failing PFA and student progress is monitored closely.

At the elementary level, grade level teams and RtI teams meet weekly with the building administrator to review progress of each student. At these meeting, the teachers and administrator review multiple data points to determine the progress of each student, select the relevant research-based intervention, plan and implement the intervention plans and then monitor examine intervention is working.

These are just some examples of how we have strategically created a continuous cycle of improvement with various stake holders and used data to inform meaningful actions

Results

The results of using the methodology mentioned above and triangulation of Leadership, Data Scientists, and key staff (ie: teachers, counselors) is impressive. Figure 23.5 shows the 4 Year Graduation Outcomes as of August 2019 for Baldwin SHS in comparison to Nassau County, Suffolk County, New York City, and New York State.

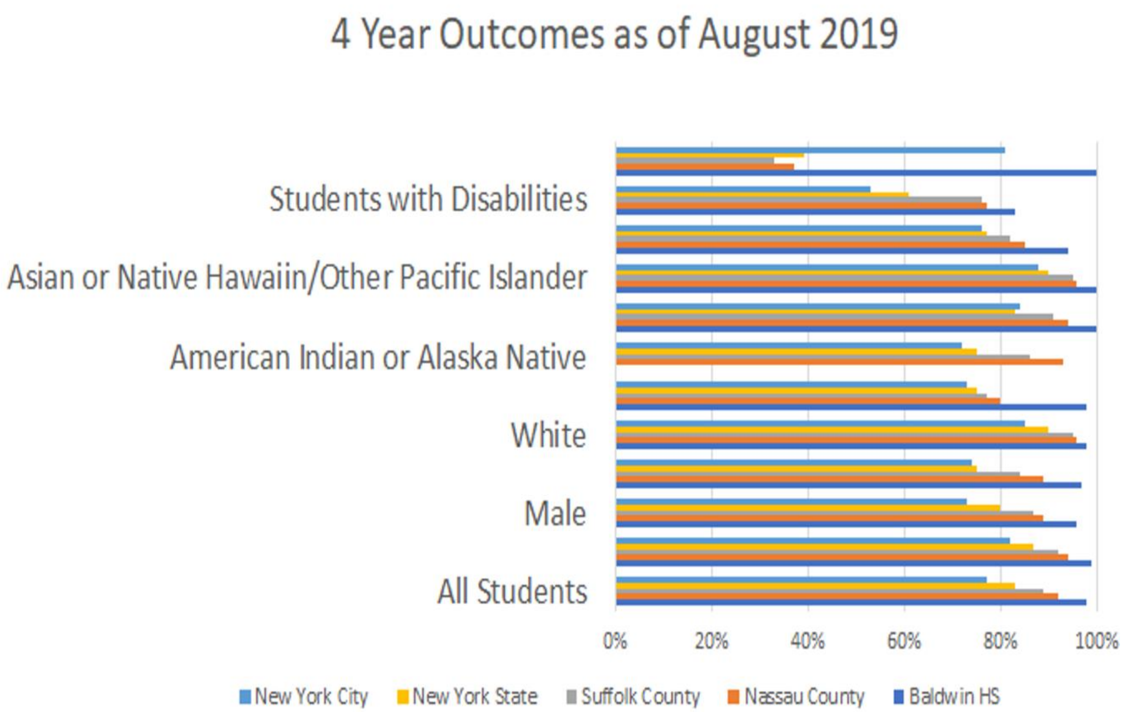

Figure 23. 5: 4 Year Outcomes as of August 2019

In addition, we are proud to note the following:

- 6% increase in 4-year graduation rate outcomes as of August 2015-2019 (7% increase in 4-year graduation rate outcomes as of June 2015-2019) despite a growing economically disadvantaged population.
- No achievement gap between subgroups
- Baldwin High School was named as a Recognition School by New York State in 2018-2019 and in 2019-2020 under ESSA accountability measures.

Lessons Learned:

While participating at the NSF Collaborative, we chose to work on another way to streamline the movement of key student level data in order to aid in the success of all students. Under ESSA accountability rules, all districts must meet assigned standards of student absenteeism. Also, our datasprint team aligned to the district goal to ensure timely graduation of all students as students who are chronically absent are at risk of meeting graduation requirements. The district team collaborated with a data scientist to engineer an R code scheme to pull student daily attendance from the data set already reported to the state, merge it with local student household information and produce a letter to parents alerting them with actual student attendance details and explaining the importance of student attendance. It was hoped that the R program produced would replace the repetitive district work of periodically pulling data from two data sources, compiling it to produce a mail merge to inform parents. The team wanted the program to be something which could be actually implemented, appreciated and easily run by building principals.

Other lessons learned during Baldwin's practices and refinements on using data to make informed, meaningful decisions and actions is it is:

- It is vital to have an engaging, rigorous, relevant and vertically aligned curriculum that is aligned to state standards. Analyzing the right data can help ensure that your curriculum is aligned to state standards.
- Moving some high school courses to 8th grade can help propel students to a successful freshman year of high school.
- Several low-cost interventions such as 9th grade academic teaming, credit recovery programs, and modifying the master schedule to drive instructional initiatives can successfully increase graduation rates.
- Schools need to make sure their courses are mapped to the proper departments in their SIS.
- Job embedded, explicit professional development is important. This professional development has to cover pedagogy, curriculum development, and using data to inform decision making (continuous improvement cycle models)
- Identifying at-risk students early is key to supporting them to graduate with their cohort.
- Creating a dashboard with visualizations of the reports saves time in preparing the reports and more time to hold data discussions using the reports.

Conclusion

When stakeholders (leadership, data scientists, and staff) are brought together regularly to examine data and develop reports that can be used to inform and empower meaningful action, students across all subgroups can be successful and graduate from high school with their cohort thereby reducing the drop-out rate. This was reinforced during the NSF Collaborative Summit work we were fortunate to participate in with Dr. Bowers and his team. Baldwin UFSD looks forward to the continued collaboration with the IDW data scientist team from Nassau BOCES. We are also continually looking to improve our own data discussion and will utilize lessons learned from the NSF Summit and continue to focus on improving data visualizations to help improve the quality of our data discussions and thereby further empowering our actions and decisions.

We hope that investments in setting up data rules, data flows, data systems, and a master dashboard will save time in producing the repots so more time can be spent on holding more data discussions and engaging in continuous cycle of improvement discussions using the reports and visualizations. The district seeks to use innovative advanced analytic technologies to work smarter and more efficiently and continue to propel all students to success.

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CHAPTER 24

The Components of a Successful Transdisciplinary Workshop: Rapport, Focus, and Impact

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Abstract

A surfeit of data are collected in the American educational system, but there is a shortage of educators who know how to analyze the data to convert them into action. One way to help bridge this gap between researchers and educators is to host transdisciplinary education workshops, in which researcher data scientists and educators work together to explore a dataset. Transdisciplinary group work, however, can be challenging because the group members bring different perspectives from their different backgrounds. I have participated as a data scientist at two transdisciplinary conferences and identified three key components for a successful workshop - rapport, focus, and impact. Rapport refers to the establishment of mutual understanding and respect that facilitate open communication between two people. It sets the tone for the whole workshop. Focus, defined as intense concentration on a single thing, affords the structure necessary to make progress on a specific problem in a short time period. Impact, defined as a major effect on something, involves creating the foundation so your efforts at the workshop will extend past the workshop itself. The existence of these three key components can

help ensure the productive collaboration of a trandisciplinary workshop group.

Keywords: trandisciplinary, rapport, focus, impact, workshop

Background

A surfeit of data are collected in the American educational system, but there is a shortage of educators who know how to convert these data into action (Bowers et al., 2019). Currently, education researchers analyze data, and administrators use data to demonstrate compliance, but the researchers and administrators have yet to come together to regularly use data to inspire innovative action that could improve and revolutionize educational practices (Boser & McDaniels, 2018). Developing a capacity for applied data analytics in educators and researchers, and communication on the topic between the two groups, could be greatly beneficial (Bowers et al., 2019). Researchers' work could be more impactful if they knew educators' questions and educators could take more meaningful action if they knew of applicable researchers' work (Bowers et al., 2019).

Leaders in the field of education research believe that regularly hosting transdisciplinary education workshops could help educators and researchers meet at the intersections of their respective fields (Bowers et al., 2019; Gray, 2008). In these workshops, educators are grouped with experts in data science research and together they discuss challenges in education and analyze education data to come up with solutions (Boser & McDaniels, 2018; Bowers et al., 2019). These workshops can be quite impactful, as noted by a participant from a workshop recently held in New York, who said, "Our 2-day session served as evidence that the challenges can be met when practitioners meet with data scientists and researchers to share what is needed in the field" (NSF Education Data Analytics Collaborative Workshop, 2019). However, although often leading to novel discoveries that improve practice, these workshops can be very costly, making it important to ensure a successful workshop.

Analysis

Transdisciplinary Group Work

I have participated as a data scientist at two transdisciplinary workshops. My first workshop was outside of San Francisco, California. For two days, I worked with other data scientists and several educators from a California charter school system to analyze the clickstream data of students completing online coursework. My second workshop was in New York City, New York; myself and other data scientists worked for two days with educators from a Long Island school district to inspect students' standardized test scores and attendance data. For both workshops, the first day focused on icebreakers and ideation. The icebreakers helped group members, a diverse mix of educators and data scientists, get to know a little about each other, and the ideation prompted group members to select an idea they wanted to explore in the data. The second day at both workshops focused on coding to actively explore the data and to produce findings that the educators could use to take action.

The ultimate goal of both workshops was to maximize the two days of collaborative work to provide the educators with information they could use to improve their practice, and ideally, to generate momentum for a larger project the educators could undertake based on their workshop experience. To develop meaningful work with a group in two days is challenging. The type of transdisciplinary research being conducted at these workshops is especially challenging because misunderstandings and disagreements are more likely to happen in transdisciplinary groups (Gray, 2008). Members of transdisciplinary groups come from different backgrounds with different perspectives, which can lead to dissonance, but it is important for such dissonance to not dominate or impede the ability of the group to accomplish its goals.

Satisfaction with group members' interaction generally leads to a more impactful outcome. An analysis of 67 post-workshop survey responses (NSF Education Data Analytics Collaborative Workshop, 2019) revealed a significant correlation ($r(65) = 0.33$, $p = .006$) between how satisfied participants were with how their group worked together and whether the participants had at least one take-way from the workshop that they would use in their practice (see Appendix A for the variables' descriptive statistics). This correlation is not only statistically significant, but can also be interpreted as a moderate effect size (Cohen, 1988), suggesting that harmonious group work is important for a workshop to be impactful, and therefore, successful. Harmonious collaboration and meaningful work are possible for a transdisciplinary group that is committed to having rapport, focus, and impact. Rapport is imperative for the group members to effectively collaborate. Focus is key for not over committing, and impact is required for having the workshop's results extend past the workshop itself.

Rapport

Rapport refers to the establishment of mutual understanding and respect that facilitates open communication between two people (rapport, 2020). It sets the tone for the entirety of the workshop; for example, one workshop participant stated that, “We grew in our relationship with one another which [was] critical to establishing a trusting environment to support data use” (NSF Education Data Analytics Collaborative Workshop, 2019). Rapport is especially important for collaboration among people from different disciplines because such people view problems differently and come with different pre-conceived notions (Gray, 2008). Therefore, to successfully address a problem together, they must be open to listening to each other and learning from each other (Lydon & King, 2009; Wilson & Ryan, 2013).

The development of rapport can be characterized by four dimensions. First, the data scientists and educators need to enter with a positive disposition and belief in the value of the workshop (Buskist & Saville, 2001). Second, they must respect each other as experts in their fields (Buskist & Saville, 2001). Third, they must be committed to ensuring a smooth, collaborative working relationship for the duration of the workshop (Buskist & Saville, 2001; Patton et al., 2015). Fourth, they need to acknowledge each other’s roles in the group – educators should lead the generation of research questions and the explanation of findings, and data scientists should lead the execution and interpretation of analyses and visualizations used to generate insights (Buskist & Saville, 2001; Gray, 2008). You must plant these seeds of rapport before group members can begin engaging in research together, and you can use the following three methods to help facilitate the development of rapport among group members.

First, school districts should be thoughtful about who they send to workshops and the workshop host should be careful to invite data scientists who can easily collaborate with people from other fields. Specifically, organizers of these workshops should look to have attendees who are open to different perspectives, strong verbal communicators, and upbeat. Openness to different perspectives is important for facilitating group work (Gray, 2008). My diverse background, spanning archaeology, education, and data science, has helped me understand the perspectives of group members from different fields at these workshops. Strong verbal communication is important for sharing ideas across disciplines (Gray, 2008). I make sure to understand my group members’ thoughts by asking questions, rather than filling the gaps in my understanding with assumptions, which can lead to disagreements. Positivity is important for quickly garnering rapport because smiling helps others feel comfortable around you and positivity motivates group members to engage in the workshop (Buskist & Saville, 2001; Tickle-Degnen & Rosenthal, 1990). Whenever I introduce myself at these workshops, I always make sure to give a big smile, a strong hand-shake, and to express my excitement for the work on which we are about to embark.

Second, workshop organizers should group together attendees with similar perspectives. Even though attendees come from different fields, they may still share similar perspectives about the larger topic of education data science. This similarity should be used to inform groupings because people are more likely to like those who they perceive to be similar to them (Morry, 2007). For example, mimicry, producing similarity in behavior, facilitates the development of rapport because the two people involved will sense the similarity in behavior, making them feel more comfortable with each other (Duffy & Chartrand, 2015). The host at my most recent workshop ran a topic model on the pre-workshop survey text responses and used the similarity in topics to group attendees, ensuring some level of similarity among group members.

Third, opening the workshop with icebreakers can efficiently help group members get to know each other. Organized activities, like icebreakers, are most effective in this type of setting because they provide attendees with a time-bounded structure around which to center their personal introductions. Icebreakers may feel awkward, or be difficult for some group members, but it is worth encouraging all group members to participate because they can be a bonding experience. An icebreaker presents each group member with the opportunity to introduce themself, guarding against the establishment of power differentials (Gray, 2008) and giving the group members a shared experience in which to anchor the start of the development of their rapport. The host at my most recent workshop had each of us draw a map on the board showing how we ended up at that workshop in three stops. Others then drew a line through shared stops, when they told their path to the workshop. I recommend this icebreaker in particular because it not only encouraged group members to share their backgrounds, but also encouraged shared experiences to be identified, both of which help breed a sense of familiarity among group members (Guéguen & Martin, 2009; Sprecher et al., 2012).

Focus

Focus, referring to concentrated effort (focus, 2020), is the next important component for a successful workshop. Once the seeds of rapport have germinated, group members can comfortably discuss their questions of the workshop data and decide what they want to spend the rest of the workshop exploring (Patton et al., 2015). A participant at a recent workshop provided evidence of the growth of focus from established rapport when they explained, "The collaboration with our assigned team members was an incredible experience. We were able to really hash out some different ideas to eventually find a best path to present to our Data Scientists to explore/create" (NSF Education Data Analytics Collaborative Workshop, 2019). As stated by this participant, the collaboration/rapport enabled the group members to focus, "to…hash out…ideas to…find a best path." These workshops only last a limited amount of time, and this temporal constraint requires attendees to hone in on a small, well-defined task that is within their skill sets, to make sure the workshop time is used most effectively (Gray, 2008).

The task chosen to be focused on must be small and well-defined because the human brain cannot multi-task – it cannot tackle a problem from different angles at once. A poorly defined task leads to confusion, with group members trying to address the problem from different angles, with no clear direction, ultimately achieving nothing (Nakamura & Csikszentmihalyi, 2014; Rosen, 2008). Clearly defined parameters allow group members to know the starting point for the task and the desired end point for the task. This elucidated linearity gives group members a clear path to follow. It also allows them to track their progress, which gives them immediate feedback that in turn motivates them to continue to forge ahead with their work (Eisenberger et al., 2005; Nakamura & Csikszentmihalyi, 2014).

Additionally, the task must be within the group members' preexisting skill sets. Having the agreed-upon task be within group members' skill sets makes sure that the process to reach the end point is well understood and means the group members can reasonably estimate how long the task will take. Knowing how long the task will take is important for knowing that the task can be accomplished within the workshop time period, and thus, avoiding demotivation by committing to too large a task (Eisenberger et al., 2005; Nakamura & Csikszentmihalyi, 2014).

Focus affords the necessary structure for making progress on a specific problem in a short time period, but it is not necessarily easy to accomplish. The datasets provided at these workshops can be rife with information and lead to a seemingly infinite number of questions. From my workshop experiences, however, I have identified a few practices that can help achieve the necessary level of focus for a successful workshop.

First, in advance of the workshop, make workshop attendees aware of the data with which they will be working. Specifically list each variable and its description and encourage attendees to begin thinking about what they would like to learn or generate from these data a few days prior to the workshop. Before entering either of my previous workshops, I was sent not only the datasets in advance, but also documentation describing those datasets, so I could enter the workshop prepared with a comprehensive understanding of the data and what questions educators may have of the data.

Second, both data scientists and educators should, in advance of the workshop, gather information to help them at the workshop. Data scientists should gather code for a small group of analyses and visualizations that can be reliably completed within a short period of time. These analyses/visualizations should have a short run time, require limited data preparation, and be easy to explain to a non-technical audience. The need for ease of explanation is especially important because educators should be able to readily interpret the analytical output. Educators should reflect on their practices and noticings in the field of education and select those thoughts that are most salient to the workshop dataset (Darling-Hammond & McLaughlin, 2011; Patton et al., 2015; Stoll et al., 2012). They should then write down their selected ideas, or questions about problems they experience, and be prepared to share them with their group members. At the workshops I have attended, the groups with educators who came prepared with thoughts on their practice seemed to be the best at identifying a focused issue to address. Also, prior to attending workshops, I collect the code for a couple of visualizations and descriptive statistics that could be meaningfully applied to a variety of datasets. I primarily focus on descriptive data exploration because descriptive methods often run more quickly and are usually easier to explain, while yielding meaningful output.

Third, all the group members should understand and support the goal of the selected task. A well-articulated goal is important for making sure that all group members know what they are working toward, and buy-in is important for feeling motivated to work towards that goal (Buskist & Saville, 2001; Rosen, 2008). At the most recent conference I attended, we addressed a well-known problem in the education field and clearly articulated a single piece of it to tackle at the conference. All group members agreed that absenteeism was a serious problem and that writing letters notifying family members of truancy was necessary, but time-consuming. Therefore, we agreed that writing code to automatically customize letters based on students' attendance data would help the educators send letters home regarding absenteeism and give them back time which they could then use to develop other methods for tackling truancy.

Impact

Impact, referring to a major effect on something, is the final component of a successful workshop, and is the byproduct of the two prior components (impact, 2020). Rapport allows group members to identify and work on a focused problem; and a focused problem lays the foundation for impactful work that can extend past the bounds of the workshop. Work that is the fruit of rapport and focus, but confined to just the days of the workshop, is ultimately meaningless - it also must have an impactful outcome, extending past the workshop, to be meaningful (Patton et al., 2015; Stoll et al., 2012).

To foster impactful work, group members should not try to produce totally complete work, or even work meaningful in its own right, in the two-day period, but should build the foundation necessary to spur action that could lead to profoundly meaningful work outside the bounds of the workshop (Boser & McDaniels, 2018). For example, one participant said "This workshop offered potential elixirs for some of these local 'ailments' and certainly generated plenty of food for thought" (NSF Education Data Analytics Collaborative Workshop, 2019), and another participant said, "I intend on bringing strategies back for [professional development] with my teacher teams" (NSF Education Data Analytics Collaborative Workshop, 2019). Such comments reflect the idea that impact includes spurring future actions. Therefore, impact does not mean a perfectly completed product is built and ready to go within the two days of the workshop, rather it means that the work accomplished during the workshop inspires educators to think differently, or take action, after the workshop (Patton et al., 2015; Stoll et al., 2012). Impact is hard to achieve within a short time period, but it is vital to the value of these workshops and is evidence of a successful workshop (Patton et al., 2015; Stoll et al., 2012). I analyzed the behavior of group members with impactful work at the conferences I attended and identified a few key behaviors that made impactful work more attainable.

First, you should link the issue on which your group is focusing to a real-world outcome (Agasisti & Bowers, 2017; Stoll et al., 2012). Consider how the work you are doing at the workshop could ultimately change how an educator thinks or acts at their job after the workshop (Darling-Hammond & McLaughlin, 2011; Patton et al., 2015). Make sure that the workshop work is not an isolated creation with no association to the real-world and is just being completed for the sake of being completed. Educators leaving the workshop should feel that they have something tangible to use to inform their practice in the field and that they have information they now want to take back and share with their colleagues at work. At the most recent workshop I attended, we knew that truancy was a problem and that sending letters home was a first step to combating it; therefore, an automatic letter generator would directly link to this real-world problem and would use data to help address this problem in a more scalable fashion.

Second, identify the minimum amount of work that you must complete during the workshop to set the stage for the desired outcome to occur. Put all your effort into setting up a framework that can be used/built on outside the confines of the workshop. Time at these workshops is very limited and the datasets will not necessarily have all the variables needed for a complete analysis, so you need to make sure that you build a complete foundation for the educators to use after the workshop (Patton et al., 2015). When creating the letter generator I knew that we did not have the complete set of variables needed to fully customize the letters; therefore, I focused my efforts on building a representative R code function (R Core Team, 2017) that the educators could take back with them and build on, using all the data they needed.

Third, the data scientists must teach the educators how to use their code and interpret its output, and educators must make sure to learn from the data scientists how to run the code and interpret the output. This exchange of information is imperative for the educators to continue the work after the workshop (Darling-Hammond & McLaughlin, 2011). The data scientists must be careful to include the educators in their analytical work along the way to make sure that the educators are learning the process and feeling included in the work (Darling-Hammond & McLaughlin, 2011; Lydon & King, 2009). As a data scientist at these workshops, I gave the educators updates when I was at pivotal intervals in the code generation and made sure to code in the language in which all the educators were at least somewhat familiar. I used R (R Core Team, 2017) at both of my previous workshops because it was both a language I knew and with which the educators were familiar.

Discussion:

Working collaboratively as a transdisciplinary group to produce meaningful work in a two-day time period is no easy feat. Collaborative group work can be challenging. Working with group members from other disciplines is even more likely to lead to disagreements, and producing meaningful work in two days, approximately 16 hours, can be difficult under any circumstance. Bringing all these factors together makes it especially challenging to have a successful transdisciplinary workshop. If a group is committed to having rapport, focus, and impact; however, success is possible.

At my most recent workshop, my group members and I were committed to having rapport, focus, and impact, and we produced meaningful work. To develop rapport, we fully engaged in the icebreaker. On a white board, each of us sketched three icons, connected with a line to a central icon, to demonstrate three events in our life that led us to the workshop. While drawing the icons, each of us explained their meaning and how they led us to the workshop. Some group members had more straightforward paths, while others had paths with unexpected twists and turns, others had funny stories to share, and excitement always followed the identification of a shared event. Regardless of the type of path followed, however, all were fun to hear about and elicited dialogue among us. Each of us learned something about the others, creating a sense of belonging and helping us to see the group as a community. Taking an interest in each other's experiences helped foster a sense of camaraderie among us, making it easy for us to transition into a discussion of the workshop data and consider the different approaches we could take to explore the data.

After the icebreaker, we launched into a discussion of the workshop data and focused in on a particular problem and a particular dataset we could use to help resolve that problem. Upon learning about the types of variables in an attendance dataset, the educators asked about using the variables to automate the creation of letters regarding absenteeism. The educators had entered the workshop with a good understanding of the problem of truancy and knew that it should be more effectively addressed because attending class is a crucial step in helping students learn. The educators already knew the types of students at risk of truancy, the threshold of absences at which it would become impossible for a student to graduate, and that sending letters home to notify household members of students' absences was the first step to combatting truancy. The manual creation of these letters, however, was very tedious and time consuming; therefore, we decided to focus on creating a tool that would automatically generate these letters to empower the educators to address this well-known issue in a more scalable fashion.

I worked with the educators to create a letter generator they could use and build off after the workshop. First, I wrote the code to generate a single document with an example sentence that drew on variables from the dataset. Then, I paused at this key juncture in the coding process and showed the educators the code. This short piece of code afforded them the opportunity to easily see how the code could generate a letter. At this time, I set up the educators' computers with R and shared the code with them, so they could begin learning how to customize the content of the letter. I showed them the functionalities needed for customizing the letter, including how to load the data, call variables, and how to run the code. Then to give them the opportunity to use these new skills, I asked them to insert into the code the text they typically use in truancy letters. As they played with customizing the letter content, I generalized the code to extend past a single case and included explanatory comments for the educators to reference in the future. This breakdown of the workload afforded the educators the opportunity to meaningfully contribute to the code by creating the content of the letter and experiment with coding in a "safe space," where they could easily ask me and the other data scientists for help.

Ultimately, we produced a letter generator that could save educators hours of work (See Appendix B & C for the code and example letter). For example, if you spend 15 minutes on each letter, you send out letters three times a year, and you send them to 20 students each time, you spend 15 hours composing letters to notify families of students' truancy. With the code, however, a letter can be generated in less than one second, so less than 1 minute would be needed to compose all the letters for one whole year. This code then gives back educators around 15 hours to engage in other activities. One of the educators was so inspired after running the letter generator code in R, she signed up for an R class; therefore, the educators left with not only code to automatically generate letters, but also with the motivation to learn a new skill.

