DATA USE FOR WHAT AND FOR WHOM?:
A CLOSE LOOK AT THE POLICIES AND TEACHER PRACTICES THAT SHAPE DATA-
DRIVEN DECISION MAKING AT AN ELEMENTARY SCHOOL

BY

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DISSERTATION

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Abstract

In this thesis, I present an analysis of how educators practiced data-driven decision making (DDDM) at Greenbrook Elementary, a school that has historically struggled to facilitate equitable learning outcomes for students. The findings from this study suggest DDDM may look quite different in practice than how it is described in the literature. The literature often characterizes DDDM as a practice where teachers are active participants who systematically collect data, interpret these data, formulate action plans, and continuously evaluate and adjust their plans based on further data (Coburn & Turner, 2011; Mandinach, 2012). At Greenbrook, this was not typically what was observed. Teachers were often passive recipients of data and directives on how to interpret and use these data. In this context, I offer an examination of how particular policies and practices mediated teacher data-use.

Specifically, I present three essays on practices or policies associated with DDDM at Greenbrook. In the first essay, I describe teachers' engagement with color-coded students' performance data. While the color-coding of data are meant to *support* teachers' interpretations of data (Love, 2004; Marsh 2012), I argue that at Greenbrook, students' color-coded data was primarily used to sort students into different educational offerings. In the second essay, I examine aims for data use. Borrowing the concept of "matchmaking" (Oakes & Guiton, 1995), I describe how educators' data use targeted matching students to pre-determined educational programs. I argue that matchmaking promoted particular data-use conversations and decisions while stifling inquiries into other issues that might have merited attention, like inequities in the learning environment. In the third and final essay, I present an overview of the political mandates that governed teachers' work at Greenbrook. I argue that teachers had little autonomy to respond to students' data in meaningful ways.

Acknowledgements

Over 70 years ago, my grandmother was 6th in line to receive a scholarship to college. The first 5 women declined and my grandmother accepted. I thank my grandmother for having the courage to accept such an opportunity. I thank my mother for continuing this legacy. By completing this doctorate, I honor their legacy and continue it for my daughter.

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TABLE OF CONTENTS

Chapter 1: Introduction

In a recent story on NPR, a Harvard-trained doctor became the mayor of Cali, Columbia. This small town suffered from abhorrent gun violence. Members of the community believed the proliferation of shootings stemmed from gang violence and that local leaders had little recourse to combat gangs and gang-related murders. However, this widely held belief was untested. The new mayor's training in evidenced-based medicine led him to systematically collect and analyze data on the town's gun violence. He identified a trend in the data—shooting were more likely to occur on Friday nights. With further investigation, he determined that shootings were most likely to occur on Friday nights when local citizens used their paychecks to drink in the bars. Contrary to popular belief, the mayor found evidence to support the assertion that a large proportion of gun violence occurred spontaneously in bars, rather than as a part of targeted gang violence. By enacting particular policies to combat excessive drinking and the carrying of firearms in bars, shootings in town dropped 30% and further dropped by 50% over 10 years (Akpan, 2014).

I start with this example to demonstrate what is possible when practitioners use data to investigate intractable social problems. Longstanding assumptions are challenged and in the process, novel, effective solutions can be developed. In the context of public education, this type of data use has the potential to test assumptions about root causes of the achievement gap and to facilitate the creation of novel solution. Educators can and have used data in order to investigate assumptions about our students, their capacity to learn, and the quality of education provided to them.

By conceptualizing data use in this way, I aim to illustrate a theme in the discourse on data use—data use is powerful and transformative. In educational policies on data use, this

practice is often described as *the* tool for transforming our schools and ending the immoral achievement gap (Coburn & Turner, 2012; Duncan, 2009; Means, Padilla, & Gallagher, 2010). Data use is perceived as having many useful purposes and solutions; it has been described as the "Swiss-army knife" of educational reform (Simmons, 2012, p. 1).

The problem is that data use in educational settings is not living up to the hype. The early research on the outcomes of DDDM suggests that data use alone does not enhance students' education. Multiple studies document that data use does not necessarily bring about school reform or changes to students' instruction (Barrett, 2009; Booher-Jennings, 2005; Earl, 2009; Jennings, 2012).

This disconnect between the promises of data use and the realities of data use is currently under investigation. Researchers are actively studying data use in action in order to understand how this practice works in schools (Coburn & Turner, 2012; Kallemeyn, 2014; Klostermann, White, Litchtenberger, Holt, & Illinois Educational Research Council [IERC], 2014; Little, 2012). This need to better understand the practice of data-driven decision making and how it operates in educational settings fostered a call for research proposals from the Spencer Foundation for Educational Research.

Upon winning a grant from the Spencer Foundation, a small team of researchers[1] including myself, set out to investigate data-driven decision making in K-8 schools. Specifically, our team aimed to understand the role of student characteristics in teachers' interpretations and uses of student performance data. We planned this study in the spring of 2013 and started to collect data in the fall of 2014. This study is currently ongoing and is described further in the methods section of this dissertation.

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[1]1The research team included Jennifer Greene, Thomas Schwandt, Nora Gannon-Slater, Hope Crenshaw, Priya La Londe, and Rebecca Teasdale. Their efforts, ideas, and support made this dissertation possible. These team members deserve a tremendous amount of credit for the research presented in this dissertation.

In this broader study on the role of student characteristics in DDDM, I became particularly interested in the types of data-driven decisions educators were making about students' academic strengths, weaknesses, and instruction in response to their understandings of students' performance data. Further, I became intrigued with how particular conditions at one school site mediated teachers' uses of data and students' access to different educational opportunities. The following research questions specifically guided my inquiry.

1. In what ways do grade-level teams of teachers at Greenbrook Elementary analyze, interpret, and make instructional decisions with data?

2. In what ways do particular data-use practices or policies support (or limit) teachers' use of data to make instructional decisions?

With approval from the research team, I conducted my dissertation on data-driven decision making in coordination with the larger, Spencer-funded research project. I specifically investigated data use at one school site with two grade-level teams, using the above research questions as my guide. This dissertation documents this study.

Overview of the Dissertation

The aim of this dissertation is to tell the story of data-driven decision making at Greenbrook Elementary [pseudonym]. At this particular school, data-driven decision making unfolds in an environment where educators face political pressure to enhance the test scores of their students. A sizable proportion of their struggling students are African American students who qualify for free and reduced lunch. A smaller proportion of their students who exceed on standardized tests are white, affluent and often segregated in a gifted program that is housed at this school site. In this way, Greenbrook is representative of the broader, prevalent achievement gap within public schools between students of color and their wealthier, white counterparts. This

study describes how data-driven decision making operates in a school that struggles to foster more equitable educational outcomes amongst its students. Further, by telling the story of DDDM at Greenbrook, I aim to illustrate how the particular occurrences at Greenbrook relate to broader issues and ideologies present in educational policies and research.

To fully appreciate the phenomena of data-driven decision making, the following