Conclusion

Transdisciplinary workshops can be impactful if well executed, but they are costly to implement; therefore, you should employ the three key components, rapport, focus, and impact to get the most out of these workshops. First, set the stage so all attendees can easily establish rapport with their group members. Second, make sure that each group works on a focused, well-defined task. Third, make sure that the focused task is linked to a real-world outcome so it will have an impact extending past the bounds of the workshop. If all three of these factors are in place at the workshop, it should have a meaningful influence on the practice of educators and spur the dissemination of education data science outside the realm of the workshop itself.

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Appendices

Appendix A

Table 1

Descriptive Statistics for Pearson Correlation

Variable	Description	*Min*	*Max*	*M*	*SD*
Q26_1	One goal of the workshop event was to bring together current researchers and educators to be able to network with others in this field and identify new ideas for your practice. Please rate how well you agree with the following statement. - I identified at least one new idea, theme, theory, or technique that I plan to use in my practice.	1	3	2.52	.587
Q27_1	For the workshop event, please rate your satisfaction with how well you think your datasprint team worked together. - How satisfied were you with your datasprint team and how you worked together?	1	3	2.63	.546

Appendix B

R code to generate a letter regarding a student's absenteeism

```
############### Define variables for loading data and exporting letters

path <- "C:/Users/"  #Path to load data and export letters
data_folder <- "Total Daily Absence Counts/"
dataset <-"Total Daily Absence Counts by Student.csv"
letters_folder <- "Truancy Letters"
absences_threshold <- 100  #Threshold that defines chronic absenteeism
letter_variables <- c('Student.ID', 'Student.Name', 'Building.Name',
      'Count.of.Absences')

############### Define a function for loading & processing data

load_data <- function(workDirPath, dataFolder, datasetName,
      absenceThresh) {
  file = read.csv(file=paste0(workDirPath, dataFolder, datasetName),
      header=TRUE, stringsAsFactors=FALSE)
  dataSet <- subset(file, select = c(letter_variables))
  dataSet$Student.First.Name <-sub('.*,','',dataSet$Student.Name)
  truantData <- subset(dataSet, Count.of.Absences >= absenceThresh)
  truantDataUnique<-truantData[!duplicated(truantData$Student.ID),]
  return (truantDataUnique)
}

############## Define a function to generate a letter regarding a
      student's absence

library(rtf) #Package for exporting Word documents
```

```
 generate_letter <- function (studentID, dataset){
    select_student <- subset(dataset, Student.ID == studentID) #Extract
      the student of interest
    message <-  paste0(select_student$Building.Name, "\n\n To the
      Parent/Guardian of",
            select_student$Student.First.Name,",\n\n ",
            "          Please be aware the New York State Department of
            Education Student Information Repository System collects
            attendance and punctuality data on all students in order to
            generate a list of chronically absent students, as well as
            students who are at risk of being chronically absent. It is
            imperative for students to arrive at school on time so they
            are present for the beginning of the instructional day.
            Please note that our day at ",
            select_student$Building.Name, " begins at 8:40 a.m., and it
            is crucial that students are in their classrooms at this
            time.\n\n",
            "To date this school
            year,",select_student$Student.First.Name, " has missed ",
            select_student$Count.of.Absences, " days.\n\n          In
            an effort to maximize the instructional day, please make
            every effort to ensure that your child comes to school
            daily in a timely manner.  Consistent attendance and
            punctuality is crucial to students' success in school.  I
            thank you for your support in this important matter.

            \n\n Sincerely, \n\n\n\n PRINCIPAL'S NAME\n Principal
            \n\n\n\n\n cc: Student Folder\n Health Office\n School
            Social Worker")

fileName <- paste0("Student Absence Letter - id ",
      select_student[1,1],".doc")
rtffile <- RTF(fileName) #Name the document to be exported
addParagraph(rtffile, message) #Insert the message into the document
done(rtffile)
}

## Generate letters for all students whose absence count exceeds the
      given threshold

absence_data <- load_data(path, data_folder, dataset,
      absences_threshold)

#Create folder for storing letters and reset working directory to it
dir.create(file.path(path, letters_folder), showWarnings = FALSE)
setwd(file.path(path, letters_folder))

truant_students <- absence_data[,1]

for (i in truant_students){
    stuId <- i
    generate_letter(stuId, absence_data)
  }
```

Appendix C

Example exported letter

BUILDING NAME

To the Parent/Guardian of STUDENT,

Please be aware the New York State Department of Education Student Information Repository System collects attendance and punctuality data on all students in order to generate a list of chronically absent students, as well as students who are at risk of being chronically absent. It is imperative for students to arrive at school on time so they are present for the beginning of the instructional day. Please note that our day at BUILDING NAME begins at 8:40 a.m., and it is crucial that students are in their classrooms at this time.

To date this school year, STUDENT has missed 109 days.

In an effort to maximize the instructional day, please make every effort to ensure that your child comes to school daily in a timely manner. Consistent attendance and punctuality is crucial to students' success in school. I thank you for your support in this important matter.

Sincerely,

PRINCIPAL'S NAME
Principal

cc: Student Folder
Health Office
School Social Worker

Monroe, 2021

CHAPTER 25

Moving the Conversation Forward for the Way Educators Would Like to View and Interpret Educational Data

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Nassau BOCES

Abstract

The purpose of my mini chapter is to discuss the notion of moving the conversation forward, for the way users, which consist of Superintendents, principals, teachers, and students, would like to view/interpret their educational data, based on the National Science Foundation (NSF) workshop held in early December of 2019. As a programmer analyst, for Nassau Boces, I am working on creating data tools, dashboards, that will display visualizations based on educational data for the county/districts that Nassau County Board of Cooperative Educational Services (Nassau Boces) works with. Educational data is data that corresponds to the county, district, schools, teachers, students, and any other factors that can affect them. Such factors can be tied to poverty, location(city), disabilities, language barriers, and many others. As a person walking fresh into the educational industry there are many

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ideas that I can have for how to interpret data. However, the biggest challenge is creating visualizations that are usable/interpretable. Solving this issue entails having users voice what they would like to be presented with and how. As a data analyst/scientist I can present data in ways that won't be interpretable to many users unless they go through training. District officials and teachers are busy running schools and teaching that they don't have the time to do training on visualizations. Thus, the issue at hand is making the visualizations as interpretable as possible, at a glance, for users, because of their daily activities. The best way to do this is to reach out to the users and ask what they want to see on a dashboard or visualization.

Keywords: Boces, District, data, officials, NSF

Background

My background is in computer science, pertaining to software development/engineering. Currently, I am a Programmer Analyst for Nassau Boces (Boces), for the Instructional Data Warehouse (IDW). At Boces we handle school data that pertains to the county of Nassau. The information stems from school districts, school buildings, teachers, students, and much more. Before coming to Boces, I was a Software Developer/Engineer for an insurance company. Making the jump from an insurance agency to an educational agency was huge, for me. This, however, was a challenge that I was very excited to take on. Being part of this industry provides a method to give back to the community. Hopefully, providing a better understanding on how to handle information, or read it.

I was brought on to Boces to find a way to extract data and present the findings in visualizations. Data must be presentable in a way, such that, district officials will be able to interpret. This happens to be one of the main issues, at hand. The data that is being brought into the IDW stems from multiple Student Information Systems (SIS), also known as Student Management Systems (SMS). The SISs are used directly by school districts/schools. They provide a means, for Boces, to retrieve data from them. Once this data is migrated, over to us, we process it and create reports. Processing data can be extensive causing reports to idle until processing is done. SIS data is not always readily available, to us here at Boces. Therefore, I have been working on a system where data can be extracted from the SISs, as soon as it is available within a district/school. This makes the processing faster, won't have to wait for data migration, and we can now work on creating reports and visualizations.

The trouble, that arises, with visualizations is being asked for a dashboard to present them. What type of dashboard is being asked for? What visualizations do users want to see? How will they access this? Are they going to require training? These are some of the questions that come up when trying to create a dashboard for school districts, schools, and teachers.

NSF Workshop Summary

Firstly, thanks to the organization of Alex Bowers, from the Teachers College, Columbia University, and Meador Pratt, from Nassau Boces, along with the help of many other organizations the workshop was able to take place and be a huge success. Planning a two-day event and sticking to schedule can get challenging. Especially when many folks travelled from far to attend the workshop. However, it was this resolve to make it to the workshop and the participation from everyone that made this event a huge success.

The NSF Education Data Analytics Collaborative Workshop was the final event of the NSF funded research project (NSF #1560720) "Building Community and Capacity for Data-intensive Evidence-Based Decision Making in Schools and Districts". This research project is a collaborative partnership on data use and evidence-based improvement cycles in collaboration with Nassau Boces.

The purpose of this workshop was to bring data scientists/analysts, district officials, teachers, principals, superintendents, and Nassau Boces IDW team together to discuss data in schools. All that attended the event were split up into teams. The teams were organized by filling out a pre-event survey. The discussion of data deals with how the data is used in schools, currently, as well as how officials would like to see the data that they are providing, to the IDW. For instance, from an initial discussion with an elementary school teacher, at the workshop, there is no way for assessing young elementary school students using early literacy assessments because data is not being uploaded to any data management system. The data is only available to the teachers because they upload them to their own personal files without uploading them, or having the ability to, anywhere that is accessible by the IDW. If data that was being stored personally were viewable, about how a student performs when they start being assessed, it would be easier to evaluate them over time. Currently evaluation does not start until students start taking New York State (NYS) Assessments. If the data before students start testing were available and measures can be taken to evaluate correlations, if any, between early literacy and NYS Assessments, there could potentially be an influence to store early education performance into data systems. From walking into the workshop and speaking with my fellow peers, before even getting to the notion of what was going to happen throughout the two-day event, it became clear that there is a want for better management systems and dashboards to help in assessing students with an explanation of what a user would like to see. This made me eager to listen carefully, and see, to where the workshop would lead.

Day One

The first day of the conference started with getting to meet the teams that we were assigned. I was in team Triangle. Introductions were handled by stating how we arrived at the NSF workshop, see figure one below. The way we arrived at the NSF conference was based on key events, from the past. We were asked to use three events from our past that guided us to NSF, on this day. It seemed, everyone in my team had a scientific background. Whether it was biology, chemistry, or computer science we all shared an interest in science. During these introductions we were discussing our backgrounds and how they shaped the events that led us all to being on the same team. At this point I let my teammates know that I am not a data expert on educational data and was hoping to understand more about what school officials wanted to view using data. As well as was going on within the school districts that may impact the data being used. Apart from this, I would be able help in summarizing ideas and help lead discussions. As I have an understanding as to how the data would come into IDW. Doing so helps the team stay on track with our tasks and finding solutions.

Once done, with introductions, workshops were set around the conference floor. The workshops were informationals, including data driven visualizations, on what field experts examined. The examinations were from close observation, and/or data mining, within educational settings from kindergarten to twelfth grade (K-12). The teams then split up to attend the workshops. No two team members were at the same workshop, at the same time. The purpose was to share what each team member learned with their teammates. A few rounds of attending workshops was done. After each round, the teams gathered to makes Post It Notes. Post its were used to organize them into groups. Organizations of the notes was based on the content of the notes. Note content would stem from a variety of topics, as there were many workshops displaying something different. However, as different as the workshops were, they could be grouped together as the subject matter could be like other workshops. Once the post it notes were grouped together, we started labeling the groupings, as closely and accurately, to what they represented. The purpose for the labelling was to take the title of each grouping and make a statement for each, see figure two. These statements were used to formulate ideas on attacking the findings. Followed by the information that would be helpful to use and make decisions.

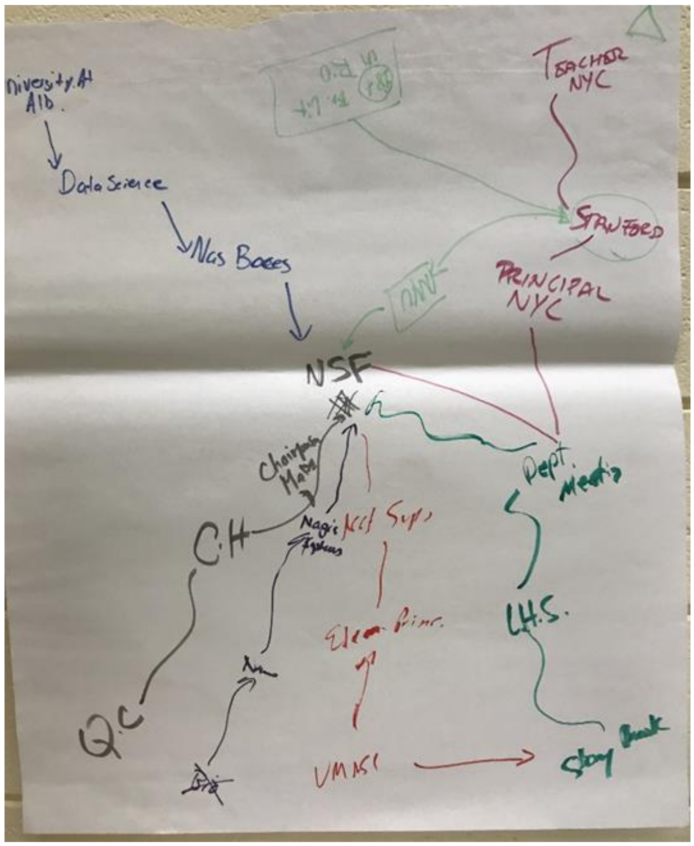

Figure 25.1. *Figure representing how group members ended up at NSF Conf*

As a data analyst, it was informative engaging with educational data professionals, which consisted of teachers, principals, and superintendent officials, to absorb what was said on the observations from the workshops, and anything else that was mentioned about their own experiences. All my team members had input about the statements and were excited with finding a solution to bring their thoughts to light, they were able to sympathize with the sentiments of the workshops. As an analyst, I began to ponder on whether their solutions were possible, which consisted of visualizations and reports, and they certainly are only set back is the demand must be there. With the demand there must be an explanation as to how the thoughts were to be carried out. From experience, I produce what is being asked for. The issue that arises is that I may create something far from what is being asked, or something that is not understandable, or readable by an everyday user. Going back to what was stated previously this would cause more training sessions needed and more reminders on how the visualizations work. This leads to users being overwhelmed and driven away from using data visualizations. Instead they find them confusing and unflattering. Eventually, leading back to asking for more visualizations later when the originals fall on the back burner.

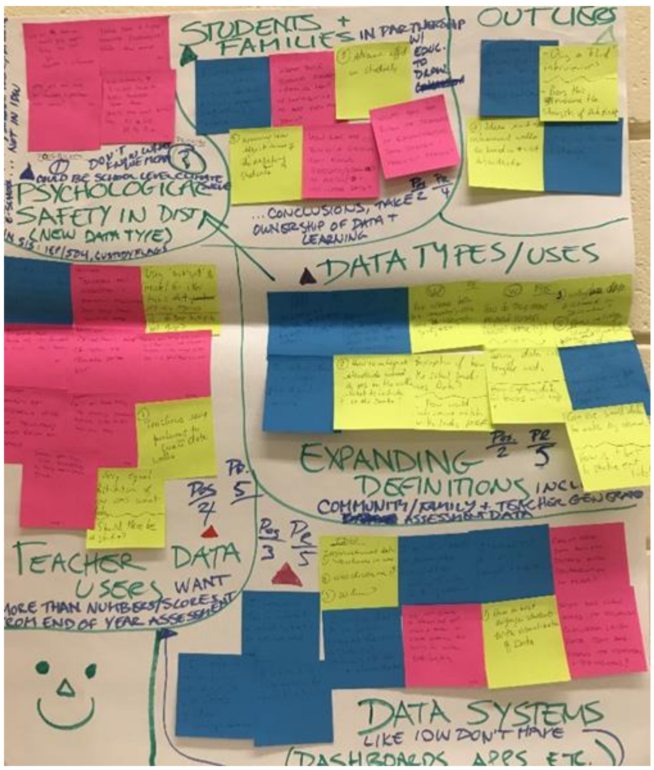

Figure 25.2. *Represents grouping and statements of post its*

Continuing with the statements was an analysis on how feasible it was to produce what the statements were indicating. This was handled by "Possible vs Probable", a way to act on the statements in question, see figure two. Done by assigning a point system to possible and probable, each category was out of five points, with one being the least possible/probable and five being the most possible/probable. Being that possible vs probable scenarios would come down to how it would be managed within Boces, later on the statements and thoughts may have gotten picked up by Boces, I was able to steer the team with how possible and probable the statements, or scenarios, created from statements, were to be implemented. If you look closely in figure two you will be able to find that the sections have their possibility and probability rating. Factors that were taken to decide the ratings were based on the availability of data for each statement/section and the urgency of pursuing a solution. I let my teammates understand how each statement could be handled, by the IDW, seeing as most want to be using the IDW for their data access. Working with the IDW, I understand what can be achievable, compared to what is not. There are scenarios that are both possible and probable, if we have direct access in the IDW. Points were assigned to the statements and plotted on a chart, see figure three. The purpose for this was to visualize where each statement stacked up against one another. This helped in selecting a point to use to continue working with.

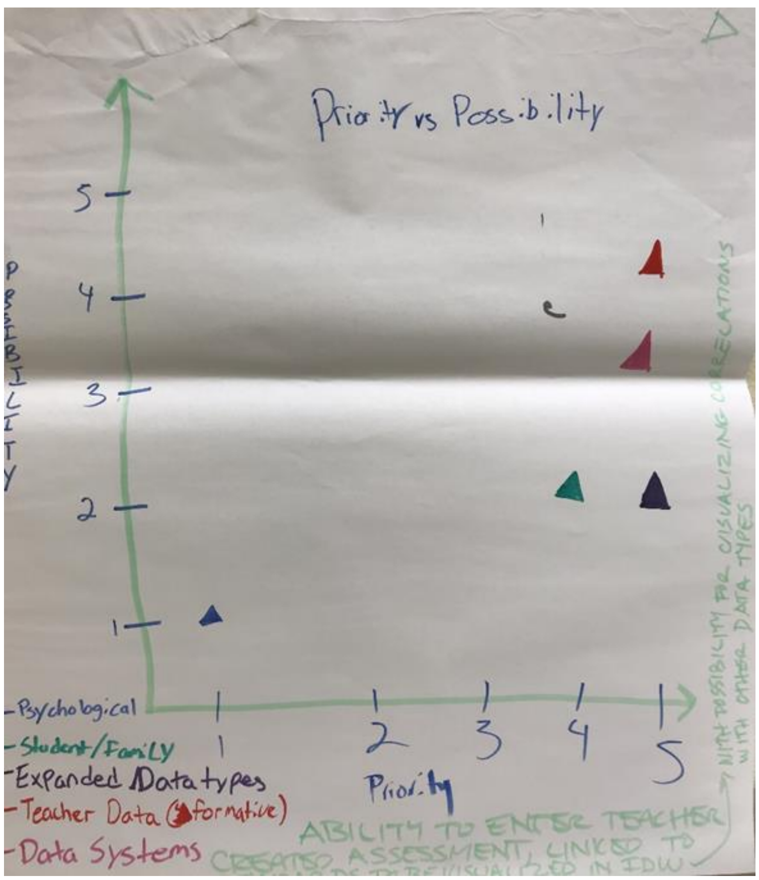

Figure 25.3. *Priority vs Possibility based on Figure 25.2.*

Now, having selected a point, Teacher Data, to work with, for the continuation of the conference, we tackled the next and last part of the day. We selected to utilize "Teacher Data" because this was the highest priority and most possible means to work with. Looking at what the IDW stores this seemed like the best option. There wouldn't be a huge turnaround time from the IDW to the user, given that we can work with data that we already have stored, in the IDW, without going through a standardizing period and asking for more data. Having selected the point, we formulated a question that revolved around the topic of our statement. The main question, see figure four, that we asked ourselves was the following: How can we create a dashboard that will allow stakeholders to utilize student related, including teacher assessments related, data in a quick and efficient manner? As a team we decided that we can switch teacher data to "Stakeholders" because the dashboard would be utilized by stakeholders. The stakeholders include teachers, students, principals, superintendents, and any other governing body that oversees performance of the mentioned. With this question in place we proceeded to ask ourselves who is affected, what to base our data off, initially, when to implement, and where it was going. After answering these questions, the basis for day 2 was set.

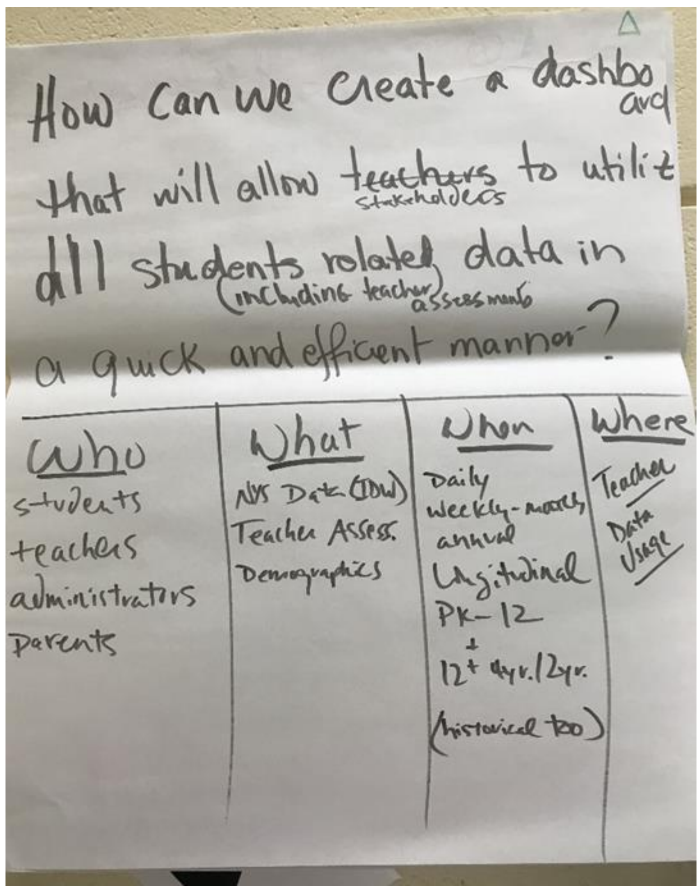

Figure 25.4. *Questions and answers pertaining to Figure 25.3.*

Day Two

Day two started with going around the conference floor and viewing workshops about educational data that was available to data experts. The workshops presented visualizations and reports that could be recreated for use within schools, based on the data that was being used. As well as data driven tools that may be helpful within classrooms or school districts. There were visualizations, in my opinion, that seemed difficult to understand. The tools, however, were very interesting. As a data analyst, I use data manipulation tools with my own work. It was informative how many tools can be used for creating dashboards. There are limitations to each tool, although working within the limitations of each tool then wonderful visualizations or dashboards can be created, as were shown across the conference floor. After the workshop sessions, attendees gathered back with their teams from the day before.

Once together, a data set was presented, by Jeff Davis, Nassau Boces IDW, to the conference that could have been used for the activity of the day. The data set was anonymized student/teacher/school data. The anonymization of the data was done by Davis, his team, and I. The groups were to take the data set, or any data that was willingly shared by team members, as their own data, which would not be anonymized, they had to authorize this, and tackle the question from day one. In our case, we were to tackle how to use student/teacher data and create a visualization that would represent the case and answers of our question. To create the visualization, we had a data scientist on the team, that was assigned to us, take our ideas and turn them into visualizations to present to the other groups. From the perspective of the data scientist, I was eager to hear how the teachers, superintendents, and principals wanted to convey data and what data they wanted to present because later I can turn back around to the team I work with, Boces IDW, and start planning for what is being asked. To answer the question with a visualization we decided to use the data set that was provided by the IDW, as it contained information on teachers and students. A component of the data set that was given, was analysis on how students performed on test standards and questions, commonly known in the IDW as the wrong answer analysis report and referred to as the Wasa. Now, a system that would allow teachers the ability to assess their own students was thought of. This would enhance the data by having a system that would allow teachers the ability to assess students and cross examine them with data already in the IDW. The analysis for student progress on a standard can be graphed on a bar chart. On the same bar chart, analysis on student performance from an assessment is plotted as a line. County analysis is plotted as another line across the chart. Allows for visualizing how accurate a teacher's assessment was and whether students are meeting their standards, based on comparing them to their class and to the exam given, New York State Regents or New York State Testing Program (NYSTP), see figure five below. As soon as this was decided, by the data experts of the team, the data scientist started to portray the visualization by creating an R script. R is a programming a language that is highly likened by data scientists. While this was happening, I was excited about where this could go when I brought the idea back to my team, IDW. The only set back is currently there is no way, currently, for teachers to upload data on how they are assessing their students. Another topic to note is that not every standard appears on a test and certain standards are assessed more than others. The method in showing the performance score must be revised as well as currently there is no real definition for this. This is coming from an analyst perspective that works within the Boces IDW team.

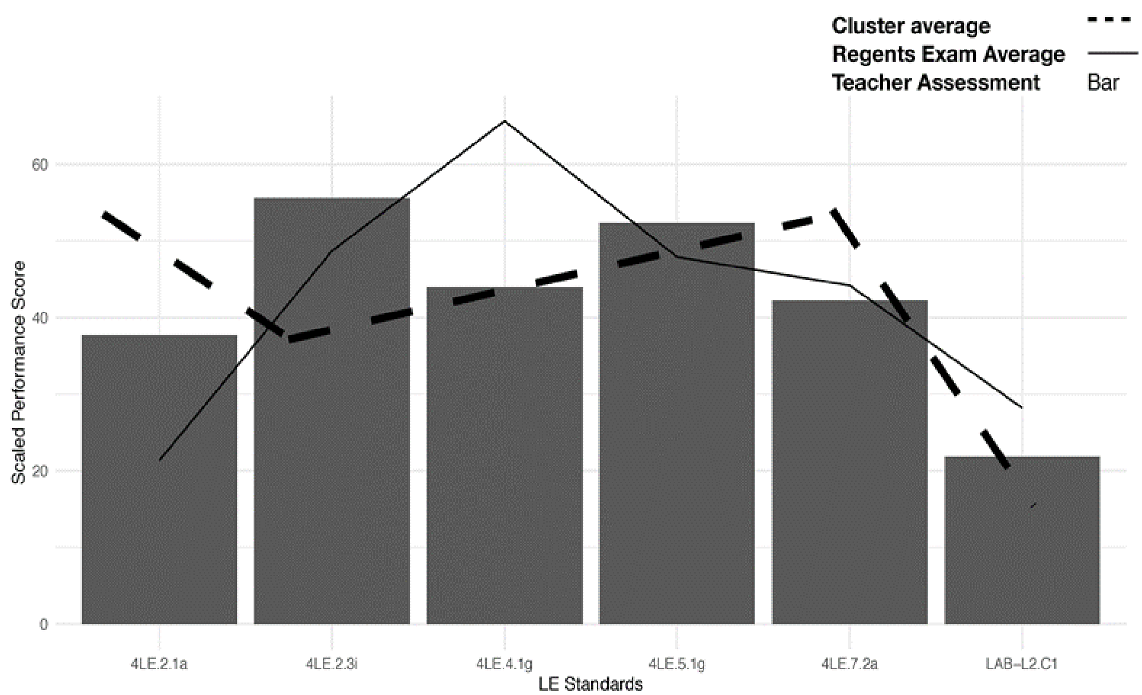

Figure 25.5. *Graph that shows how a teacher assessed her student to do on a testing standard compared, shown in bars. Lines represent how they did compare to the class and the regents.*

While working within our team a few of us had the liberty of visiting other teams to question them, and give them feedback, on what they were working on. I had the liberty of going over to view a report that was working on wrong answer analysis by standard, later to be implemented by IDW by question. The idea of the visualization was to take the Wasa and turn it into a visualization. This was done by showing how many people scored correctly on a standard and how many scored poorly on the standard, each representation was based on multiple choice questions and answer chosen, shown using bar graphs. The graph spanned negative to positive where the positive was the count of students that scored correctly with the bar representing the answer choice and the negative were stacks of blocks that counted students that didn't score correctly. This can prove to be a great way to quickly analyze an exam within districts as the visualization will show you clearly which questions scored better in, or worse, and what answer students were selecting to follow up on instruction to better the questions students got wrong.

After traveling around the room, we came back to our teams and prepared for a one-minute sales pitch as to why our visualizations should be implemented. I don't feel this was enough time to thoroughly express what the data was conveying or give an understanding as to what was being presented. One-minute is little time for presenting a visualization that was created in a few hours. Metrics could not be understood, and the messages were hard to convey for each visualization. Although, some visualizations did have a huge impact and were simpler to understand, if the data was readable and properly labeled. Once all the teams were done with the sales pitches, everyone in attendance went around the room and placed a key fob on the team table one perceived to have the greatest impact from the sales pitches.

Final Remarks

As the two-day conference ended, I began thinking about the impact the conference had. As a data analyst/scientist for Nassau Boces I began to wonder how this conference could go further. At Boces I have been tasked with creating visualizations and dashboards for school districts within Nassau County, New York. The major setback is when asked for a dashboard what exactly is being asked? I am constantly questioning the goal of what I am creating. Many times, I create a visualization that I think will be impactful, only to find that the data was not conveyed in the best method. Meaning that the visualizations were hard to understand for personnel that understand the data being worked with. Part of this is due to not putting myself in other people's shoes. I have had training to read many visualizations while others have not had that liberty. Working in schools there isn't time to learn something new, as curriculum is already extensive and ever expanding. Meaning school personnel must spend a lot of time already doing their immediate tasks. Therefore, creating a dashboard that is only readable by me, and maybe a few others is not ideal. User's will be discouraged to use the dashboard because of not having the proper training. Which brings up the following: as analysts should we be given data and just be told to create a dashboard without knowing what a user wants? I don't think so. The data scientist in my team didn't even start creating a visualization until he understood what the team was asking for. Once understanding the goal then execution was possible. Creating a dashboard without understanding the goal may lead to many not wanting to use our dashboards because there is a chance I, or anyone, misses the mark on what was expected. First glances at a dashboard a user may not find what they are viewing appealing or will need very thorough training of what they are looking at.

The conference brought data users together and were able to express what they wanted to see within a dashboard or visualization, which was fantastic. At this point analysts are sitting with the users and asking questions of what the result should be for a visualization and how it is to be viewed. This will have little difficulty in understanding what is being displayed. To me being able to understand what a user wants is essential in delivering a product. The idea is to make the user happy and wanting more. This allows for user friendliness and pushing of the dashboard onto their peers because most of the time success, and use of a product, comes from word of mouth and usability.

The idea from here is to come up with solutions to bridge the gap when delivering dashboards. A district or school asked for a dashboard? Let's set up a meeting with them to properly ask what it is that they wish to see, before we present the wrong data, which will lead to not continuing discussions. Users also must start asking, and pushing, for the ability to upload data that is not yet loadable to the IDW, for processing. Many times, users have personal markings they want to visualize but can't because there is no way for them to access the data online. It's great they want to use more of our tools to be able to do so, there just needs a push for this to be implemented and then worked upon.

There must be "townhall" meetings at least once a month, quarter, every six months, or every year to bring to light what users would like to see and what their priorities are. Doing this in a group makes it more engaging because everyone is in accordance with what is happening and have an understanding about what the goals will be while their thoughts on visualizations are being worked on. This idea of working out the goals is the same concept as what is possible and the priority for each goal. At Boces we want to provide, to the best of our ability, what we can with the data that we have. If we have a means of securing data from another source and understand what is being desired, then we can provide that as well. After we can provide modifications to adjust. We need to start bringing people in and expanding the conversation.

The conference hosted about seventy school officials, we need to expand this and make it more known what we are doing and what others would like to see. Only then will we be able to have an impact with big data in schools and provide to the best of our ability a standard that can be used by all school districts within Nassau County. At Boces we held a follow up meeting to the conference and quite a few attendees from the conference were present. We need to keep doing so and bringing the people together. Education is too important to isolate the educators they need to be brought in together and figure out means of how we can help them. We are on the right track and must keep pushing forward.

SECTION III

Tools and Research for Data Analysis in Schooling Organizations

CHAPTER 26

Data Viz in R with ggplot2: From Practical to Beautiful Visualizations

Tara Chiatovich
Panorama Education

In my role as Research and Data Scientist at Panorama Education, an education technology company, I constantly create data visualizations during all phases of analysis—from first peeks at data to understand what cleaning tasks lay before me, to final visualizations that communicate complex insights to an audience, and all of the in-betweens. My go-to tool for these visualizations is ggplot2. The package ggplot2 in R is a powerful and flexible tool for data visualization, yet its syntax can be unnecessarily complicated.

This chapter will serve three purposes:

1. Un-complicate ggplot2 for new users;
2. Allow more advanced users to layer additional information and add beauty to their visualizations; and
3. Show the thought process for engaging with new education data, especially in regards to identifying and resolving problems with the data.

The third aim is especially important for educational data scientists. Prior to joining Panorama, I spent two years as a Data Specialist in a school district.

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That time taught me just how messy education data can be, and unlike the datasets that a statistics professor shares, there is typically no codebook to tell you how the data are formatted or what information each variable gives. All of that insight has to come directly from the data. Now I work with data from multiple districts, and the complexity (and sources of confusion) appear many times over. Data visualizations of course communicate findings to an audience, but they also allow the data to communicate with you, the educational data scientist, so that you know what data you have, their limitations, and how you can best put them to use in your analyses.

For each type of visualization, I share the code used to create a plain version (using minimal code) and fancier versions (using additional lines of code). Importantly, the plain versions may be lesser versions than the fancy versions of the visualizations but nevertheless offer valuable insights about the data.

This chapter will start with syntax for installing and loading tidyverse (of which ggplot2 is a part). It will then describe the data used in all the visualizations. After these introductory sections, it will get to the main point of the chapter, which is creating plots through ggplot2. Specifically, it will cover:

- Bar charts;
- Histograms; and
- Scatterplots.

Admittedly, there are many, many more types of graphs that educational data scientists would want to create. The specific examples below may only serve to whet your appetite! For that reason, I end with additional resources and advice for continuing your ggplot2 journey.

Installing and loading tidyverse (which includes ggplot2)

The package ggplot2 is part of the tidyverse suite of packages. Before we can use any of the tidyverse packages, we must install and load them, as shown by the syntax below.

```
# Install the tidyverse suite of packages if not already installed
install.packages("tidyverse", dependencies = TRUE)
# Load tidyverse
library(tidyverse)
```

Description of the data

All participants in the NSF Collaborative Data Workshop received a series of data files that contained mostly authentic educational data from actual districts, though some variables were changed to protect student anonymity. The fact that the data were mostly authentic makes this entire chapter more useful because we can use ggplot to discover problems with the data and likely solutions based on my knowledge of education data. I will use just one data file that contains scores for assessments and refer to it in my code as assessment_data. Below is a description of each variable used or examined in this chapter as provided to us for the workshop, edited for brevity:

1. **School.Year**: The year the assessment was taken
2. **STUDENT_ID**: The local district student ID
3. **Building**: The name of the school building where the student is enrolled
4. **Test.Subject**: The subject area being tested (ELA, Mathematics, etc.)
5. **STANDARD_ACHIEVED**: Indicates the performance level description for students with valid scores
6. **RAW_SCORE**: Raw, un-scaled score (not available for all assessments)
7. **SCALE_SCORE**: The final, scaled score (not available for all assessments)

Here is a snapshot of the data to make clear what each variable gives:

STUDENT_ID	School.Year	Building	Test.Subject	STANDARD_ACHIEVED	RAW_SCORE	SCALE_SCORE
1054	2016/2017	Sample SHS	ELA	Not available	7	53
1054	2016/2017	Sample SHS	ELA	Not available	7	53
1054	2016/2017	Sample SHS	ELA	Not available	18	77
1054	2016/2017	Sample SHS	ELA	Not available	7	61
1054	2017/2018	Sample SHS	ELA	Not available	6	51
1054	2017/2018	Sample SHS	ELA	Not available	10	56
1054	2017/2018	Sample SHS	ELA	Not available	8	62
1054	2017/2018	Sample SHS	ELA	Not available	4	50
1054	2018/2019	Sample SHS	ELA	Not available	10	58
1054	2018/2019	Sample SHS	ELA	Not available	10	54
1054	2018/2019	Sample SHS	ELA	Not available	2	42
1057	2018/2019	Sample SHS	Social Studies	Scored 85 - 100	86	86

I acknowledge that the variable names are a hodgepodge of uppercase and lowercase letters, periods, and underscores. Renaming is relatively simple in R, but I elected to leave these variable names untouched for greater consistency with other chapters in this book, which used the same data files from the NSF Collaborative Data Workshop.

Understanding the anatomy of a gpplot object through bar charts

When creating a visualization through ggplot (or a ggplot object), you need to specify three "parts":

1. The dataset, which here is called assessment_data;
2. The variable to use as the x-axis (and the y-axis if applicable);
3. The "geom" type, which tells R the type of graph you are creating (e.g., scatterplot, bar chart).

Everything else is icing on the cake! So if you can feel confident specifying those three components, you can make great use of what ggplot2 has to offer.

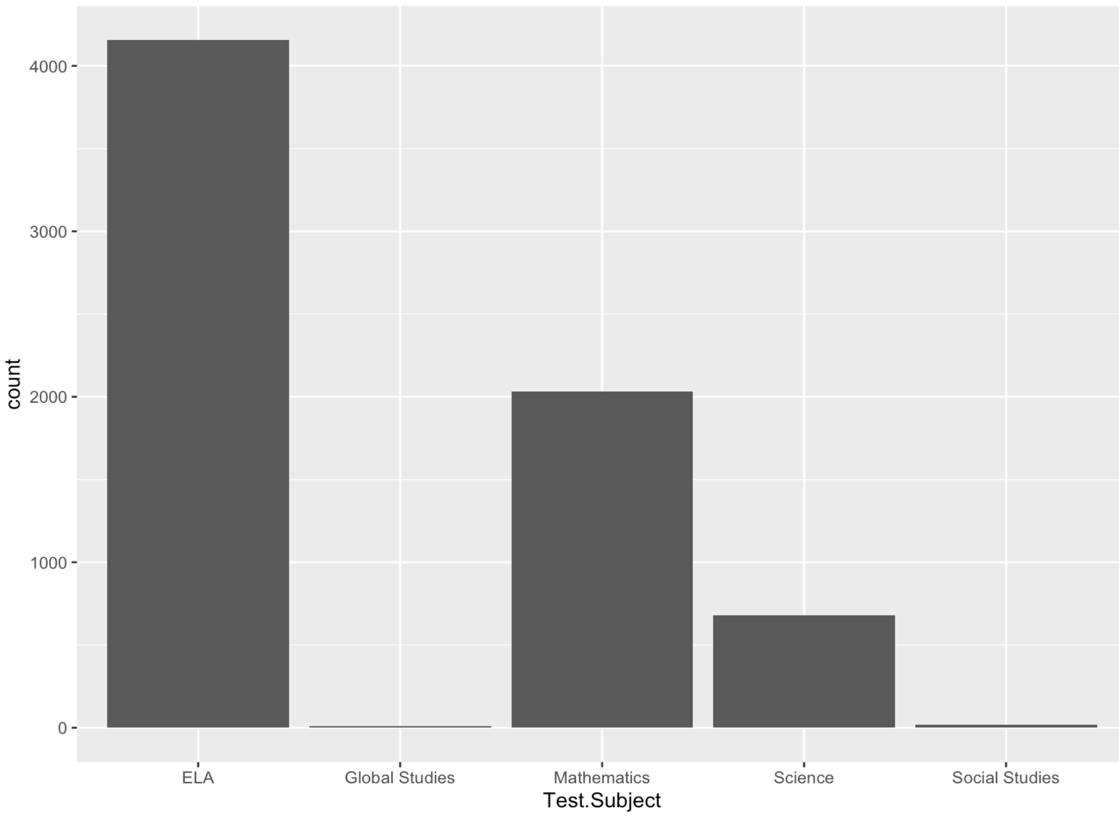
Plain bar chart

In this first example, we will make a very plain bar chart of the number of students with assessment scores in each Test.Subject across values of School.Year.

```
# In the line below, we name the chart and specify the dataset to use
bar_chart_plain <- ggplot(data = assessment_data,
                          # Test.Subject as the x-axis gives one bar
                          # per Test.Subject
                          aes(x = Test.Subject)) +
  # Specifying a bar chart
  geom_bar()
```

We've created the bar chart with the above code and saved it under the name bar_chart_simple, but it doesn't show up in your R plots window until you call up its name, as shown below.

```
# Calling up the bar chart by name to make it appear
bar_chart_plain
```



The above clearly tells me that both Global Studies and Social Studies are rarely-assessed subjects. Any statistical models I might build would suffer from having such a limited number of students with Global Studies and Social Studies scores. I would filter these subject areas out as part of the data cleaning process due to the small number of students with assessments in them and instead concentrate on ELA, mathematics, and possibly science.

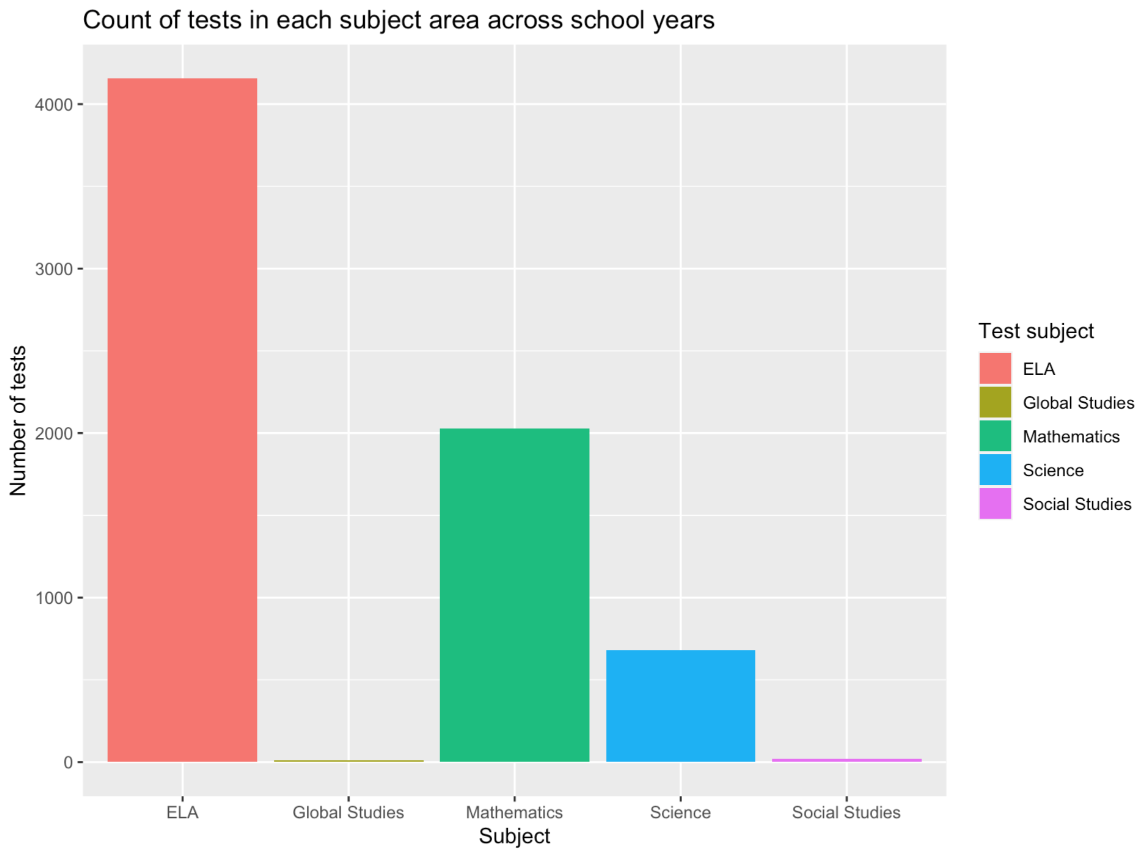
Bar chart with color and custom labels

Now let's add color to the bars, labels to our axes and legend, and a title to show how providing a bit of extra code in ggplot2 can provide wonderful returns on your investment.

```
# Name the bar chart and specify to use assessment_data for it
bar_chart_color <- ggplot(data = assessment_data,
                          # We give the x-axis column;
                          # "fill" colors bars by Test.Subject
                          aes(x = Test.Subject,
                              fill = Test.Subject)) +
  # Specifying a bar chart
  geom_bar() +
  # Adding a title and specific labels for the axes and the legend
```

```
  labs(title = "Count of tests in each subject area across school years",
       # Below"fill" is what labels the legend
       x = "Subject",
       y = "Number of tests",
       fill = "Test subject")

# Calling up our bar chart with colors by name to make it appear
bar_chart_color
```



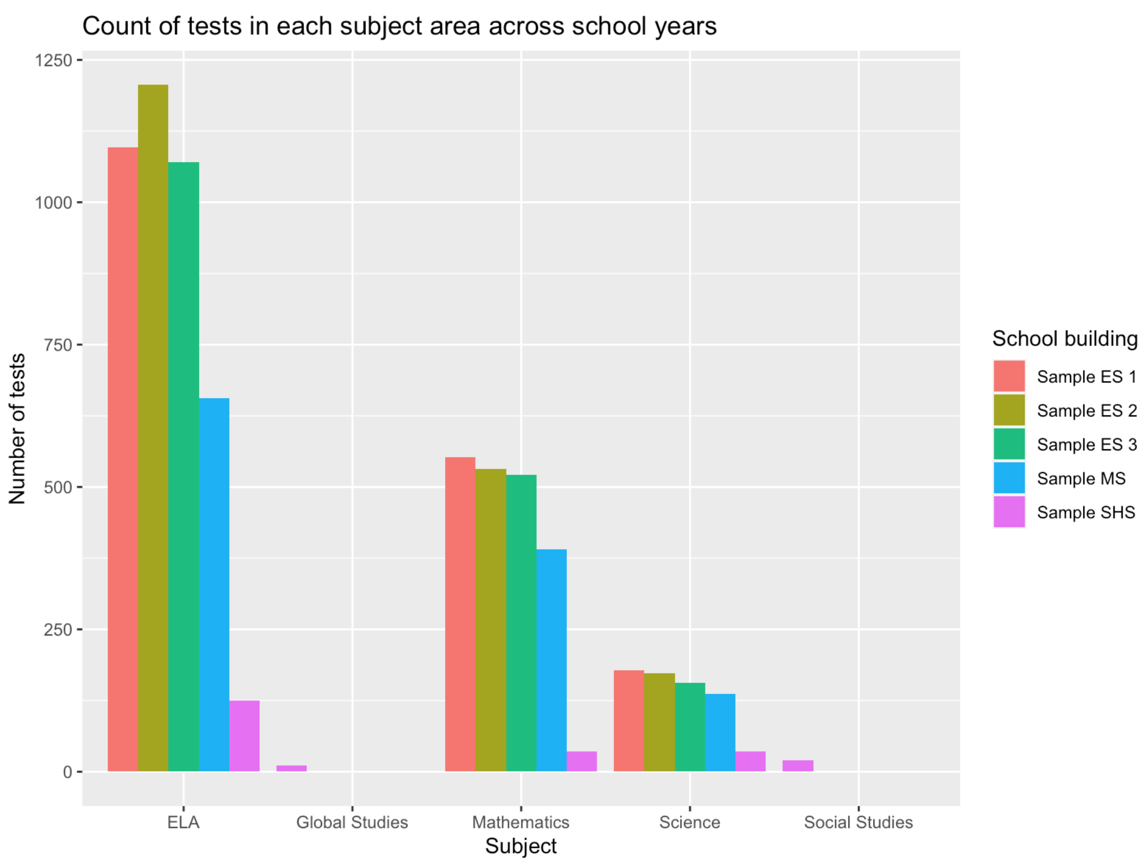
The above adds some clarity and, well, color to our plain bar chart, but it does not add any additional insight. When I see such small numbers for Global Studies and Social Studies, I wonder whether we have a variable in our data to help explain it. Could it have anything to do with which individual school students attend and what subject areas are given priority for assessments in those schools?

Grouped bar chart

To find out, we can create one final bar chart, but this time where color reflects the school building students attend (the Building variable). This is an example of a grouped bar chart.

```
# First line is as before, with new name for the ggplot2 object
# but specifying the same assessment_data
bar_chart_grouped <- ggplot(data = assessment_data,
                            # The x-axis is also the same, but fill
                            # is set so that color reflects Building
                            aes(x = Test.Subject,
                                fill = Building)) +
  # Specifying a grouped bar chart with position_dodge
  # Note that the combination of posistion_dodge and
  # (preserve = "single") makes it so that all bars will
  # have the same width, even with only one Building
  # represented for a subject area
  geom_bar(position = position_dodge(preserve = "single")) +
  # Adding a title and specific labels for the axes and the legend
  labs(title = "Count of tests in each subject area across school years",
       x = "Subject",
       y = "Number of tests",
       fill = "School building")

# Calling up our grouped bar chart to make it appear
bar_chart_grouped
```



We now have a better understanding of why the numbers are so low for Global Studies and Social Studies. Only one school, the high school, has assessment scores in these subject areas.

If you are new to ggplot2, you may not recognize it, but the code for the above plot makes clear how lucky we are to live in an internet age. While initially drafting code for this plot, I used the following line to make the visualization a grouped bar chart:

```
geom_bar(position = "dodge")
```

This line of code is typically what I use for grouped bar charts. But, after seeing the plot, I was dissatisfied with it because that line of code resulted in very wide bars for Global Studies and Social Studies, which were taking up all the space for the five schools. I wanted the bars to have constant width, whether one school or all five had assessment scores for the given subject area. A quick search in Google sent me to this page where Stack Overflow (2018, August 7) user aosmith provided the answer:

```
geom_bar(position = position_dodge(preserve = "single"))
```

You may notice the lack of quotes following "position =", which is unlike the alternate line of code from above. Even as someone who loves and relies on ggplot2, I admit that this tweak to the code to produce the desired result is not something I would ever guess on my own or am likely to even remember two months from now. The lesson is, if there's something you don't like about your plot, use a search engine to come up with example code that will provide a workaround.

Histograms and a crash course in dplyr for data manipulation

When I was first starting out in ggplot2, I took an online course that showed me the basics, and I was instantly discouraged. Why? The problem wasn't the ggplot2 syntax per se. Instead, it was everything I had to do to my data to get them in a format that would allow me to create the plots I wanted. I have no solution to this problem except to encourage you to master the basics of dplyr, the package in R that is all about managing your data. I love dplyr, and though I am asking a lot for you to learn the basics of it alongside ggplot2, at the very least, dplyr's syntax is pretty intuitive. Note that I'm not going to show you all you need to know to move forward with dplyr; I'm only going to show you enough to make the visualizations for this chapter. Fortunately, *R for data science: Import, tidy, transform, visualize, and model data* (Wickham

& Grolemund, 2016) is a free ebook with a chapter devoted entirely to dplyr and data manipulation: Chapter 5: Data Transformation.

At first, we'll use dplyr to accomplish a simple aim. When calling up the data to create our ggplot2 histogram, we'll filter to keep only rows where the value of Test.Subject is Mathematics, ensuring that all scores are math scores. We can accomplish this filtering without having to save a separate dataset in R thanks to piping, which is important to understand.

This symbol in R %>% (made with the keyboard shortcut Shift + control + M on a Mac) is piping, and it "pipes" the object from the previous line into the new line. So, for example, imagine you want to use a function of this general format:

```
function(data_for_function, specifics_of_function)
```

Piping in this case would work like this:

```
data_for_function %>%
  function(specifics_of_function)
```

The piping "pipes" the data frame from the above line and places it as the first object inside of the parentheses for the function. In ggplot2, piping is incredibly helpful because it allows us to tweak the data for the plot without having to go through the trouble of creating several different datasets that we save under a myriad of different names. Not only does saving datasets clutter up your R session and use up memory, it also has the annoying habit of pausing your workflow as you struggle to think of yet another name to distinguish your 16th dataset from your very similar 15th dataset. The following example will help drive home how handy the combination of piping and some basic dplyr code is when creating data visualizations in ggplot2.

Plain histogram

Below is code for a plain histogram showing scores for math assessments only (thanks to filtering in dplyr).

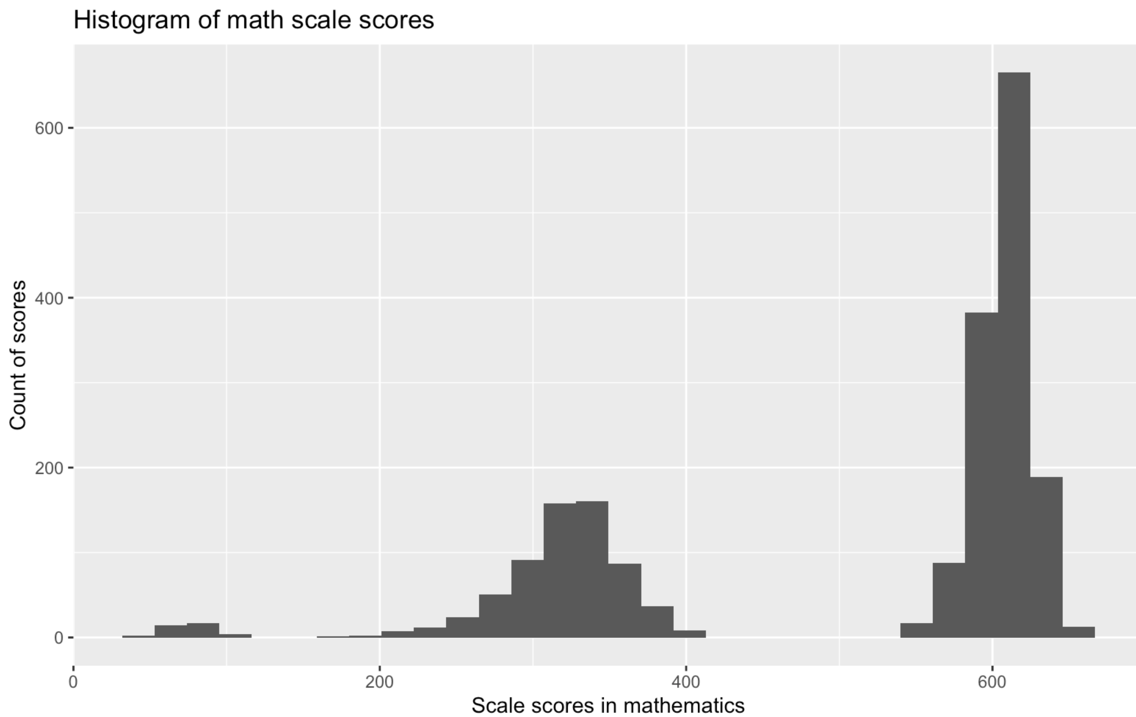
```
# Plain histogram of math assessment scores
histogram_plain <- ggplot(data = assessment_data %>%
                            # Filtering to have only one
                            # Test.Subject (Mathematics)
                            filter(Test.Subject == "Mathematics"),
                          # Specifying SCALE_SCORE as the column to
                          # display and having color reflect height
                          # (the count of scores)
```

```
                          aes(x = SCALE_SCORE)) +
  # Specifying histogram for the viz
  geom_histogram() +
  # Making nicer labels
  labs(x = "Scale scores in mathematics",
       y = "Count of scores",
       title = "Histogram of math scale scores")

# Calling up the histogram
histogram_plain
```

Note that the plain version of the plot contains extra lines of code to make nicer labels. Although nicer labels aren't strictly necessary, from now on, every plot will feature clear labels because labelling is important for understanding what the plot shows us.

Here is how our plain histogram looks:



The above makes clear why I rely on histograms when understanding a new dataset. We clearly have a problem with our math SCALE_SCORE values. We see a chunk of scores that range from about 200 to about 400 and a larger chunk of scores (as evidenced by the higher bars in the histogram) ranging from about 550 to about 650. Additionally, a very few number of scores are under 150. I see this pattern and immediately think about what could be causing it. Did the school district switch which math assessment it gave students partway through the three years of data? Are students therefore taking different assessments on different scales (with different minimum and maximum scores possible)? To find out, let's make use of paneling in ggplot2.

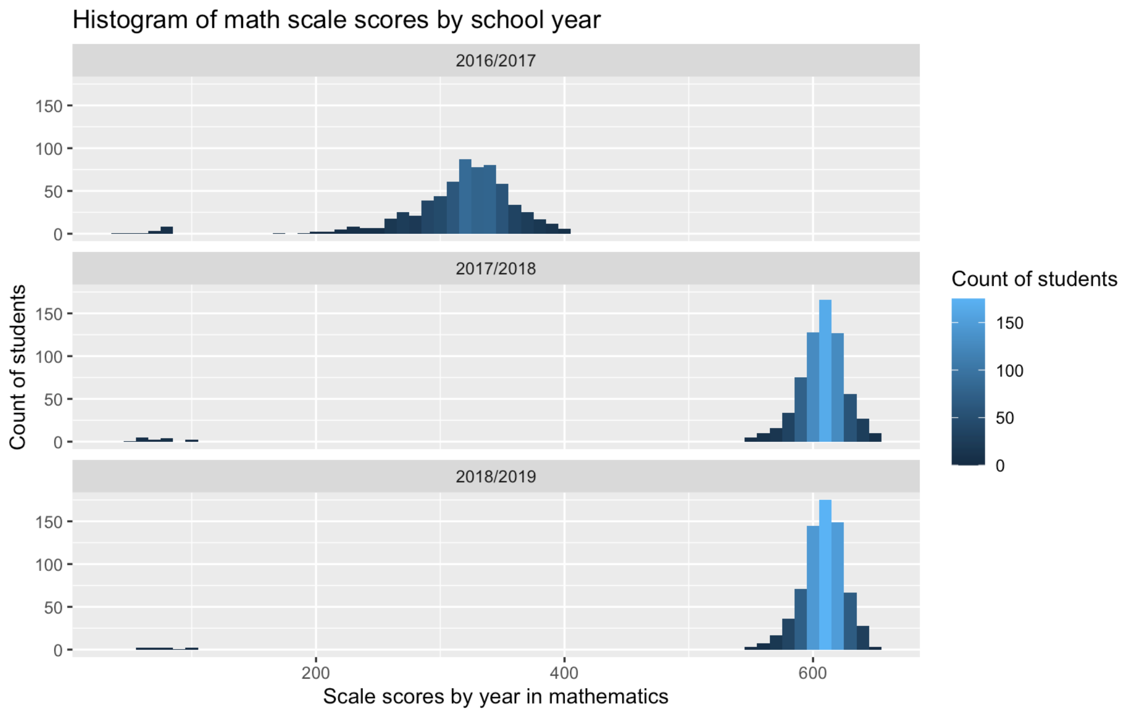
Histogram to show how paneling works in ggplot2

Paneling in ggplot2 allows us to have multiple plots side by side or stacked on top of each other or even in a grid without having to recreate the code for each data viz. I want to panel by year because I have a hunch that the assessment changed from one year to the next, resulting in the pattern that we saw above. I also want to specify the bin width (the width of each bar in the histogram) to have that detail constant across the panels. Finally, I'll have the color of the bars reflect the count. Although doing so does not offer any additional information (since we can see from the height of the bars alone what the count is), it does give us another way to identify differences in count while making the histogram more visually appealing (inspired by this blog post; Burchell & Vargas Sepúlveda, 2016, February 28).

```
# Making our histogram with paneling by year where color reflects count
histogram_paneled <- ggplot(data = assessment_data %>%
                              # Filtering to have only one
                              # Test.Subject (Mathematics)
                              filter(Test.Subject == "Mathematics"),
                            # Specifying SCALE_SCORE as the column to
                            # display and having color reflect height
                            # (the count of scores)
                            aes(x = SCALE_SCORE,
                                fill = ..count..)) +
  # Specifying histogram for the viz and setting the binwidth
  # (width of each bar making up the histogram) to 10
  geom_histogram(binwidth = 10) +
  # Creating separate panels on top of each other by value of School.Year
  # The dir = "v" part of the code stacks the panels vertically
  facet_wrap( ~ School.Year, dir = "v") +
  # Making nicer labels, adding a title
  labs(x = "Scale scores by year in mathematics",
       y = "Count of students",
       fill = "Count of students",
       title = "Histogram of math scale scores by school year")

# Calling up our paneled histogram
histogram_paneled
```

Here is the resulting histogram:



This data visualization shows that the scale of the math assessment scores differs by years and thus supports my hunch that this school district changed from one math assessment in the 2016-2017 school year to a different math assessment for subsequent years. Regarding the very few scores that are under 150, the problem appears across all years. An inspection of the data reveals that some rows have raw scores and scale scores that differ whereas some have identical scores for the two types:

School.Year	Test.Subject	RAW_SCORE	SCALE_SCORE
2016/2017	Mathematics	55	389
2016/2017	Mathematics	31	290
2017/2018	Mathematics	73	73
2017/2018	Mathematics	80	80
2017/2018	Mathematics	65	65

Thus, as evidenced by the paneled histogram above and the snapshot of the data, some rows appear to have erroneous values of SCALE_SCORE, and we can identify which rows those are by checking whether the RAW_SCORE and SCALE_SCORE values are equal to each other. I will filter out these rows in remaining data visualizations of SCALE_SCORE.

Histogram with vertical line for the mean

I see some next steps for our work with histograms. District leaders often want to know the trend for assessment scores. Are scores improving from one year to the next? Are they staying the same? Are they decreasing? We also want to do some filtering, dropping any cases where the raw score is equal to the scale score and excluding scores from the 2016-2017 school year since they are on a different scale. (Obviously, an upward or downward trend is only meaningful if students' performance on an assessment changed, not if the assessment itself and its possible scores changed.) We can highlight the trend from 2017-2018 to 2018-2019 by adding vertical lines to our histogram that show the mean score for each year. Doing so will require more work in dplyr.

We start by storing the means of math assessment scores by year for 2017-2018 and 2018-2019. This part is strictly in dplyr, and we save it as its own R object so that we can refer to it in the code we write to create the paneled histogram.

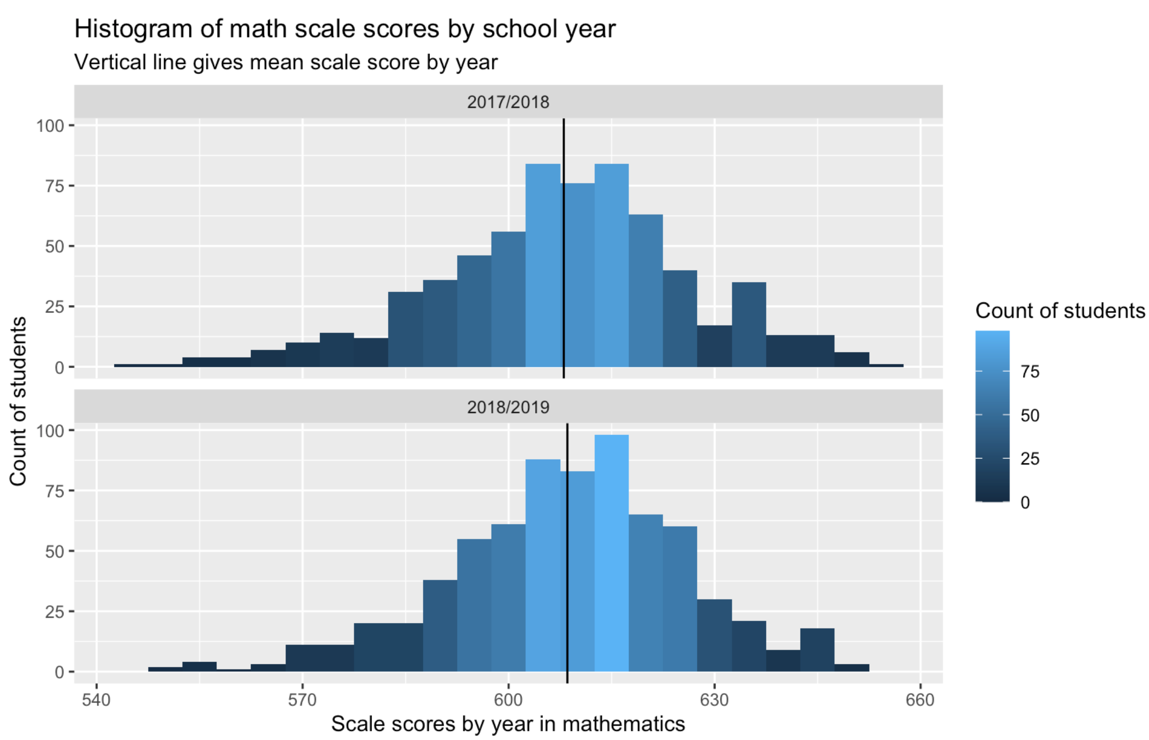
```
# Store the means for SCALE_SCORE by year
means_by_year <- assessment_data %>%
  # In the graph below, we will filter our data to only have Mathematics
  # and leave out the 2016-2017 school year as well as any rows
  # where the scale score equals the raw score. We do the same
  # filtering here to ensure means match the data for the histogram.
  filter(Test.Subject == "Mathematics" &
           School.Year != "2016/2017" &
           SCALE_SCORE != RAW_SCORE) %>%
  # Selecting only the variables needed to calculate mean by year
  dplyr::select(School.Year, SCALE_SCORE) %>%
  # Grouping by School.Year to get separate means by year
  group_by(School.Year) %>%
  # Storing mean in the variable scale_score_mean
  summarize(scale_score_mean = mean(SCALE_SCORE, na.rm = TRUE))
```

Now that we have our means, we can use very similar code as before but leaving out the 2016-2017 school year and layering vertical lines for the mean for each year on top of their respective histogram panels.

```
# Making paneled histogram with vertical lines showing mean by year
histogram_w_mean_lines <- ggplot(data = assessment_data %>%
                           # Filter our data to only have
                           # Mathematics and leave out the 2016-2017
                           # school year plus any rows where the
                           # scale score equals the raw score
                           filter(Test.Subject == "Mathematics" &
                                    School.Year != "2016/2017" &
                                    SCALE_SCORE != RAW_SCORE),
                           # Specifying SCALE_SCORE as the column to
```

```
                                  # display and having color reflect height
                                  # (the count of scores)
                                  aes(x = SCALE_SCORE,
                                      fill = ..count..)) +
  # Specifying histogram for the viz and setting the binwidth to 5
  geom_histogram(binwidth = 5) +
  # Putting the means stored in scale_score_means as vertical lines over
histogram
  geom_vline(data = means_by_year,
             mapping = aes(xintercept = scale_score_mean)) +
  # Creating separate panels on top of each other by value of School.Year
  facet_wrap(~ School.Year, dir = "v") +
  # Making nicer labels
  labs(x = "Scale scores by year in mathematics",
       y = "Count of students",
       fill = "Count of students",
       title = "Histogram of math scale scores by school year",
       subtitle = "Vertical line gives mean scale score by year")

# Calling up our histogram with mean lines
histogram_w_mean_lines
```



The above visualization allows for easy comparison of the mean math assessment score across the 2017-2018 and 2018-2019 school years. We see practically no change from one year to the next in mean scores, showing that on average, scores held pretty steady in these schools across the two years.

Scatterplots and reshaping data in dplyr

Let's continue with the exploration we've done above, focusing on math SCALE_SCORE values for the 2017-2018 and 2018-2019 school year, but now we want to examine these scores not overall by year but instead for each student. We will do so with a scatterplot, which is a key data visualization to examine before calculating associations between two variables.

This time, we will use dplyr to reshape our data. The assessment data are in long format, with students having one row per year. To create the scatterplots, we will put the data into wide format, with one column for each year giving the student's value of SCALE_SCORE in math for the specified year. After viewing the data, I discovered a few students who had more than one math assessment score for a single year because, for example, they took an algebra assessment and a geometry assessment. To solve this problem, we will also deduplicate the data before creating the scatterplots. Both reshaping and deduplicating data are tasks I perform nearly every time I work with a new dataset, so learning the syntax for both in dplyr will prove valuable.

For the scatterplot examples, we will take a different approach to working with our data. Instead of filtering, deduplicating, and reshaping in the same way whenever we use the ggplot command, we will save our filtered, deduplicated, and reshaped data as a separate dataset in R, much in the same way that we saved the means by year above. Then we can use this new dataset anytime we create a data visualization with ggplot2.

```
# Filtering, deduplicating, and reshaping the data
math_data_wide <- assessment_data %>%
  # Keeping only math scores and excluding the 2016-2017
  # school year and cases where scale and raw scores
  # are equal
  filter(Test.Subject == "Mathematics" &
           School.Year != "2016/2017" &
           SCALE_SCORE != RAW_SCORE) %>%
  # Deduplicating the data to have only one row
  # per student ID per year
  distinct(STUDENT_ID, School.Year, Test.Subject,
           # This keep_all option tells R to keep all
           # variables, not only the ones named above
           .keep_all = TRUE) %>%
  # Making one column for each school year,
  # where the values are from SCALE_SCORE
  pivot_wider(names_from = School.Year,
              id_cols = c(STUDENT_ID, level_change),
              values_from = SCALE_SCORE) %>%
  # Dropping rows with NA values in any column
  drop_na()
```

Note that the use of the distinct command above is a haphazard way of getting rid of duplicates. In the case of duplicates by STUDENT_ID and School.Year, R will keep the first row and discard subsequent rows. Typically, one would want to have a set rule for which duplicated row to keep (e.g., the row with the highest score, the row with the most recent date). Here, we proceed by eliminating duplicates based on just their order in the data set for efficiency, but I advise first conducting a careful exploration of the data and if possible discussing with stakeholders to make an informed decision about how to deduplicate data when analyzing educational data in the real world.

The data now look like this:

STUDENT_ID	level_change	2017/2018	2018/2019
4979	No change in level	588	590
4980	Increased level	587	608
5009	No change in level	599	602
5014	Decreased level	618	618
5039	No change in level	612	618
5048	No change in level	594	598
5057	No change in level	577	595
5078	Decreased level	609	609
5091	No change in level	607	610
5102	No change in level	624	624
5113	Decreased level	610	609
5117	No change in level	615	615
5126	No change in level	644	630
5128	No change in level	602	607
5134	No change in level	594	608
5165	Increased level	591	610
5168	No change in level	616	618

A couple of points about the above data are worth noting. First, we do not have any NA (or missing) values because I used the drop_na() command in dplyr to exclude them from the dataset. Dropping missing values results in us having considerably fewer students in this dataset than we did in the dataset for the last histogram above. That's because younger students in our sample may not have been in a high enough grade level in 2017-2018 to take the assessments, and any graduating seniors in 2017-2018 would not be in school in 2018-2019 to take the assessments for that year. Relatedly, the data in the scatterplot that we will create are not the same as the data in the last histogram above because any student with missing math scores for either year will drop out of the scatterplot.

The second point to note about the data is that only the variables specified in the pivot_wider statement appear. There are ways to keep all variables when using pivot_wider (such as by omitting the id_cols option). However, do so with caution as you may end up with data where every row is missing scores for either the 2017/2018 variable or the 2018/2019 variable, making it impossible to create a scatterplot from the data. (If that sentence is hard to interpret, try using pivot_wider without the id_cols option on your own data and observe the results!)

Finally, I have a new variable—level_change—that reflects whether students' standard level achieved on their math score went up, down, or stayed the same from 2017-2018 to 2018-2019. This variable is based on the STANDARD_ACHIEVED variable that categorizes assessment scores as low performance, high performance, or other levels in between. My time in a school district taught me that the standard level achieved on an assessment, and whether it is improving or decreasing from one year to the next, is something that district leaders really care about. It took a decent amount of code to create and so is beyond the scope of our dplyr lessons. But this serves as another plug for building your dplyr skills since they will expand what you are able to show with your data visualizations (as demonstrated by the second scatterplot below).

Plain scatterplot

Let's use this new dataset to create a plain scatterplot.

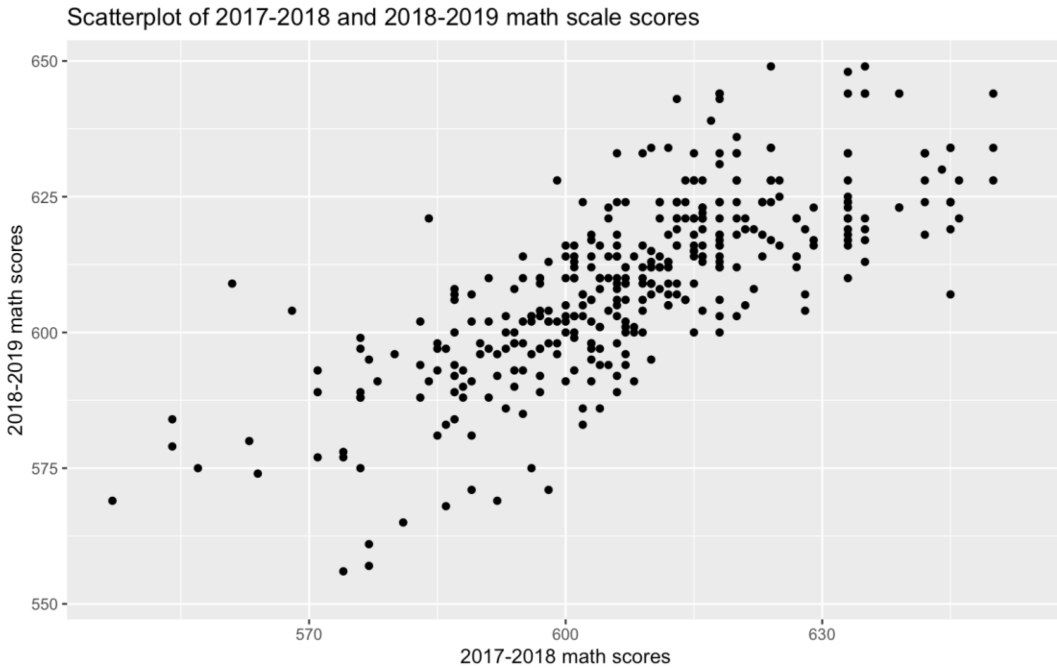
```
scatter_plot_plain <- ggplot(data = math_data_wide,
                             # Specifying 2017/2018 for the x-axis
                             # and 2018/2019 for the y-axis
                             # Notice the backticks (`)
                             aes(x = `2017/2018`,
                                 y = `2018/2019`)) +
  # Here, geom_point() makes the graph into a scatterplot
  geom_point() +
  # Specifying title, x-axis label, and y-axis label
  labs(title = "Scatterplot of 2017-2018 and 2018-2019 math scale scores",
       x = "2017-2018 math scores",
       y = "2018-2019 math scores")
```

Before calling up the scatterplot and sharing how it looks, I want to make clear why the backticks (` located on the same key as ~) in the aes statement are necessary. When we reshaped the data, we used the values for School.Year — 2017/2018 and 2018/2019 — as the basis for the new variables. These values then became the variable names. But in R, 2017/2018 and 2018/2019 are also ratios; in other words, they are numbers that R should evaluate that come out to be very close to 1. We need backticks around 2017/2018 and 2018/2019 to make clear that they are variables in the dataset and not one number divided by another number. In fact, any variable that starts with a character other than a letter needs a backtick when referring to it in code. I know about this quirk when referring to variables with atypical names, but there was a time when I did not and had trouble figuring out why I was getting an error message. R has many quirks like this, so it's a given that people who are new to R can feel frustrated. To that, I say that I feel your pain, and searching Stack Overflow (n.d.) for the exact error message you are getting can provide relief. You can read more about the type of dataset in R that allows atypical names—called a tibble—in this chapter of *R for data science: Import, tidy, transform, visualize, and model data* (Wickham & Grolemund, 2016).

Now that we have that detail settled, let's inspect our scatterplot.

```
# Calling up the name of our scatterplot to display it
scatter_plot_plain
```

Here is the scatterplot:



The scatterplot looks much as we would expect. We see a fairly strong correlation between math scores for the two academic years, and they appear to be linearly related in that a straight line better conforms to the shape of the points than a curve. Unlike the paneled histograms above, this scatterplot makes clear that, overall, students who earned high scores in 2017-2018 also tended to earn similarly high scores in 2018-2019, and the same is true for students who earned low scores. Although we might have assumed this to be true by looking at the very similarly-shaped histograms across the two years, only the scatterplot can confirm it by helping us see each individual student's score for both years.

Scatterplot with semi-transparent points colored by category

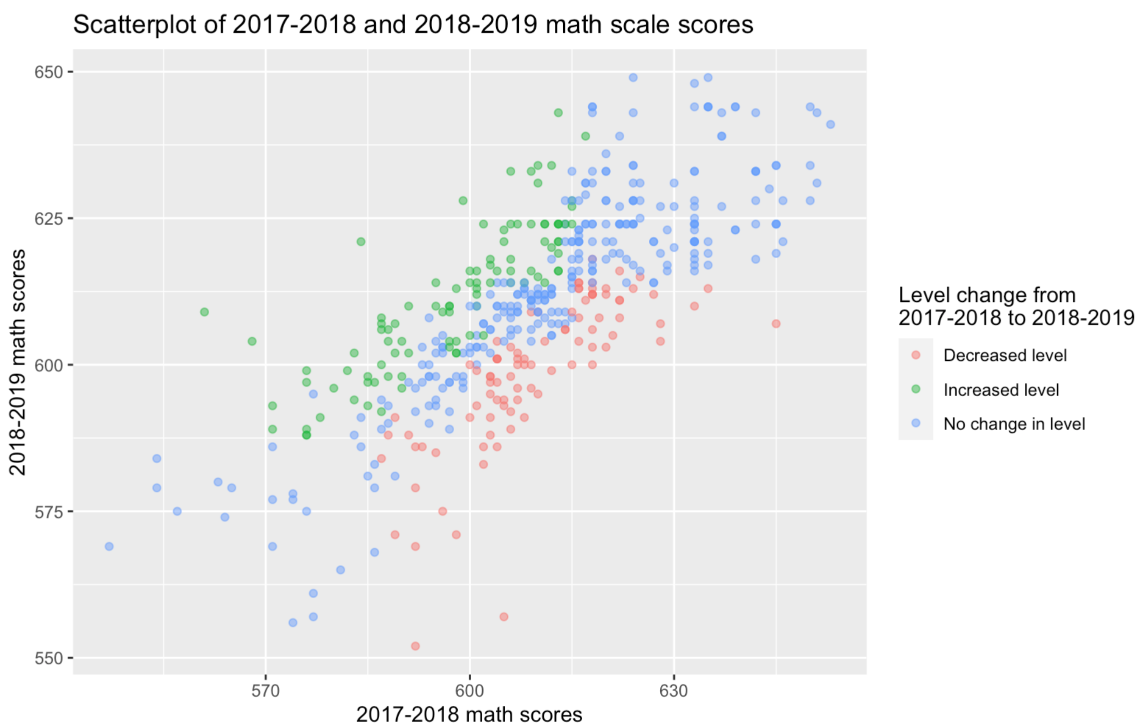
Another trick we will learn with scatterplots is how to make each point semi-transparent so that we can see when multiple points overlap. We will also make use of the level_change variable I created to color each point according to whether students' standard assessed level increased, decreased, or stayed the same and provide a visual cue for how common each of the three categories is. The following code accomplishes both these aims.

```
# Same scatterplot as before but with color by level_change
# and semi-transparent points
scatter_plot_color <- ggplot(data = math_data_wide,
```

```
                              # Specifying 2017/2018 for the x-axis
                              # 2018/2019 for the y-axis
                              aes(x = `2017/2018`,
                                  y = `2018/2019`,
                                  color = level_change)) +
  # Here, geom_point() makes the graph into a scatterplot, and alpha
  # makes each point semi-transparent, which allows us to see when
  # points are on top of each other
  geom_point(alpha = 0.5) +
  # Specifying title, x-axis label, y-axis label, and legend ("color")
  # label
  labs(title = "Scatterplot of 2017-2018 and 2018-2019 math scale scores",
       x = "2017-2018 math scores",
       y = "2018-2019 math scores",
       # The \n in the label below puts everything that follows it
       # onto a new line
       color = "Level change from\n2017-2018 to 2018-2019")

# Calling up our new graph by name to display it
scatter_plot_color
```

Here is the end result:



The above scatterplot shows how making the points semi-transparent helps us understand the data, with more density in the mid-range of scores for both years as evidenced by the darker colors for the (overlapping) points. We also gain new insights from the colors of the points, which show us that similar numbers of students decreased as increased one or more levels but that the largest group was students with no change in level.

Chiatovich, 2021

Resources and advice for continuing your ggplot2 journey

By now, I hope that you feel at the very least equipped to explore your data with ggplot2. But I of course couldn't blame you if you are passive-aggressively making a long list of all that I did not cover and wondering how you will bridge the gap in your knowledge. An excellent resource put together by the makers of ggplot2 is this website (tidyverse, n.d.).

Under the heading "Layer: geoms", you will find succinct information on which "geom" creates which type of visualization (e.g., geom_boxplot() and geom_dotplot() for, you guessed it, boxplots and dotplots, respectively). Use these geoms to branch out well beyond the handful of plot types we created here. You can keep reading this reference for all kinds of variations on the more advanced plots demoed above.

Another compact source of guidance on ggplot2 is this cheat sheet (Grolemund, 2019). Users wishing for more explanation along with code examples can turn to the aforementioned *R for data science: Import, tidy, transform, visualize, and model data* (Wickham & Grolemund, 2016). It has a chapter on ggplot2 that you can access here.

One reason why ggplot2 is my go-to tool for data visualizations is that I am confident I can create exactly the plot I want, even as my vision for how the end product should look goes through a thousand tiny and increasingly nit-picky changes based on what I discover through earlier plots. What is the source of my confidence? Certainly not my vast stores of knowledge. Rather, it's my ability to hit on the right search terms combined with my patience to repeat this process for each individual change I want to make with my plot. I may not be able to find complete code for the plot I want to make, but I am very likely to find a snippet of code that shows me how I can override ggplot's default of ordering categories alphabetically and instead have them ordered from least to greatest. And with that small discovery plus another dozen or so more, I can create the data visualization of my dreams.

But the other reason I use ggplot2 near constantly is that minimal code can give me plain but useful data visualizations. I make plain plots—even ugly plots—all the time! When an ugly plot tells me what I need to know about my data, I save the fussy additions of nicer colors, clearer labels, and reference lines showing trends for data visualizations that other people will see. Because unlike statistical models where all are "wrong" but "some are useful" (Box, Luceno, & del Carmen Paniagua-Quinones, 2011, p. 61), I would argue that some data visualizations are beautiful, but all data visualizations are useful. So go make some useful data visualizations!

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CHAPTER 27

Predicting High School students' performance with Early Warning Systems: a theoretical framework

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Abstract

Principals and teachers struggle with the problem of identifying students at-risk and talented ones early in their educational career, with the purpose of suggesting them the adequate resources and interventions for succeed. Learning Analytics is the new discipline that attempts to provide empirical evidence about the factors that positively affect students' performance, in a personalized and data-driven way. Specifically, Early Warning Systems (EWSs) are becoming a popular tool for this aim, holding the promise to predict students' success and risk early in their educational journey. The existing academic literature is mostly focused on proposing the best algorithms for prediction, but less attention is paid to the theoretical foundations of the empirical models. This chapter attempts filling this gap, by proposing a theoretical model which can complement and guide the efforts directed towards the empirical modelling. The framework is based on considering the educational process like a cumulative one, in which each stage in the educational career affects the subsequent ones. The ability to properly describe such process and to collect sufficient and reliable data is crucial for the success of EWS in formulating accurate predictions. In addition, we claim for the use of findings obtained from EWS for designing (personalized) remedial education interventions for at-risk students and honor programs for talented ones.

Keywords: Learning Analytics, Early Warning System, remedial education, talented students

Introduction

As a part of common research agenda, I (Tommaso) has been invited by my friend and colleague prof. Alex Bowers to attend the NSF Education Data Analytics Collaborative Workshop, held on December 2019 in New York City. As the attendance of the 2018 ELDA (Education Leadership Data Analytics) Summit the year before, the 2019 Workshop has been a great experience, in which I had the opportunity to see how my friends in Teachers College, Columbia University, are developing their research effort int the field of data analytics for supporting key decision-makers in the educational domain. Actively taking part to the work of datasprint teams, I understood how similar the challenges are, for practitioners – teachers and principals – and scholars, between the two sides of the Atlantic Ocean.

In Italy, the research group that I coordinate at Politecnico di Milano (PoliMi) School of Management works on several projects related to Data Analytics in education. Specifically, the research team develops initiatives to support school principals and teachers to use administrative data and evaluation registers for making better-informed decisions. In so doing, we list a number of relevant topics which are a priority for current Italian school managers, from (i) the use of data for continuous improvement (ii) to understanding factors correlated with students' success. These and many others are the main questions that the NSF Collaborative Workshop intended answering, with leveraging the potential advantages of the Learning Analytics techniques and approaches. Working with the people who attended the NSF Collaborative Workshop helped me to focus more on one of the research team's specialty.

Since when I attended the 2018 ELDA Summit, the interest of the PoliMi's research group moved towards the use of data for creating Early Warning Systems (EWSs), with the aim of detecting at-risk students early in their educational path. The educational policy idea is that by identifying these students early, it would be possible to help them through tutoring, remedial courses and/or other supporting initiatives. As the 2019 NSF Collaborative Workshop demonstrated, this issue is of central interest also in the context of US K-12 education, thus I decided to develop a chapter dealing with this topic.

The chapter has been written together with Marta Cannistrà, who collaborates in the PoliMi's research group with the primary responsibility of managing projects related with the use EWSs in schools and universities. Marta and I agreed on the necessity to develop a theoretical framework for EWSs, which are too often confined to a purely empirical perspective. This chapter is our contribution to this field.

1. Motivation – predicting (or analyzing) students' performance is important

Over the last years, governments point out the importance of a quality education for all students worldwide. Anyway, despite the considerable efforts spent to improve access and participation, 262 million children and youth aged 6 to 17 were still out of school in 2017, and more than half of children and adolescents are not meeting minimum proficiency standards in reading and mathematics (UN 2019). To point out this challenge, the 2019's Sustainable Development Goals underlined the need to "*ensure inclusive and equitable quality education and promote lifelong learning opportunities for all*" (objective #4). United Nations also indicates technologies as the major source of opportunity to assure this goal's achievement.

To stress the importance of guaranteeing education for all, the latest edition of the Commission's Education and Training Monitor (2019) shows that, despite national education systems are becoming more inclusive and effective, still the students' educational attainment largely depends on their socio-economic backgrounds. This aspect underlines, once again, the necessity to refocus efforts to improve learning outcomes especially for marginalized people in vulnerable settings and belonging to minorities. The Report finds out that 10.6% of young people in EU are "early leavers" from education and training, so they have never obtained a secondary school degree. A further worrying aspect is that no progress is registered over the past two years about this indicator. Individuals who leave education before obtaining an upper secondary qualification struggle with lower employment rates, even the risk of being unemployed or becoming inactive while peers are attending school. Education is included among the indexes for better life developed by OECD (2015). In particular, obtaining a good education greatly improves the likelihood of finding a job and earning enough money to have a good quality of life. Highly educated individuals are less affected by unemployment trends, typically because educational attainment makes an individual more attractive in the workforce. Lifetime earnings also increase with each level of education attained.

To respond to this threat, EU policy interventions include improving data collection and monitoring, strengthening teachers' capacities, education and career guidance, also supporting re-entry of early leavers (UNESCO, 2017). In this vein, a more structured use of data analyses and policy evaluation is considered as a key to the success of interventions aiming at reducing the achievement gap between advantaged and disadvantaged students.

A robust body of academic research confirms the importance of reducing the dropout rates, i.e. percentage of early leavers in the education system. As also underlined by EU Commission, the risk of experiencing unemployment or unstable careers (and consequently becoming a public cost for society) is higher for early leavers (Rumberger & Lamb, 2003, Prause & Dooley, 1997). In particular, the consequence of dropout phenomenon in high school can be different, both at individual and system level (De Witte & Rogge, 2013); people may face higher unemployment risks (Solga, 2002) and increasing health problems (Groot & van den Brink, 2007). At an aggregate (collective) level, there are higher costs for society with greater risk of criminality (Lochner & Moretti, 2004), less social cohesion (Milligan et al., 2004) or a lower rate of economic growth (Hanushek & Wößmann, 2007).

In this challenging context, detecting students at-risk of dropping out as early as possible will give institutions and schools the opportunity of setting out remedial interventions, with large potential benefits in the long run. This problem can be rooted in the emerging field of Learning Analytics (LA), which can be defined as *" (...) the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs"*[2]. Specifically, for the context described in this chapter, the exploitation of new technological development in the field of predictive analytics and Early Warning Systems (hereafter, EWS) holds the promise to improve the fight against dropout rates in schools.
As a data analytics process, the main aim of using such technique is to provide powerful insights to the decision-makers, for assuming their decisions in the most informed way. The prediction of students' performance allows institutions and schools management to set clearer

[2] This formal definition of Learning Analytics has been formulated in the 1st Conference of Learning Analytics (2011), see here for more details: https://www.solaresearch.org/about/what-is-learning-analytics/.

objectives regarding the learning outcomes (Heppen & Therriault, 2008), as well as discussing practical strategies and interventions for reducing the risk of dropout for individuals and groups of students.

The present chapter provides a short overview of the existing literature dealing with the implementation of predictive analytics in secondary schools. The main purpose is to give a general guidance to researchers and practitioners when developing Early Warning Systems. Meanwhile, we propose a theoretical framework for developing an adequate list of indicators to be used in the analysis and to interpret the results.

The chapter is organized as follows. After this introduction, section §2 contains a brief literature review about Early Warning Systems; section §3 develops our theoretical framework about the components of an adequate EWS; section §4 concludes with some practical indication about how using the results obtained through an EWS, in a policy and managerial perspective.

2. Early Warning Systems in secondary education: a (brief) literature review

The discussion about the use of analytics for predicting students' performance and accompany remedial programs stem from the traditional attention to the serious problem of dropout. Academic research on secondary-school students' dropout can be classified in two categories (Finn, J. D. 1989). On one hand, empirical studies define and estimate dropout rates with ever-increasing precision and examine the factors associated with dropout of individual students, including race, socioeconomic status (SES), school ability and performance or school characteristics (Christle et al., 2007, Allensworth & Easton, 2007, Bowers, 2010). On the other hand, papers, articles and reports describe the efforts and interventions to prevent students from leaving school (Dynarski et al., 2008, Balfanz et al. 2007, Mac Iver, 2011). In fact, simply identifying at-risk students does not alleviate the risk these students face. EWSs to make an impact and prevent students from dropping out, school districts must tailor intervention and prevention efforts based on the data (Pinkus 2008). The present chapter provides some insights about the first stream of this literature, although it also suggests some reflections about how handling remedial interventions in an effective way, leveraging data analytics. Indeed, we can consider the two research streams as sequential: the outputs produced by the analyses of dropouts functioning as the key information source when setting the remedial interventions. We define this two-steps process as Early Warning System (EWS). Commonly, the use of EWS is related to diverse fields of applications where detection is important – as, for example, military attacks, conflict prevention, economical/banking crisis, environment disasters/hazards, human and animal epidemics, and so on. In the educational domain, an EWS consists of a set of procedures and instruments for (i) early detection of indicators of students at risk of dropping out and, in a second moment, (ii) the implementation of appropriate interventions to make them stay in school (Heppen & Therriault, 2008). Early warning indicators are used for early identification and intervention with students to help them get back on track and meet major educational milestones, such as on-time graduation and college and career readiness (Blumenthal, 2016b). Detecting these indicators or factors is really difficult because there is no single reason why students drop out: it is a multi-factorial problem. Consequently, the second step of EWS needs to take into consideration that at-risk students are not a homogenous group, therefore policy makers need to design specific interventions to efficiently target them (Sansone 2019). Surely, the policy and managerial attention of decision-makers towards planning and implementing remedial interventions needs to target disadvantaged and at-risk students. These interventions must be effective in order to get students back on track: attending regularly, filling their prior educational gaps, behaving well, and passing their courses (Mac Iver et al., 2019). The first recommendation in the IES (Institute of Education Sciences) Practice Guide on Preventing Dropout in Secondary Schools is to "(…) *Monitor the progress of all students, and proactively intervene when students show early signs of attendance, behavior, or academic problems*" (Rumberger et al., 2017). In this vein, it must be emphasized that identifying students at risk of dropping out by using an EWS is only the first step in addressing the issue of school dropout (Márquez-Vera et al. 2015).

The literature which focuses on developing the empirical models for predicting dropout is now more concentrated on the adoption of Machine Learning (ML) techniques to implement new and well-performing algorithms, which predict students' outcome as early as possible. These models allow identifying and prioritizing students for remedial intervention assuring high prediction accuracy together with early timing. In the remainder of this paragraph, we report and comment some academic papers which specifically deal with the use of ML in the development of Early Warning Systems; the main message emerging from this part is to provide a state-of-the-art about the main methodologies and works related to the emerging and consolidating field of EWSs. As can be clearly judged in looking at the contributions listed here, the development of EWSs is growing and is gradually applied in many different geographical contexts and educational grades. Moreover, the underlying empirical models are diversifying and, nowadays, they cover a wide range of statistical, econometric and machine learning techniques. The Table 27.1 resumes the key characteristics of selected academic articles about the prediction of at-risk students in high school.

Table 27.1: *A review of literature about Early Warning Systems in secondary education*

Papers' title (authors, year and journal)	Analytical method	Years of data	Country	Grade analyzed
Fernandes, E., Holanda, M., Victorino, M., Borges, V., Carvalho, R., & Van Erven, G. (2019). Educational data mining: Predictive analysis of academic performance of public school students in the capital of Brazil. Journal of Business Research, 94, 335-343.	Gradient Boosting Machine (GBM)	2015 and 2016	Brazil	From 9th to 12th
Adelman, M., Haimovich, F., Ham, A., & Vazquez, E. (2018). Predicting school dropout with administrative data: new evidence from Guatemala and Honduras. Education Economics, 26(4), 356-372.	Logistic Regression	2009, 2010 and 2011	Guatemala and Honduras	5th, 6th, 7th, 8th and 9th grade
Sansone, D. (2019). Beyond early warning indicators: high school dropout and machine learning. Oxford Bulletin of Economics and Statistics, 81(2), 456-485.	Support Vector Machine, Boosted Regression and Post-LASSO	2009	USA	9th grade
Aguiar, E., Lakkaraju, H., Bhanpuri, N., Miller, D., Yuhas, B., & Addison, K. L. (2015). Who, when, and why: A machine learning approach to prioritizing students at risk of not graduating high school on time. In Proceedings of the Fifth International Conference on Learning Analytics And Knowledge (pp. 93-102).	Random Forest and Logistic Regression	From 2007 to 2013	USA	From 6th to 12th grade
Márquez-Vera, C., Cano, A., Romero, C., Noaman, A. Y. M., Mousa Fardoun, H., & Ventura, S. (2016). Early dropout prediction using data mining: a case study with high school students. Expert Systems, 33(1), 107-124.	Support Vector Machines, Decision trees, Classification rules and Naïve Bayes Classifier	2012	Mexico	9th grade
Woods, C. S., Park, T., Hu, S., & Betrand Jones, T. (2018). How high school coursework predicts introductory college-level course success. Community College Review, 46(2), 176-196.	Logistic Regression	2014	USA	12th grade
Rebai, S., Yahia, F. B., & Essid, H. (2019). A graphically based machine learning approach to predict secondary schools performance in Tunisia. Socio-Economic Planning Sciences, 100724.	Regression Tree (RT) and Random Forest (RF)	2012	Tunisia	10th grade
Steinmayr, R., Weidinger, A. F., & Wigfield, A. (2018). Does students' grit predict their school achievement above and beyond their personality, motivation, and engagement?. Contemporary Educational Psychology, 53, 106-122.	Regression	2014, 2015 and 2016	Germany	10th, 11th and 12th grades
Sara, N. B., Halland, R., Igel, C., & Alstrup, S. (2015). High-school dropout prediction using machine learning: A Danish large-scale study. In ESANN 2015 proceedings, European Symposium on Artificial Neural Networks, Computational Intelligence (pp. 319-24).	Support Vector Machines (SVM), Classification Tree (CART), Random Forest (RF) and naïve Bayes classifier	2009	Denmark	9th grade

A clear element that emerges from the current literature about Early Warning Systems is that analyses are fundamentally based on empirical approach. It is glaring the lack of a common theoretical framework to drive analysis and prediction. This lack of theoretical foundations is further highlighted by the common settings given by a data-driven (DD) approach, aiming at finding the best algorithm to predict student's outcome. This DD approach is not easily generalizable because is mostly dependent on data availability (and specificity), which in turn will provide better or worse algorithms' predictions performance. In this chapter we innovate this field of study by proposing a comprehensive theoretical framework. This proposal should move the analysts and decision makers' attention from *algorithms* (which are, therefore) to *information*. We try to contextualize the empirical analysis of the determinants of the students' performance into a student-specific process of skills' formation. In this research-based light, the theoretical framework proposed here gives the possibility to interpret the results about students' dropout taking into consideration their path, experience and characteristics.

3. Proposal of a comprehensive theoretical framework for developing EWS

The most relevant aspect underlined in this framework for EWSs is the prevalent attention over the social, economic and educational determinants of dropout, rather than algorithms. Specifically, the key indicators of Early Warning Systems are grouped into macro-categories, with the specific aim to tailor the analysis to different and heterogeneous contexts.

The theoretical framework poses its foundations on students' educational journey, buying this approach from the seminal contribution by Cunha & Heckmann (2007) – hereafter, C&H2007. In the authors' work, the formation of individual skills (both cognitive and non-cognitive) is the result of a process where investments, environments and genes are jointly and simultaneously involved. These factors interact and influence each other, to produce behaviors and abilities, which in turn are observed and investigated by analysts and decision makers. As postulated by C&H2007, the "technology" governing this process is *multistage* and *interrelated*, so each period's activities and results are influenced by the previous ones and, in turn, influence the next ones. According to this view inputs, investments and experience in each stage produce outputs, which will be the inputs of next stages themselves.

For the purpose of our theoretical framework, specifically designed for developing EWS, we consider the stages proposed by C&H2007 as school cycles (see Figure 27.1): childhood, primary, middle school and high school (K12) and university.

Figure 27.1: *Key stages of the educational path, by educational steps*

Childhood	Primary school	Middle school	High School	University
(0 – 6 y.o)	(6 – 10 y.o.)	(10 – 13 y.o.)	(13 – 18 y.o.)	(18 – 24 y.o.)

Note: The references ages are approximated and refer to the case of some specific countries (for example, Italy). Source: authors' elaboration

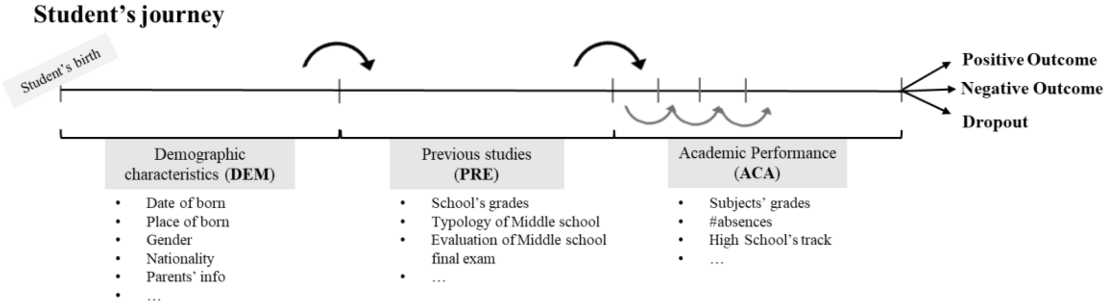
During each stage, it is possible to collect students-level information related with their specific educational path, such as grades or school data, and/or with personal and demographic information, for instance the citizenship or family's situation. Coherently with the dynamics of the educational process, the time frame to which the information relates with the individual's stage is highly important to characterize the available evidence about the student's educational journey and timeline.

Starting from the assumption that process of skills' formation is multistage and interrelated, the milestone of the proposed framework relies on the possibility to predict student's dropout, considering blocks of variables related to the educational timeline's stages, in a sequential and multivariate way. Educational data scientists may take into consideration the value of each variable about the educational stage to predict students' results at a given point of time. This perspective allows analysts to consider students' performance as the result of a process started time before and with a specific trajectory. Further and most important, educational data scientists may predict students' outcome, in this case dropout, standing on different points along the timeline/journey. It is empirically functional to predict student's outcome considering the evolution of her experience stage by stage, adding blocks of additional variables at each point of time. Consequently, this model is also well-featured for finding the optimal moment to observe each student's outcome, balancing between (i) prediction accuracy – which normally improve when adding more available information to the empirical models – and (ii) time to intervene. The proposed framework aims at addressing the managerial challenge for education: helping students deemed as at-risk the earliest moment possible.

From an operational standpoint, the informative picture about each student's educational career and experience is always limited and partial, so a reduced view of the proposed theoretical framework is necessary to contextualize it into real-world practice. Schools and institutions have an incomplete outlook about student's educational path, but at the same time they have powerful and rich administrative databases. These repositories of crucial data and information are collected for various purposes but can be easily adapted and used for analyses in a Learning Analytics modality. The schools' databases normally contains two macro-types of variables: (i) *dynamic*, such as information about academic career, collected on a periodic basis during the schools' years and across years; and *(ii) static*, such as information related to previous educational stages and general features of the individual (e.g. born year, gender, parents' education level, etc.).

A possible way of practically representing the students' journey by means of the available data in ordinary datasets, the reader can refer to the Figure 27.2. Here it is represented the student's timeline divided into the "educational stages" the individual passes through. Since her birth, a student's data are stored in their timeline when they occur. For instance, at birth the timeline is filled with data about parents and place and date of born. When considering the school's perspective, the student's timeline is reduced according to the information available and collected by such institution. It is worth to consider the different types of data present into the timeline. We propose to consider three blocks of features: demographic, previous studies and actual career. The first type of indicators refers to personal and family information, such as gender, residency or family income, while the second one includes all the information coming from the prior studies of student. The main characteristic of these blocks of features is that are constant over time, so they are considered *static* data. The third set of characteristics comprises all the information collected during the school journey, such as grades, absences or family notes. Since this typology constantly changes, enriching student's timeline week by week, it comprises all the *dynamic* data. It is worth to mention how the timeline proceeds over time, according to high school standpoint: for some students, it ends with degree, while for some others with dropout.

Figure 27.2: *The educational journey of the students – a theoretical scheme*



Source: authors' elaborations

Once the student's profile and performance is complete with the available information in the school's database, educational data scientists can position their point of observation along the timeline and predict future educational outcome (e.g. degree vs. dropout). It is interesting to consider the case of a dynamic modelling when high schools register students' data dynamically. In these circumstances, the analyst can "stand" on the first educational stage and (with available information) make the prediction; then, in a sequential manner, the analysis can move further on the second stage and can make the second prediction with available information of present and past stage. This process keeps going on until the end of the timeline, so collecting predictions about students' outcome based on an increased (and cumulated) amount of information. Hence, decision-makers and scientists are called to find the best position on the student's path/journey, which balances between prediction accuracy and earlier momentum. Early Warning Systems can be used for the sake of the earliest prediction (so to maximize the time to support students with remedial interventions). However, intuitively the more information is available, the more accurate is the prediction. Anyway, educational data scientists should be interested in finding the right balance between the prediction accuracy and the number of stages considered – interestingly, this is a typical *optimization problem*. From a policy and managerial perspective, which aims at improving the chances of all students to succeed, the timing of the prediction is equally important to its accuracy. Indeed, it is preferable to have the 85% of prediction accuracy at the beginning of the school period (so there would be room for policy makers and school administrators to intervene), rather than the 95% at the end of it when the margins for affecting educational trajectories are more limited.

The main message provided through this framework is that (i) theoretical foundations, (ii) information-driven empirical models together with (iii) judgments about the timing of the academic results' prediction are the key components to designing and deploying a comprehensive Early Warning System.

4. Some notes about practical employment of EWS results

The explicit purpose connected with the proposed theoretical framework is the possible managerial use of the findings derived from Early Warning Systems. As described in the previous sections, these systems can be incredibly useful in supporting the decision-making process within schools oriented towards student success. Such process is often not as structured and systematic as it could and should be. It is important to underline that human intelligence is normally in action, and teachers detect at-risk or excellence students very early in the careers. The proposed models do not aim at substituting this ability, but instead these systems allow supporting and strengthening teachers' intuitions, which are proved to be reliable (Soland 2013). Complementarities are evident here. Indeed, even though the ML algorithms act over objective data, teachers can qualitatively evaluate student attitudes, behavior and effort that are not captured by the statistical models (Soland 2013). In such perspective, we can state that the ML and (artificial) intelligence can be integrated into the not-substitutable human intelligence. An open issue related with the adoption of Learning Analytics is that schools need to guarantee an adequate set of opportunities for talented student as well. Facing this further challenge, similar tools based on ML can be adopted, with a different perspective, i.e. detecting and predicting high-achievers as soon as possible to formulate them some attracting initiatives for exploiting their academic skills. This approach would imply two strengths for each school. First, a real personalized learning path can be enforced. Second, the method can allow schools and institutions increasing their visibility and attractiveness for (potential) high-performing pupils. While the use of EWS for contrasting dropout is becoming popular, less experience is available for the application to detect excellent/talented students early in their career.

A common consideration holds: besides the baseline main goal of the analysis (which is the identification of poor or high achievers), the exercise of prediction is only the first step for the development of a complete Early Warning System, which needs to be complemented with the setting of interventions specifically directed to the target population.

When considering the phenomenon of dropout, remedial education interventions are the proposed solution for students deemed as at-risk by the predictions. Hence, the practical implications concern mainly the development "experiments" to find out the best way to help poor performing students. In other words, the aim of such a second step deals with the testing of different remediation intervention for assessing causal effects of the program in place on the student's educational improvements (see the literature review in Marinelli et al., 2019). When targeting talented students, principals and teachers have the responsibility to find key (curricular and extracurricular) activities to empower them, for example through specific "honor programs", which stimulate their abilities and skills towards more ambitious educational paths.

Summing up, this chapter deals with the definition of a common ground of study, devoted to the development of the first step of an Early Warning System: the theoretical framework to be applied for conducting accurate predictions of students' success or dropout risk. The theoretical model proposed here aims at supporting the key managerial problem, i.e. the detection of at-risk students, through a comprehensive perspective well established in a conceptual framework. If traditional approaches focus on the algorithms as the common ground of study, in the proposed model the information brought by the single students is more relevant. The message attached to the model moves from the context to the student, who is observed in specific educational and personal path. The managerial perspective is, in this sense, oriented towards finding more individual-centered solutions to the educational offer and activity. This chapter starts with formulating the problem of inclusivity and facing early leavers in school, and presents the Early Warning System as a potential policy and managerial response.

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CHAPTER 28

A Complex Systems Network Approach to Assessing Classroom/Teacher-level Baseline Outcome Dependence and Peer Effects in Clustered Randomized Control Trials

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Abstract

Well-executed random assignment to intervention and control conditions along with individuals' participation compliance are fundamental prerequisites for eventually making causal claims based on the results of randomized control trials. After forming intervention and control groups, researchers usually test for baseline equivalence of participants' pre-treatment assignment outcomes. These tests are considered best practices when measuring whether intervention and control groups look the same in their observed and unobserved baseline characteristics. This study's main assertion is that violations of baseline equivalence are more prevalent than typically captured by aggregated tests of participants' baseline outcomes. Accordingly, the study presents an analytic framework that relies on complex systems

networks to comprehensively assess baseline equivalences of participants' pre-treatment assignment outcomes considering their network-based classroom/teacher-level pre-intervention performance, rather than comparing their aggregated measures given treatment and control statuses. Additionally, the analytic framework employed makes it possible to test for spillover effects, or the influence of participants' baseline performances on their peers' post-intervention outcomes. This test is important because it can be used to analyze the assumption that participants do not interfere with or affect each other's outcomes. The findings consistently indicate that traditional aggregated tests of baseline equivalence fall short in detecting classroom/teacher-level baseline outcome dependence, which violates the goal of randomization and threatens causal claims. Moreover, multilevel models confirm the presence of peer effects hence corroborating participants' interference. The importance of peer effects prevailed even after controlling for individual pre-intervention performance, which corroborates the need to control for these effects over and above individual performance.

Introduction

Well-executed random assignment to intervention and control groups along with individuals' participation compliance are fundamental conditions for making causal claims based on the results of randomized control trials (RCT) (What Works Clearinghouse [WWC], 2018). After groups are formed and participants agree to comply with their assigned intervention or control statuses, researchers usually test for the baseline equivalence of their pre-treatment assignment outcomes (e.g., pre-intervention math if the intervention is assumed to affect math achievement). These tests are considered best practices when measuring whether randomization and assignment compliance were successful in the creation of intervention and control groups that look the same in both their observed and, arguably, their unobserved baseline characteristics. After meeting optimal conditions for baseline equivalence, fidelity of implementation, and differential and total attrition measures, researchers can be confident that any observed outcome differences may in fact be due to participants' exposure to the intervention rather than to unobserved or unmeasured factors (WWC, 2018). The main assertion of this study is that in clustered RCTs (e.g., students nested within teachers/classrooms), violations of baseline equivalence are more prevalent than typically captured by aggregated tests of intervention and control participants' baseline outcomes "due to the dependency of student outcomes within groups" (Schochet, 2008, p. 1). Accordingly, the purpose of this study is to present an analytic framework that relies on complex systems networks (Maroulis, Guimera, Petry, Stringer, Gomez, Amaral, & Wilensky, 2010) to comprehensively assess baseline equivalences of participants' pre-treatment assignment outcomes based on their classroom/teacher-level pre-intervention performance rather than on aggregated measures of treatment and control statuses.

The use of a complex systems approach in this context is appropriate considering that the resulting group formation based on both randomization and the clustering procedures implemented, may be conceptualized and operationalized as a system configured by numerous interactive elements (e.g., peers nested within teachers, teachers nested within schools) that likely impact the outcomes of individual units (Maroulis et al., 2010; Mitchell, 2006; Schochet, 2008; Zeng, Shen, Zhou, Wu, Fan, Wang, & Stanley, 2017) over and above intervention exposure. This interconnected and potentially interdependent system limits the value of analyzing individual performance under the assumption of isolation or non-interference to explain the phenomenon under study.

The comprehensive and interconnected framework that guides complex systems networks as an analytic approach makes it possible to test for peer effects, or the influence of participants' baseline performances on their peers' post-intervention outcomes. This test is important because it makes it possible to analyze the assumption that participants do not interfere with or affect each other's outcomes (Rubin, 1986, 1990). Non-interference also encompasses the assumption of constant effect or the idea that the effect of a given treatment on every unit is the same (unit Homogeneity) (Holland, 1986), implying that there are not hidden versions of a given treatment and/or that peers may not alter the effect of the intervention. Based on the inherent complexity that accounting for interference and multiple treatment versions implies, designers of analytic techniques made these assumptions more by convenience than accuracy (Tilly, 2002). Nonetheless, complex systems networks provides a straightforward framework to operationalize and measure these typically untested assumptions using peer influence or peer effects.

In sum, considering that both classroom/teacher-level lack of baseline equivalence and peer effects may impact outcome variation over and above intervention effects, using complex systems networks to test for them is an important advancement in the field. Operationalizing indicators of spillovers not only makes it possible to measure whether spillover is taking place in interventions but also to control for those effects when measuring participants' post-intervention outcomes.

The findings of this study indicate that, compared with the complex systems network approach, traditional aggregated (or naïve) tests of baseline equivalence fell short in detecting that clustered teacher-level configuration of students was based on their pre-treatment achievement, which violated baseline equivalence tenets. Moreover, multilevel models, confirmed the presence of spillover effects in all the post-intervention outcomes analyzed. In addition, interaction effects tested using multilevel models consistently indicated that there were no moderation effects based on participants' treatment status. This last finding indicates that peer effects as measured by classmates' performance was equally important in treatment and control groups. Finally, the importance of spillover effects prevailed even after controlling for individual pre-intervention performance, a finding that corroborates the need to control for these effects over and above students' individual performance.

Context

This study analyzes an RCT intervention following a cluster-level assignment (as defined by WWC, 2018), wherein teachers were randomly assigned to a treatment or control condition but the outcomes of interest were measured at the student level. Based on this level of analysis, baseline equivalence assessed whether students in the treatment and control conditions showed similar pre-treatment performance levels "to determine whether the observed effects of the intervention can be credibly said to be due solely to the intervention's effects on individuals, or whether changes in the composition of individuals may also have affected the findings" (WWC, 2018, p. 19). The composition of individuals is a key element to analyze when measuring baseline equivalence because the causal inferences may be affected by potential sorting of individuals across treatment and control conditions. In this respect, traditional aggregated tests of baseline equivalence—that is, baseline comparisons between treatment and control participants—may fall short in capturing composition based on pre-intervention performance, which is the argument of the present study.

Changes in group composition may be due to a "joiners" effects, wherein according to WWC (2018), participants (or in the case of children, their parents) decide or even request to join the intervention given the potential benefits of participating in that program (e.g., betterment of outcomes). Another possible source of changes in composition may be due to strategic or administrative school-level decisions to form groups based on participants' previous outcomes. In this latter scenario, administrators might assign students to teachers in the treatment group as a way to maximize the benefits associated with the intervention. That is, if an intervention is assumed to improve English language arts, treatment assignment (at the teacher level) may not be random; instead, administrators might assign students who "need extra help" to teachers participating in the intervention. In either case (joiners effects or administrative sorting), the nonrandom assignment mechanism may translate into clustering students with more similar outcomes across treatment and control conditions, which may bias the true effect of the intervention. More importantly, and directly related to the focus of this study, these threats to changes in composition may be more prevalent than accounted for by traditional outcome baseline tests. If these tests ignore outcome clustering at the teacher level, which also captures school-level effects (such as culture, average student-body performance), such tests may incorrectly indicate that baseline equivalence has been satisfied when in fact this result is simply a function of the level of aggregation typically employed (i.e., treatment versus control comparisons) that ignore these potential classroom/teacher- indicators that may vary from school to school but remain relatively constant within school over time.

This study's main assertion is that after treatment and control groups have been formed but before the intervention takes place, researchers can use the complex systems network approach depicted herein to test whether classroom/teacher-level composition or group formation procedures successfully rendered groups in which participants' baseline outcomes are truly independent of teacher assignment, over and above treatment condition. Accordingly, this study provides an analytic framework to test for baseline equivalence that moves beyond aggregated means based on treatment status. This complex systems approach relies on "algorithms that facilitate network characterizations of social context" (Maroulis et al., 2010, p. 39) and are straightforward to implement. To meet this purpose the study relies on data obtained from a clustered RCT, goal Efficacy and Replication funded by the Institute of Education Sciences, wherein randomization resulted in aggregated (i.e., treatment versus control) measures of baseline equivalence (see Table 1). However, as shown in Table 2, the use of complex systems networks provided evidence of baseline outcome dependence based on teacher assignment. The present study discusses the conditions required to obtain true baseline equivalence using the method proposed with particular emphasis on the steps required to model peer effects.

Research Questions:

1. Do aggregate tests of baseline standardized test scores indicate that treatment and control participants are equivalent in these pre-intervention outcomes?
2. Is there evidence of baseline outcome dependence given students assignment to teachers, regardless of treatment and control status?
3. If there is evidence of baseline outcome dependence, are these dependence issues more pronounced among treated students compared to dependence issues observed among their control counterparts?
4. Is there evidence of peer effects wherein students' performances are affected by the performance of their peers assigned to a given teacher?
5. If there is evidence of peer effects, are these effects moderated by treatment condition? If so, which group (treated or control) benefits the most by the peers' performance?
6. Do these peer effects disappear when controlling for students' own pre-treatment performance?

Intervention Procedures

The intervention implemented was defined as "Instructional Conversation" (IC), a constructivist pedagogical system that seeks to make learning meaningful and challenging to students through mastery of grade-level content based on teacher-guided small-group discussions (Gay, 2010; Portes, González Canché, Boada, & Whatley, 2018; Wlodkowski & Ginsberg, 1995). In IC, teachers promote learning by using knowledge of their students' lived experiences to increase student engagement and motivation and mastery of a high-quality curriculum (Ladson-Billings, 2009; Portes et al., 2018).

The IC for effective pedagogy was proposed by the Center for Research on Excellence and Diversity in Education (CREDE) (Tharp & Gallimore, 1989). This pedagogy seeks to: facilitate learning through collaborative and problem-based tasks, develop competence in language and academic disciplines across the curriculum by making content meaningful based on the interests and experiences of students' families, and move students to their next level of cognitive complexity or zone of proximal development, all of which is implemented in small "conversation" groups (Ladson-Billings, 2009; Portes et al., 2018; Tharp & Gallimore, 1989; Wlodkowski & Ginsberg, 1995).

Following this pedagogy, a typical and well implemented IC session takes place as follows. Teachers lead ICs in small groups of three to seven students. These sessions last about 20 minutes and have a clear instructional goal, which can involve any subject matter. During these sessions, students regulate their own speaking turns, and everyone is expected to contribute to the discussion and mastery of the content. The main challenge that teachers experience is monitoring the quality of the discussions and the accuracy of the content being discussed. The IC allows for ongoing and real-time respectful assessment and feedback, with the hope that students themselves will take the lead in detecting incorrect statements and clarifying misconceptions. Following the CREDE's framework, the topics covered in the intervention involved the disciplines of reading, science, math, and English language arts.

Before the efficacy of the intervention was measured, teachers who were randomly selected to implement the IC pedagogy were trained for one summer and subsequently coached for one academic year in how to create classroom structures that support small group instruction. In addition, these teachers were also trained to consider management strategies, such as implementing rules and norms that guide students toward collaborative work that does not depend on the teacher. Teachers also developed skills to design activities for students that are collaborative in nature and that encourage and require conversational exchange. The IC coaches (experts in this pedagogy) observed teachers' performance during training sessions and provided these teachers with feedback as well as strategies for delivering clear instructions to their students regarding active participation and discussion skills, including approaches to respectfully disagree. All in all, teachers were trained to facilitate ICs by keeping students focused on the goal of actively participating in conversations. Notably, control teachers were also required to teach in small group sessions (also including three to seven students per session) but did not receive training in the IC pedagogy or its standards.

The data analyzed herein is the first that come from a clustered RCT using the IC pedagogy. However, it is important to note that this study does not assess the efficacy of the IC pedagogy on increasing student outcomes. Such an assessment was conducted by Portes et al., (2018). Accordingly, issues related to fidelity of implementation and attrition are not the focus of this study either. Instead, this study uses standardized data obtained from that clustered RCT to address questions pertaining to baseline equivalence and potential peer effects observed within these small group interactions. The analytic procedures presented here, focus on depicting the use of network analyses under a complex systems approach—an approach that is not completely absent in education research but has yet to be widely employed (Maroulis et al., 2010).

Complex Systems Networks

There is no precise definition of complex systems (Mitchell, 2006; Zend et al., 2017); instead, experts prefer to list their properties. These properties include “nonlinearity; feedback; spontaneous order; robustness and lack of central control; emergence; hierarchical organization; and numerosity” (Zend et al., 2017, p. 4). The inherent difficulty that these properties imply for the study of complex systems has led researchers to use network thinking and network modeling for “dealing with complex systems in the real world” (Mitchell, 2006, p. 1199). Network analysis and theory are particularly useful for studying complex systems because they can be used both (a) to analyze different types of relationships and communities interacting simultaneously across the system and (b) to visualize the structure configuring the systems being studied. Network thinking has been applied to the study of many different types of complex systems, including the brain, cells and cellular processes, the immune system, traffic and transportation systems, ant colonies, and social systems such as schools and school districts (Maroulis, 2010; Mitchell, 2006; Zend et al., 2017).

According to Maroulis et al. (2010), schools and school districts can be conceptualized as complex adaptive networks because their configuring parts render patterns as a function of multilevel and concurrent interactions (e.g., students nested within teachers and peers influencing one another simultaneously). They further argue that this conceptualization is promising in our attempt to better understand decades-old issues and problems such as achievement gaps and efficiency gains. The following section depicts the essential components of a network and the analytical procedures used to analyze this study’s data under a complex systems networks approach.

Networks and Peer Effects

A network is a collection of potentially interactive units. These units are typically referred to as nodes or vertices (e.g., actors, participants, or entities that may interact with one another), and the connections resulting from their interactions are referred to as edges or links (Kolaczyk & Csárdi, 2014; Mitchell, 2006; Wasserman & Faust, 1994). When these units and their resulting connections are of the same type and hierarchy (e.g., students interacting with other students in a classroom) they form a one-mode network. When the units configuring the network are different (e.g., teachers ascribed to different teacher organizations) or there are hierarchical relationships (e.g., students interacting with teachers), the resulting networks are referred to as having two modes. The data analyzed in this study followed a two-mode network, wherein the nodes are students and their assigned teachers.

The network conceptualization employed to identify peer effects can be merged with multilevel or hierarchical analyses to account for students being nested within teachers. Network thinking, however, capitalizes on the notion that these common exposures (particularly the small group dynamics that IC entails) facilitate interactions that may meaningfully impact students' understandings and potentially their learning prospects over and above intervention effects (this is true in both the IC and control groups based on the small group interaction that this clustered RCT requires). From this perspective, these meaningful interactions among peers may translate into spillover or peer effects, wherein students may learn from one another through their interactions. Accordingly, this complex and interactive learning process benefits from students' pre-intervention knowledge or their starting level of cognitive complexity or zone of proximal development (as illustrated by Vygotsky, 1978). That is, students' individual level of competence pre-intervention along with their peers' prior achievement levels may as a whole affect individual- as well as group-level comprehension given the quality of the discussions based on students' level of cognitive complexity. This complex and interactive learning process may be reflected in significant gains in individual academic performance as measured by standardized test scores. Notably, since both the intervention and the control students were required to meet in small groups, it is possible that these peer effects took place regardless of treatment status.

Data and Methods

Data

All the data analyzed herein were taken from a clustered RCT pedagogical intervention. Given that treatment and control teachers covered all disciplines, the analyses include all available pre-treatment standardized test scores, which include reading, science, math, and English language arts. These pre-treatment scores are the fourth-grade standardized tests results of treatment and control students. Given that the IC was implemented in fifth grade, the models that include post-treatment scores as the outcomes of interest correspond to these students' fifth-grade standardized scores in the same disciplines. Twenty schools from seven school districts participated in this intervention. All districts included at least one treatment and one control teacher; 11 schools had one teacher participating in the intervention, and the remaining nine schools included up to three teachers. None of the multi-teacher schools implemented only IC or only business as usual interventions. Of the 29 teachers, 19 received training in the IC. This translated into 226 students participating in the IC and 171 in the business as usual group (with a total of 397 students).

Methods

The first question posed in this study was addressed using traditional tests of baseline equivalence based on mean differences in students' fourth-grade standardized scores by treatment and control statuses (i.e., their pre-intervention indicators). The test of baseline independence measured at the teacher-assignment level followed a complex system network approach. In this approach researchers are interested in measuring whether participants' baseline indicators, given their common exposure to a particular assignment, were more similar to one another than what one should expect to observe by random chance. Recall that in this case, students' "common exposure" is their assignment to a particular teacher. Conceptually speaking, a complex system network approach is an important test because it assesses whether students' baseline performance influenced their teacher assignment—either on purpose or simply by capturing school-level average performance—and whether the resulting group configuration may have driven post-treatment performance over and above intervention effects. From an empirical point of view, students' baseline indicators (or their fourth-grade outcomes) should not covary in relation to their common exposure to their fifth-grade teachers. None of these students were exposed to a fifth-grade teacher during their fourth-grade coursework. In addition, none of the participating school districts followed cohort-based approaches, wherein groups of fourth-grade students advanced together to become fifth-grade groups the subsequent academic year. In synthesis, the use of the complex systems network approach provides a systemic and comprehensive assessment of potential issues of sorting during group formation as a function of students' baseline outcomes that, in addition to being robust to detecting autocorrelation issues, provides a visually compelling depiction of the system being analyzed (as shown in Figures 1, 2, 3, 4, and 5).

From an analytic point of view, systematic and systemic covariance between students' assignment to a given teacher and their past performances can be captured using a social dependence network approach. Mathematically and statistically speaking, one can apply analytic techniques designed to model dependence based on connections among units, such as in those employed in geospatial and spatiotemporal analyses (Zend et al., 2017). This is possible because both network analysis and spatial techniques rely on the same notion of "matrix of influence" (Bivand, Pebesma, & Gomez Rubio, 2013). Conceptually, the main difference concerns context: In the latter the connections are based on measures of physical distance among units, whereas in the former connections are based on socially retrieved measures, such as friendships, advice relationships, or even on common participation in a given event. The data analyzed herein adhere to the final example. Students are connected to one another given their sharing of a teacher. As stated above, this network representation is referred to as a two-mode or adscription network (Breiger, 1974) with dimensions (*n*, *m*), where *n* is the row dimension of this rectangular matrix and *m* is the column dimension representing the entities to which the rows are ascribed (i.e, *n* students ascribed to *m* teachers). The matrix of influence can be retrieved from this rectangular matrix (called w from now on) by multiplying the original adscription matrix w times its transposed version w^T in the form

$$w * w^T = [(n,m) * (m,n)] = (n,n) \qquad (1)$$

The resulting matrix has dimension (n, n), which contains *n* students in the rows and *n* students in the columns, with intersections $(n_i, n_j) = 1$ if students i and j shared a teacher or 0 if they did not. Accordingly, this matrix can be referred to as $\mathrm{w_{ij}}$. Following network analysis and matrix multiplication principles (Breiger, 1974; Wasserman & Faust, 1994), the diagonal of this $\mathrm{w_{ij}}$ matrix counts the number of teachers a given student has. Given that no student has more than one teacher or no teacher, this diagonal is a vector of 1s. In network and geospatial analyses, the diagonal in a matrix of influence is set to zero to avoid self-selection. Finally, $\mathrm{w_{ij}}$ can be row-normalized to apply conventional techniques to measure outcome autocorrelation based on participants' connections. This row-normalization assumes that all units can be equally affected by their connections or that these relationships take place among peers (Bivand et al., 2013).[2] Once these transformations are conducted, the matrix of influence can be used to address the second question posed in this study, which tests whether students sharing a teacher tended to have more similar baseline outcomes than expected by random chance. This is accomplished with a technique called Moran's I

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[2] Row normalization is accomplished by dividing each non-zero cell in a row vector by the total sum of non-zero cells in such a row. This can be expressed as $\mathrm{w_{ij}}/rowsums(\mathrm{w_{ij}})$ as shown in the appendix.

(Bivand et al., 2013), which empirically tests three potential cases: the outcomes were (a) randomly distributed (best case scenario from a clustered RCT perspective), (b) more similar than expected under random assignment, or (c) more dispersed than expected under random assignment.

Moran's I

In this approach, individual mean departures are compared against the mean departures of peers exposed to the same condition. Once more, in this case, this common exposure is a function of sharing the same fifth-grade teacher. More specifically, this analytic technique focuses on the *social* dependence of variables given participants' connections. The Moran's I equation is represented as follows

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n}(y_i - \bar{y})^2}, \quad (2)$$

Equation (2) shows that Moran's *I* is calculated as a ratio of the product of the difference of the variable of interest measured at the individual level (y_i) and its social lag (y_j or average performance on each student's peers) from the overall mean ($\bar{y}$), with the cross-product of the difference between the variable of interest from the overall mean, which is then adjusted for social weights (w_{ij}) (Bivand et al., 2013). A significant value of *I* yields evidence of more similarity in students' baseline outcomes than expected under randomization. Moran's *I* is standardized to range from +1 to -1 (Bivand et al., 2013), with positive values indicating that each individual group either systematically performed above (high-performance students clustered with other high-performance students) or below (low-performance students clustered with other low-performance students) with respect to the overall mean ($\bar{y}$).

The social lag (y_j) represented in equation (2) is particularly relevant for addressing peer effects because it is obtained as the mean value of all the connections j for individual i. For example, assume we observed the baseline values of three students, with such values shown in parentheses as follows: A (85), B (92), and C (87). Assume further that all these students are ascribed to teacher T. The social lag for student A is the mean of its connections [(92+87)/2]=89.5. For student B, the lagged value is [(85+87)/2]=86, and for student C this value is [(85+92)/2]=88.5. Following a complex systems network approach, this process can be repeated over all instances of students' connections so that every participant has her/his own value and the lagged value of her/his connections. Since baseline outcomes and socially-lagged values retrieved from these baseline outcomes are *contemporaneously exogenous* from the post-treatment outcomes, we can use these baseline-lagged values as predictors of performance in the post-treatment outcomes to capture peer effects or the potential interference of students on their peers' performance, and *vice versa*. Going back to a previous discussion, these socially-lagged indicators are capturing each student's peers average pre-intervention level of cognitive complexity or zone of proximal development that is likely to impact the quality, complexity, and sophistication of the discussions taking place in these small group interactions. As with any other model, we can also include students' own baseline performance to test whether peer effects are robust to model specification and previous individual performance (as indicated in the third research question).

Multilevel Specification

Multilevel models account for the nested structure of the data. The complex systems network approach aligns with this modeling approach as the nesting structure usually leads to violating the assumption of independence among observations (Schochet, 2008). The main contributions of the present study are (a) the added ability to measure violations of independence assumptions at the group formation stage based on participants' pre-intervention performance, and (b) the prospects of measuring peer effects, which goes beyond controlling for previous individual-level performance in a regression model. From this perspective, and considering the nested data structure, post-intervention analyses should also rely on multilevel modeling to further account for the clustered nature of the data. The model specification employed in this paper to address the third research question is

$$Y_{it} = \beta_{0t} + \beta_{1t}X_{1it} + e_{it} \tag{3}$$

The subscripts represent students i nested within teachers t. X_1 represents a pre-treatment outcome of student i's peers' performance measured in fourth grade (i.e., socially lagged indicators capturing peer effects, represented as y_j in equation (2)). Recall that Y_{it} was measured in fifth grade, or in the post-intervention period. As standard, the intercept β_{0t} is allowed to vary across the t classes in the form $\beta_{0t} = \gamma_{00} + \eta_{0t}$, wherein η_{0t} is an error term measured at the nesting level. The main assumption behind this modeling approach is that the error term (e_{it}) shown in equation (3) should be the model residual after accounting for η_{0t}. Accordingly, e_{it} should be independent and identically distributed. If this is true, then the model residuals should be independent of connections among individuals (or their common exposure to a given teacher), and this assertion can be tested using Moran's I. For this test to be conducted, each student-level residual (e_{it}) is recovered after implementing a multilevel model, and these residuals are tested against equation (2), replacing the ys in such an equation with model residuals. If this test indicates that the Moran's I is close to zero and nonsignificant, then the multilevel approach successfully addressed outcome dependence based on students' common exposure to a given teacher. These tests are added to each regression table presented in the row called "Moran's I." Finally, to address questions 3(a) and 3(b), an interaction effect of intervention status with X_1 and individual performance are added, respectively.

Findings

Baseline Equivalence

Table 28.1 addresses the first research question and contains the results of the traditional tests for baseline equivalence across treatment and control groups. Note that the results consistently indicated that student performance was equivalent in the four standardized grade-level test scores measured. The lowest probability value found was 0.29 in mathematics and it is clearly higher than the 0.05 probability value accepted by convention in the social sciences. Typically, these results would have satisfied concerns regarding group configuration based on students' pre-intervention performance.

The complex systems networks approach implemented in this study allowed for the application of Moran's I tests (summarized in Table 28.2) that address the second research question. The results consistently show evidence of pre-treatment outcome dependence based on teacher ascription. This result provides enough evidence about student-teacher compositions based on students' pre-treatment outcomes as a possible source of variation over and above intervention exposure. That is, it seems that mechanisms driving group formation at the teacher level did not translate into baseline outcome independence; rather, students are grouped with students who tended to perform more similarly above and beyond random chance.

To gain more insight about the rationale followed in this complex system network approach, let us represent these students' outcomes in network form where all of them are connected to one another but only through their common exposure to a given teacher T or C, as shown in Figures 28.1, 2, 3, 4, and 5. In these figures T stands for treatment and C for control conditions over all participating fifth-grade teachers. Figure 1 is analogous to the results shown in Table 28.1, where each student baseline outcome performance is assumed to be captured by having been assigned to a treatment or control condition. An important value added of this network representation is the possibility of observing how limited this procedure is in capturing the complexity of this system. The analytic power of the complex system network approach is represented in Figures 28.2 and 28.3. Figure 28,2 shows individual-level baseline performances in the four content areas studied. The clustering of patterns of the color schemes implemented highlights a clear tendency of teacher assignment based on similar student achievement levels across content areas. This similarity is measured in Table 28.2, which corroborates these visual assessments.

Table 28.1. *Baseline Indicators by Treatment and Control Condition*

Variable	Levels	n	Mean	S.D.	Min	Max
Individual level indicators						
pre_science	Control	171	836.8	40.3	750	956
	Treatment	226	839.4	42.8	740	956
p= 0.55	Total	397	838.3	41.7	740	956
pre_math	Control	171	836.8	36.2	762	940
	Treatment	226	841.3	45.7	735	990
p= 0.29	Total	397	839.4	41.9	735	990
pre_ela	Control	171	833	28.3	768	930
	Treatment	226	834.5	30	758	930
p= 0.61	Total	397	833.9	29.3	758	930
pre_read	Control	171	836.1	27.5	774	912
	Treatment	226	838	30.2	762.5	912
p= 0.52	Total	397	837.2	29.1	762.5	912
Socially lagged indicators						
lag.sci	Control	171	827.3	93	0	885.3
	Treatment	226	832.5	83.7	0	889.2
p= 0.56	Total	397	830.3	87.8	0	889.2
lag.math	Control	171	827.4	92.6	0	883
	Treatment	226	834.3	85.2	0	920.8
p= 0.44	Total	397	831.3	88.4	0	920.8
lag.ela	Control	171	823.6	91.1	0	869.3
	Treatment	226	827.7	80.8	0	875.7
p= 0.64	Total	397	825.9	85.3	0	875.7
lag.read	Control	171	826.6	91.5	0	870.3
	Treatment	226	831.2	81.4	0	882.8
p= 0.60	Total	397	829.2	85.8	0	882.8

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Table 28.2. *Complex Systems Network Analysis of Baseline Performance Given Teacher Assignment*

Groups	Variable	Moran's I	Expectation	Standard Deviate	Prob.
Treatment and control	pre_science	0.34359	-0.0026	17.952	< 0.001
	pre_math	0.39136	-0.0026	20.464	< 0.001
	pre_ela	0.32441	-0.0026	16.977	< 0.001
	pre_read	0.37125	-0.0026	19.388	< 0.001
Treatment	pre_science	0.38923	-0.0045	13.949	< 0.001
	pre_math	0.43896	-0.0045	15.756	< 0.001
	pre_ela	0.38421	-0.0045	13.794	< 0.001
	pre_read	0.3919	-0.0045	14.044	< 0.001
Control	pre_science	0.27327	-0.006	12	< 0.001
	pre_math	0.28536	-0.006	12.534	< 0.001
	pre_ela	0.23734	-0.006	10.354	< 0.001
	pre_read	0.27627	-0.006	12.136	< 0.001
Under True Random assignment at the teacher level					
Treatment and control	pre_science	-0.0294	-0.0025	-1.3624	0.9135
	pre_math	-0.0185	-0.0025	-0.81	0.791
	pre_ela	-0.0099	-0.0025	-0.3747	0.646
	pre_read	0.00026	-0.0025	0.14123	0.4438

Table 28.2 also contains complex system network analyses separated by treatment and control statuses to address question 2(a). To reconcile these analyses with Figure 28.2, one can test whether the issue of pre-treatment outcome similarity is more pronounced in the treatment or control groups. Table 28.2 consistently indicates that the group configuration issue is more prevalent in the treatment groups than in the control groups configuration, which is indicated by the magnitudes of the Moran's I estimates. In short, baseline performances are much more similar in treatment groups than in their control counterparts. This higher similarity highlights a greater propensity toward grouping more alike students across treatment teachers than among their business as usual counterparts.

Figure 28.3 shows the lagged baselined values of each student i's peers j and is required to address the third research question. The information contained in this figure is the predictor used in equation (3) to capture peer effects after accounting for the nested data structure. To exemplify the mechanism, let us consider the treated group located on the top left side of the science sociograms in Figures 28.2 and 28.3. Note that these IC students show different individual performance levels (Figure 28.2), with two of them having high performance (indicated by purple) and two having low performance (indicated by red). In addition, one student achieved performance levels located in the median of the distribution. Note that in Figure 3, these color schemes were practically reversed, with the two high-achieving students changing from blue to orange and the two low-achieving students changing from red to light blue; a similar effect was found for the participant in yellow, who in Figure 28.3 changed to light blue. One can think of these changes as follows: if a high-achieving student is exposed to low-achieving peers, how is that exposure expected to impact the high-achieving student's performance at the end of the academic year, or how does the baseline performances of one's peers affect one's own performance in the subsequent year? These are the questions addressed with the use of multilevel modeling presented next. Finally, note that Table 1 also includes a test of baseline comparisons of these socially lagged indicators by treatment and control statuses. This test is important as it serves to highlight once more that such aggregated measures consistently fall short in detecting clustering that may be affecting the measurement of intervention effects. In addition to being informative, these mean outcomes allow for a better understanding of peer effects when interpreting the findings addressing question 3b (i.e., do these spillover effects disappear when controlling for students' own pre-treatment performance?)

Before describing the regression-based results, it is worth showing how truly random group configuration would have behaved in a complex system network approach. To achieve this goal, each student was "truly" randomly assigned to a given teacher using simulation techniques as depicted in the appendix. As part of the simulation process, the 29 teachers in the study were assigned a consistent but randomly generated ID, and then students were randomly assigned to this new teacher ID. Consequently, both treatment condition and teacher assignment were randomly generated. These networks are shown in Figures 28.4 and 28.5. Note that no patterns exist at the individual-level baseline performance (Figure 28.4) and the lagged performance consistently shows more random variation (i.e., less structure) across treatment and control groups. Finally, Table 28.2, shows the Moran's I results based on the structures shown in Figures 28.3 and 28.4. These tests consistently indicate that under true random assignment there is no indication of students' baseline outcomes being more similar to their peers' baseline outcomes.

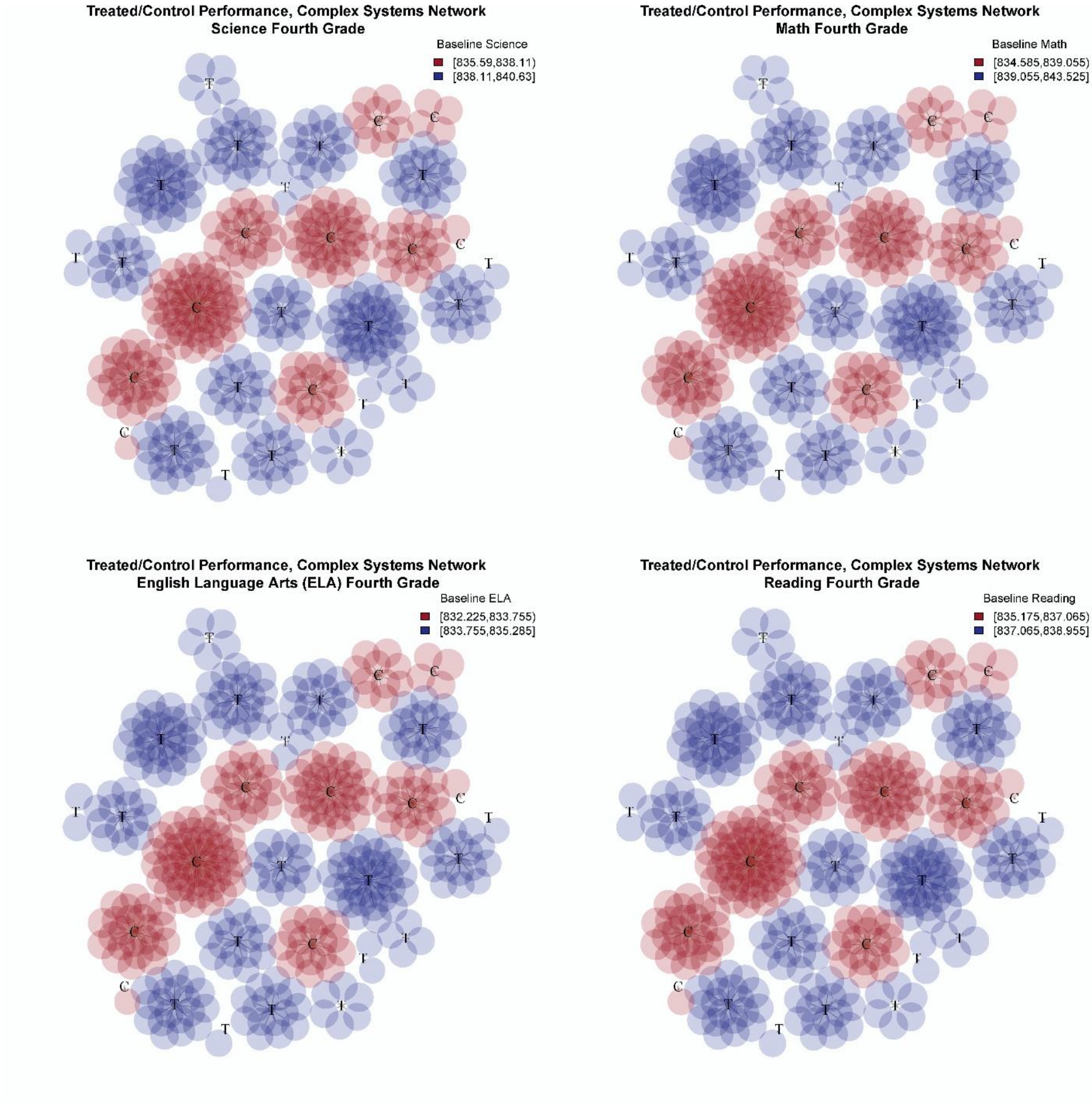

Figure 28.1. Network Representation of Baseline Performance by Treatment and Control Status

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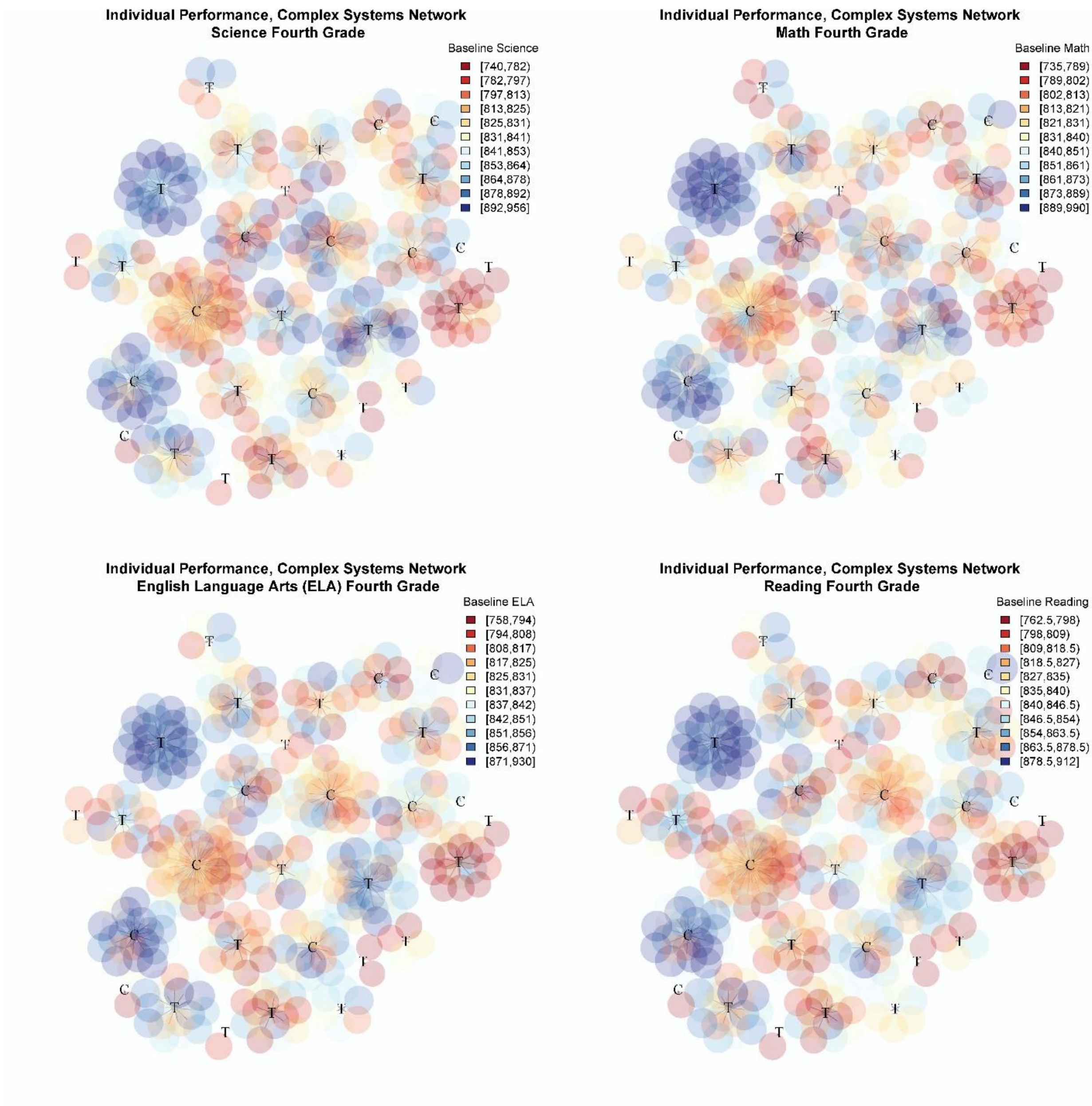

Figure 28.2. *Complex Systems Network Representation of Individual Level Baseline Performance*

González Canché, 2021

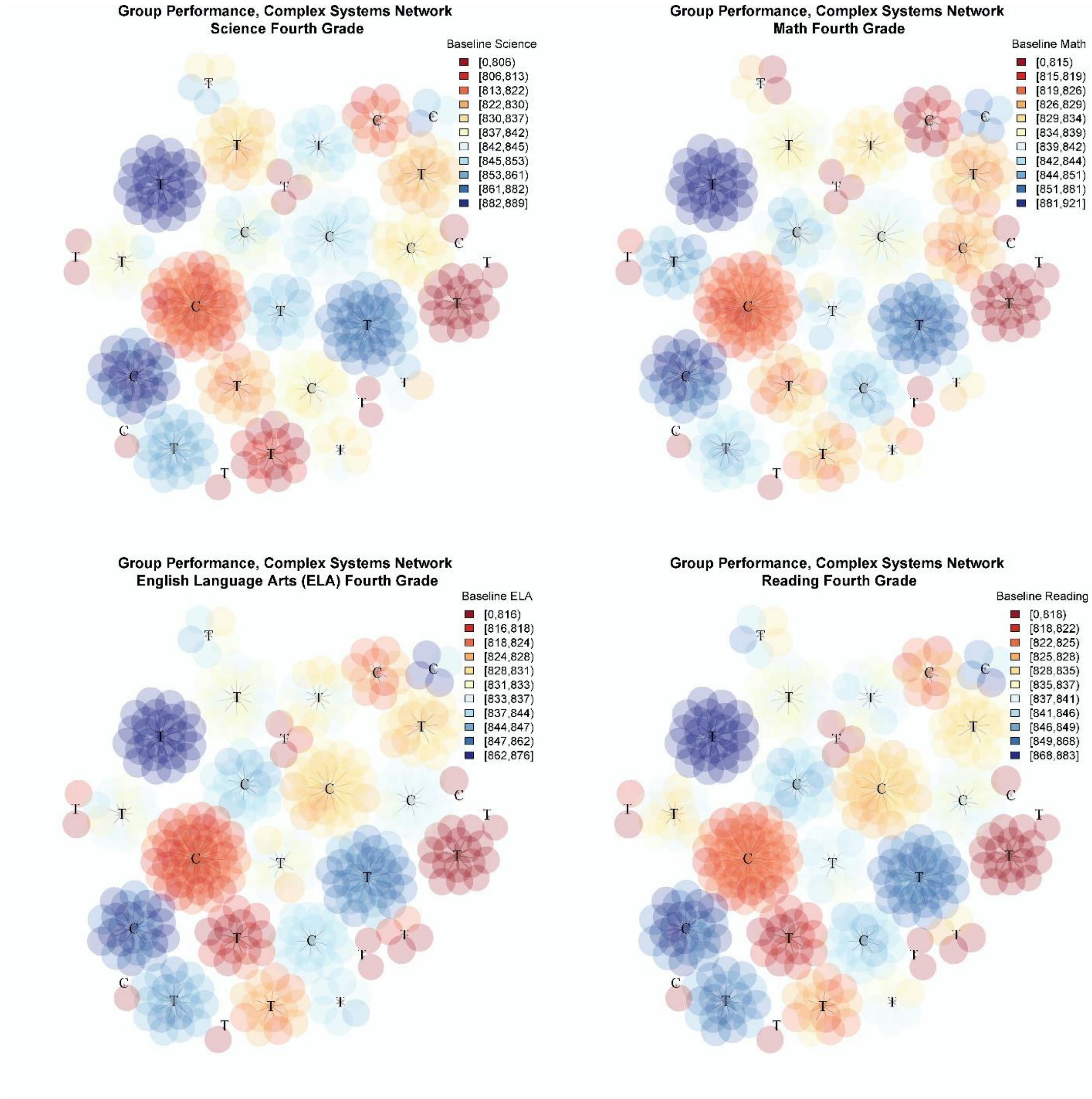

Figure 28.3. *Complex Systems Network Representation of Socially Lagged Baseline Peers' Performance*

González Canché, 2021

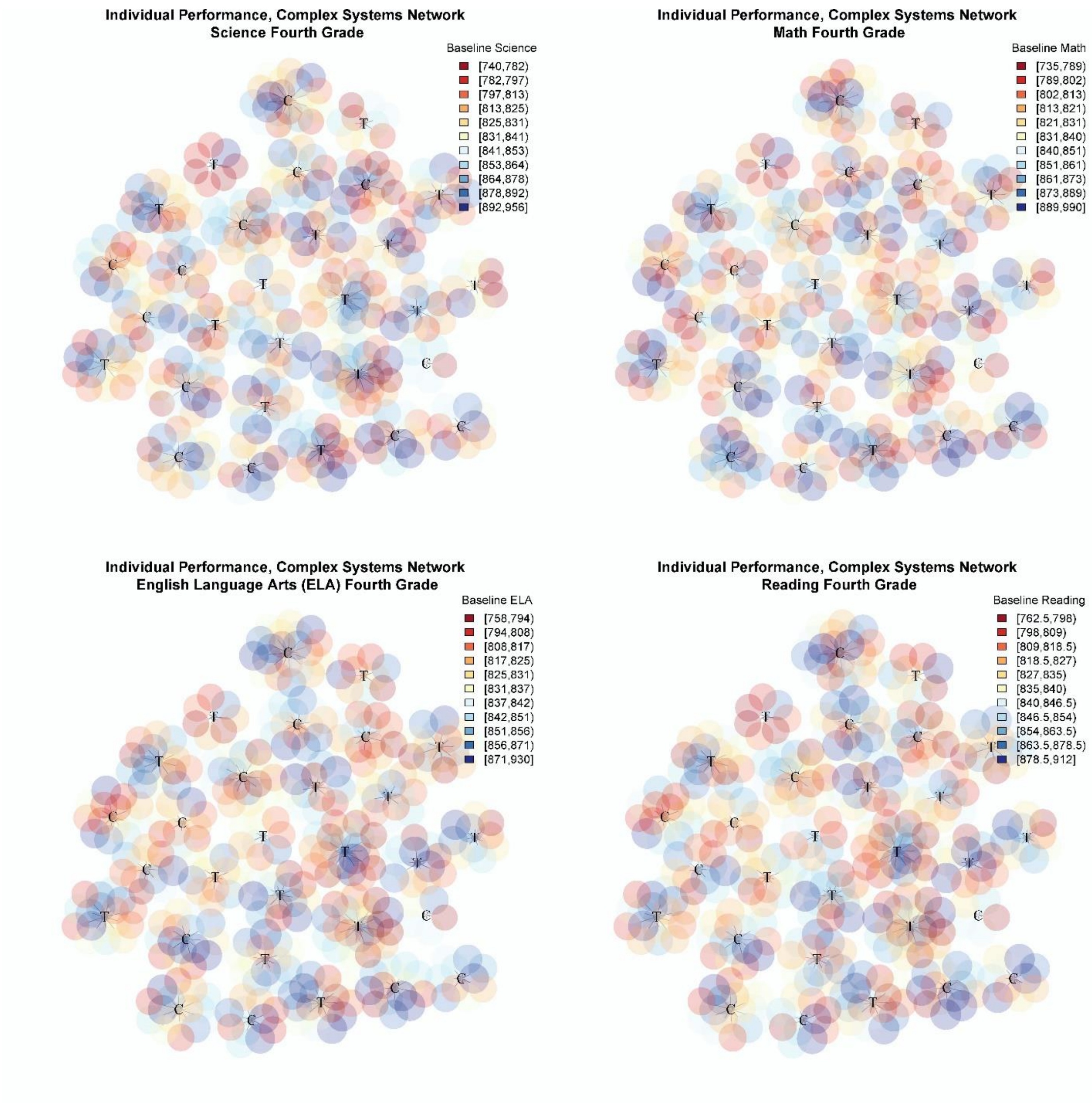

Figure 28.4. *Complex Systems Network Representation of Individual Level Baseline Performance Under True Randomization*

González Canché, 2021

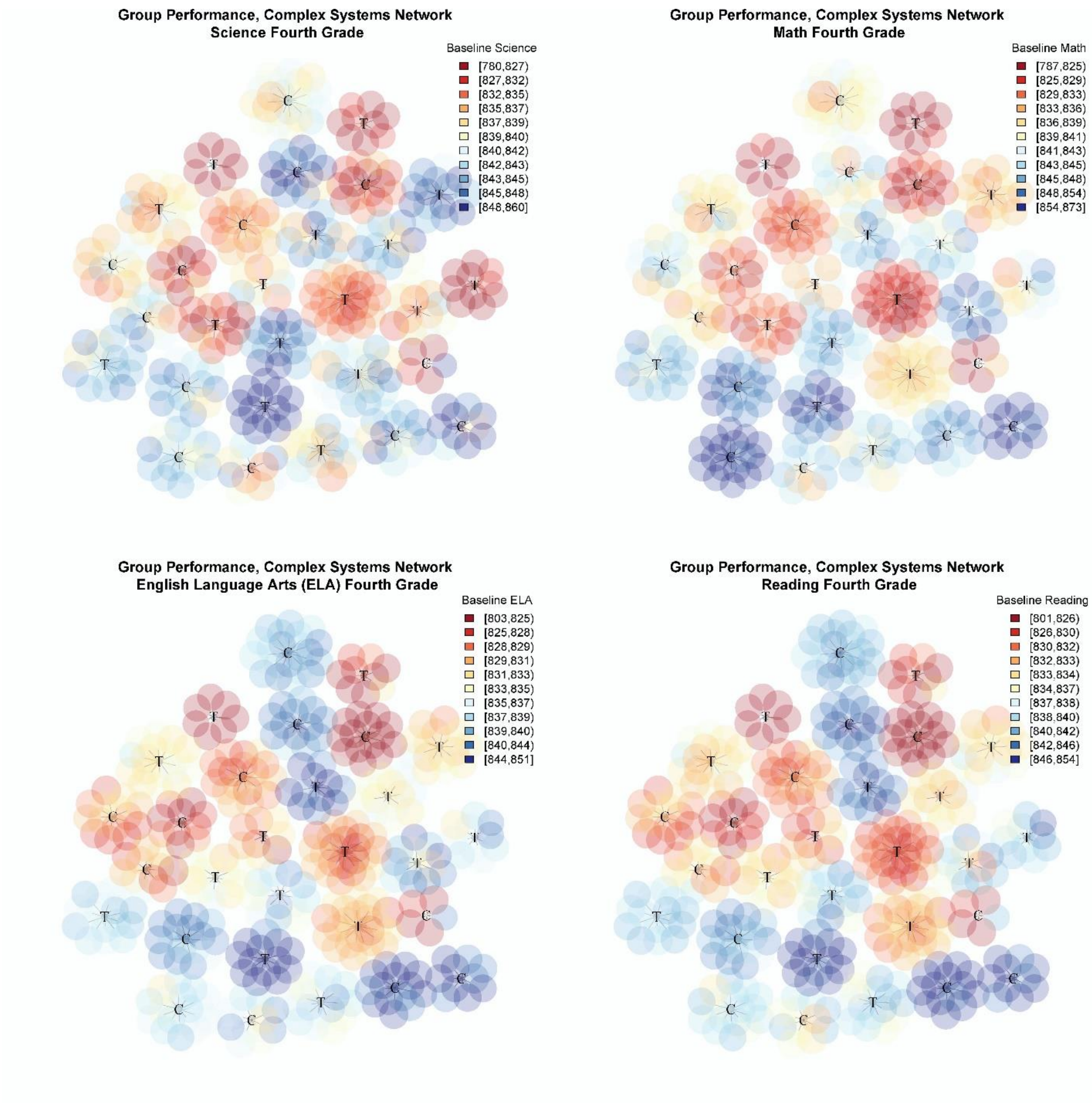

Figure 28.5. *Complex Systems Network Representation of Socially Lagged Baseline Peers' Performance Under True Randomization*

Regression-based Results

These results are presented in Tables 28.3, 28.4, and 28.5. Each table includes a naïve OLS model, which ignores the nested structure of the data, along with its multilevel specification. At the bottom of each model a Moran's I test of regression residuals (e_i and e_it for the OLS and multilevel models, respectively) is also presented. Table 28.3 addresses question 3 regarding evidence of peer effects. Table 28.4 addresses question 3(a) regarding potential moderation of peer effects by treatment condition. Finally, Table 28.5 addresses question 3(b) concerning whether peer effects dissipated when controlling for individual-level pre-intervention performance.

All the models contained in Table 28.3 consistently indicate the presence of peer effects, wherein the baseline outcomes of a given student's peers significantly influenced her/his academic performance the subsequent year. Although these findings are consistent across the OLS and multilevel specifications, the magnitude of these coefficients is higher in the OLS models. Note also that the residuals obtained in the OLS models (or e_i as they ignore the subscript t) are still subject to dependence issues, which suggests that the spillover effect coefficients shown are upwardly biased. From this perspective, a more accurate depiction of the magnitude of spillovers is found in the multilevel approaches, wherein all residuals (e_it) behaved identically and independently distributed. From a practical point of view, we can conclude that as one's peers' performance goes up in a given subject area one's own performance will also tend to increase. Figure 6a presents the expected gains given the mean values of the lagged indicators (peers' performance) contained in Table 28.1. It is worth noting the expected gains, which reach almost 60 standardized points in science and 33 points in reading. Similar analyses can be conducted at differing levels of the distributions shown in Figure 28.3, where these lagged indicators are separated in quantiles.

Table 28.4 tests whether peer effects are moderated by the IC intervention. The OLS models indicated that in all but one of the content areas, IC students benefited more by the baseline achievement of their peers. However, note once more that the residuals are autocorrelated, which threatens the validity of these conclusions. The multilevel results corroborated that there was no evidence to conclude that IC students benefited more than their non-IC counterparts from their peer's past performance across content areas. Once more, these multilevel models' residuals were not subjected to dependence issues. Accordingly, these multilevel estimates are less biased than the estimates obtained with the OLS models.

Finally, Table 28.5 controls for individual-level achievement and spillover effects. In these models, two of the four OLS results show that spillover effects remained significant even after controlling for individual performance. Notably, these inferences remained true in the multilevel approach (English language arts and science, $p < 0.05$). These latter findings are important given that they suggest the need to control for peer effects moving forward, even after controlling for individual pre-treatment

Table 28.3. *Regression Models Explaining Post-Intervention Outcomes Using Spillover Effects*

	OLS				Multilevel			
	Science	**Math**	**ELA**	**Reading**	**Science**	**Math**	**ELA**	**Reading**
(Intercept)	737.98***	762.81***	772.23***	778.71***	778.38***	804.19***	797.29***	804.25***
	(18.77)	(17.82)	(13.14)	(12.12)	(19.61)	(18.65)	(13.40)	(12.45)
lag.sci	0.12***				0.07**			
	(0.02)				(0.02)			
lag.math		0.10***				0.05*		
		(0.02)				(0.02)		
lag.ela			0.08***				0.05**	
			(0.02)				(0.02)	
lag.read				0.07***				0.04*
				(0.01)				(0.02)
R2	0.07	0.05	0.07	0.06				
Adj. R2	0.06	0.05	0.06	0.06				
Num. obs.	397	397	397	397	397	397	397	397
RMSE	39.27	37.49	26.87	24.86				
AIC					3982.72	3949.52	3654.57	3588.9
BIC					3998.64	3965.43	3670.49	3604.81
Log Likelihood					-1987.4	-1970.8	-1823.3	-1790.5
Num. groups					29	29	29	29
Moran's I	0.208***	0.207***	0.28***	0.288***	-0.06	-0.051	-0.054	-0.055

***p<0.001, **p<0.01, *p<0.05, • p<0.10

Table 28.4. *Regression Models Explaining Post-Intervention Outcomes Using Spillover Effects Interacted with IC participation*

	OLS				Multilevel			
	Science	**Math**	**ELA**	**Reading**	**Science**	**Math**	**ELA**	**Reading**
(Intercept)	779.06***	787.79***	796.21***	802.70***	797.84***	814.40***	812.19***	820.91***
	(26.85)	(25.84)	(18.58)	(17.21)	(28.04)	(26.63)	(19.10)	(17.75)
treat_teacher	-79.14*	-48.36	-46.55•	-46.73•	-37.84	-19.39	-29.39	-32.78
	(37.41)	(35.68)	(26.07)	(24.12)	(39.41)	(37.42)	(26.95)	(25.03)
lag.sci	0.07*				0.05			
	(0.03)				(0.03)			
treat_teacher:lag.sci	0.10*				0.04			
	(0.04)				(0.05)			
lag.math		0.07*				0.04		
		(0.03)				(0.03)		
treat_teacher:lag.math		0.05				0.01		
		(0.04)				(0.05)		
lag.ela			0.05*				0.03	
			(0.02)				(0.02)	
treat_teacher:lag.ela			0.06*				0.04	
			(0.03)				(0.03)	
lag.read				0.04•				0.02
				(0.02)				(0.02)
treat_teacher:lag.read				0.06*				0.04
				(0.03)				(0.03)
R2	0.08	0.06	0.09	0.07				
Adj. R2	0.07	0.05	0.08	0.07				
Num. obs.	397	397	397	397	397	397	397	397
RMSE	39.11	37.47	26.65	24.71				
AIC					3983.67	3950.48	3656.67	3590.66
BIC					4007.51	3974.33	3680.51	3614.5
Log Likelihood					-1985.83	-1969.24	-1822.33	-1789.33
Num. groups					29	29	29	29
Moran's I	0.194***	0.201***	0.265***	0.277***	-0.06	-0.053	-0.056	-0.057

***p<0.001, **p<0.01, *p<0.05, • p<0.10

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Table 28.5. *Regression Models Explaining Post-Intervention Outcomes After Controlling for Individual level performance*

	OLS				Multilevel			
	Science	**Math**	**ELA**	**Reading**	**Science**	**Math**	**ELA**	**Reading**
(Intercept)	213.40***	276.17***	241.55***	310.89***	220.65***	270.12***	292.56***	244.44***
	(27.66)	(26.94)	(26.24)	(22.76)	(30.84)	(30.95)	(28.88)	(22.64)
pre_science	0.71***				0.71***			
	(0.03)				(0.04)			
lag.sci	0.03•				0.03**			
	(0.02)				(0.01)			
pre_math		0.67***				0.67***		
		(0.03)				(0.04)		
lag.math		0.01				0.01		
		(0.02)				(0.01)		
pre_ela			0.70***				0.64***	
			(0.03)				(0.04)	
lag.ela			0.02*				0.02*	
			(0.01)				(0.01)	
pre_read				0.73***				0.70***
				(0.03)				(0.03)
lag.read				0.00				0.00
				(0.01)				(0.01)
R2	0.57	0.54	0.57	0.70				
Adj. R2	0.57	0.54	0.57	0.70				
Num. obs.	397	397	397	397	397	397	397	397
RMSE	26.75	26.2	18.25	14.11				
AIC					3719.87	3712.15	3433.2	3241.27
BIC					3739.75	3732.03	3453.09	3261.15
Log Likelihood					-1854.94	-1851.08	-1711.6	-1615.63
Num. groups					29	29	29	29
Moran's I	0.136***	0.112***	0.082***	0.164***	-0.048	-0.037	-0.038	-0.029

***p<0.001, **p<0.01, *p<0.05, • p<0.10

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Figure 28.6a. *Expected gains given peer effects without controlling for individual level performance.*

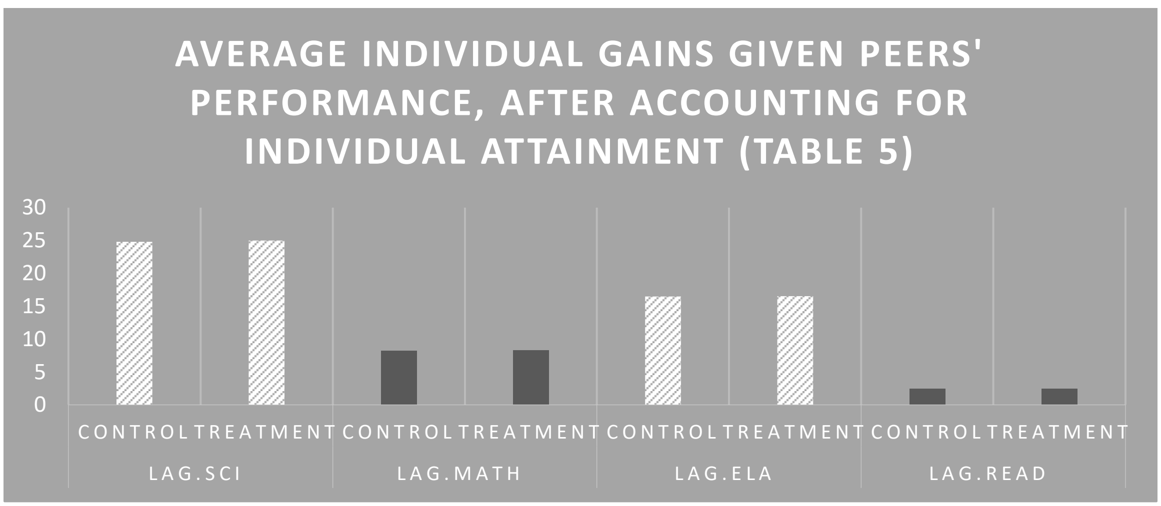

Figure 28.6b. *Expected gains given peer effects after controlling for individual level performance. Dark bars indicate not significant results at the 0.05 probability level.*

achievement, by following the methodological procedures depicted in this paper and shown in the appendix. Similar to the analyses discussed for Figure 6a, note that Figure 28.6b shows that both control and treatment participants' individual post-treatment performance in science increased about 25 standardized points, on average, based on the influence of their peers' performance, even after accounting for their individual-level baseline performances. In the case of English language arts, the observed average gains based on their peer effects were around 16 standardized points. The dark bars in math and reading show no significant effects, as indicated in Table 28.5.

Discussion and Implications

The complex systems network approach employed in this study allows researchers to capture a more comprehensive level of variation at a systemic level. The case studied justifies the need to measure for potential contamination at the student-teacher group formation stage, wherein administrative decisions, parental involvement, or even mean school-level achievement, may contribute to the potential clustering of students with more similar baseline performances that what one should expect to observe by random chance. This clustering in addition to potential self-selection, may not only have driven such group formation, but more importantly may also affect the treatment effect. This study argued that aggregated baseline comparisons may not only mask factors affecting "joining" decisions but also, and as importantly, the effects that peers have on their classmates resulting from such decisions. Both factors are considered important threats to the efficacy of randomization and its corresponding effect on potentially biasing causal claims.

The method depicted is easy to follow and replicate and can be conducted during the group formation stage to comprehensively assess group baseline performance before the intervention is actually implemented. This is possible as long as researchers have access to students' pre-treatment indicators at the group formation stage. Note, however, that the presence of peer effects is not a negative finding per se, but rather researchers could start capitalizing on these effects more systematically. For example, students who may be academically struggling may benefit the most by regularly interacting with their more academically "proficient" peers hence calling for a more balanced diversity in achievement levels within each teacher-student group. Although the discussion of what this more strategic group formation implies for clustered RCTs goes beyond the scope of this study, such a group formation could potentially balance each student-teacher group by academic performance tertiles (e.g., x students from the bottom tertile, y students from the meddle tertile, and z student from the upper tertile) to ensure the presence of students interacting with higher achiever peers and vice versa. This balance, in addition to diversifying the content and quality of the discussion and arguably being more equitable, will contribute to reach Moran's I values that are closer to zero. However, and notably, the peer effects gains highlighted in this study are not expected to disappear by following a more strategic group formation approach, but rather may even be reinforced.

To reiterate, the presence of peer effects is not troublesome, what is troubling is the assumption that peer effects are nonexistent as their omission would continue to remain a problem of omitted variable bias given the structure these indicators account for in the models. The complex systems network framework depicted herein enables both testing for this assumption and controlling for or modeling the magnitude of these effects. While the models shown in Table 5 are meant to absorb the statistical power of peer effects as predictors, this approach fell short in achieving this goal, a truly remarkable finding that justifies the need to incorporate these effects in our analytic frameworks.

To close, on a related note, it is worth mentioning that the procedures and research questions presented in this study have been replicated with data taken from a teacher professional development program that was conducted in public and private kindergartens in the Greater Accra Region of Ghana (see Wolf, Aber, Behrman, & Tsinigo, 2018). Such a professional development program consisted of a cluster-randomized trial that included 240 schools, 444 teachers and 3,345 children with a mean age of 5.2 years. Clearly, such a study has more statistical power than the study discussed here, and all models measuring children indicators of school readiness (assessed in four domains: early literacy, early numeracy, social-emotional skills, and executive function) indicated that peer effects remained significant after controlling for students' own baseline performance in their same school readiness domains measured pre-intervention. That data, however, are not yet publicly available for inclusion in this study and this replication exercise was conducted simply as a test of methodological external validity. The replication of the conclusions reached in this paper with that other cluster-randomized trial is considered remarkable as those data were collected in a different continent and by another research team. Please note that all the coding schemes are included in the appendix section for researchers to implement these approaches with their own data.

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Appendix

```
########################################################################
########################Complex Systems Networks########################
########################################################################
#These procedures enable implementation of complex systems network
analyses
#While data are not available, the procedures can be used with
researchers own data
#the code is annotated to ease replication.
install.packages("igraph")
install.packages("spdep")
install.packages("multilevel")
install.packages("RColorBrewer")
install.packages("classInt")
library(RColorBrewer)
library(classInt)
library(multilevel)
library(spdep)
library(igraph)
#Load dataset, referred to as "a" for convenience
a<-read.csv("dataset.csv")
#In this data students are represented in the column called "studentID"
and teachers in the column "teacher_id"
#The following code retrieves the student-teacher connections saved
under a graph object called "g"
g<-graph.data.frame(a[,c("studentID","teacher_id")])
#The following code adds the two-mode structure to the graph "g"
V(g)$type <- V(g)$name %in% a[,c("studentID")]
#These procedures retrieve the matrix form version of the graph "g"
saved as "Z"
Z<-t(as.matrix(get.incidence(g, types=NULL, names=TRUE, sparse=FALSE)))
#The one mode transformation is achieved as follows
z <- Z%*%t(Z)
#To avoid self-selection the diagonal is set to zeroes.
diag(z)<-0
#Row normalization procedures implemented in Moran's I are achieved as
follows
matrix <- z/rowSums(z); matrix[is.na(matrix)] <- 0
#Matrix of influence saved under the object "test.listwR"
test.listwR<-mat2listw(matrix)
#Social lags are retrieved as follows and save as new variable in the
dataset
a$lag.sci  <- lag.listw(test.listwR, a$pre_science, zero.policy=T)
a$lag.math <- lag.listw(test.listwR, a$pre_math, zero.policy=T)
a$lag.ela  <- lag.listw(test.listwR, a$pre_ela, zero.policy=T)
a$lag.read <- lag.listw(test.listwR, a$pre_read, zero.policy=T)
#Example Network Visualization Procedures
#Plotting variable should be changed as needed
plotvar <- round(a$lag.sci, 0)
nclr <- 11
plotclr <- brewer.pal(nclr,"RdYlBu")
class <- classIntervals(plotvar, nclr, style="quantile")
colcode <- findColours(class, plotclr)
colcode <- paste(colcode,"3F",sep="")
V(g)$size[1:nrow(a)]<-abs((a$pre_science)/max(a$pre_science))*15
V(g)$size[(nrow(a)+1):length(V(g)$name)]<-1
```

```
plot(g, vertex.color=colcode, vertex.label=V(g)$label,
edge.arrow.size=.25, layout=l2)
colcode <- findColours(class, plotclr)
legend("topright", legend = names(attr(colcode, "table")), fill =
attr(colcode, "palette"), title="Baseline Science", cex=2, box.col=NA)
title(main="Group Performance, Complex Systems Network\n Science Fourth
Grade",cex.main=2.5)
###Procedures to achieve Figure 1
#Aggregation of means by treatment condition
sta<-aggregate(a$pre_science, list(a$IC), mean, na.rm = T)
#Matching these values to actual IC status (IC has values 1 or 0)
a$tlag.sci <- as.numeric(sta$x[match(a$IC,sta$Group.1)])
#The resulting aggregated values can be substituted as the plotting
# value in the visualization code above
#Code to generate true random assignment
set.seed(47)
a$randomID <- sample(x = c(1:length(table(a$teacher_id))), size =
nrow(a), replace = TRUE)
# To create a new graph with the random assignment we use the following:
gR<-graph.data.frame(a[,c("std","teacher_id")])
#The graph gR can then be transformed into a matrix of influence to
implement Moran's I as done above and illustrated next
V(gR)$type <- V(gR)$name %in% a[,c("studentID")] #this indicates we are
dealing with a two-mode network
table(V(gR)$type)
ZR<-t(as.matrix(get.incidence(gR, types=NULL, names=TRUE,
sparse=FALSE)))
dim(ZR)
zR <- ZR%*%t(ZR)
dim(zR)
diag(zR)<-0
matrixR <- zR/rowSums(zR)
matrixR[is.na(matrixR)] <-0
test.listwRR<-mat2listw(matrixR)
#Example of Moran's I procedures by content area
moran.test(a$pre_science, test.listwR, zero.policy=T)
#Example of Moran's I procedures by content area using the random
structure captured in "test.listwRR"
moran.test(a$pre_science, test.listwRR, zero.policy=T)
#Example OLS and spillovers
sciencenaive <- lm(formula = post_science ~ lag.sci, data =
data.frame(a))
#Example Science and spillovers
mscience <- lme(post_science ~ lag.sci, random= ~ 1|teacher_id, data= a,
control= list(opt="optim"))
#Example Science moderated by treatment (IC)
mscience.t <- lme(post_science ~ lag.sci * IC, random= ~ 1|teacher_id,
data= a, control=list(opt="optim"))
#Example Science controlling by individual level performance
mscience.i <- lme(post_science ~ lag.sci + pre_science, random= ~
1|teacher_id, data= a, control= list(opt="optim"))
#Regression residuals' dependence are tested as follows:
jNULL <- residuals(mscience); moran.test(jNULL,test.listwR,
zero.policy=TRUE)
########################################################################
```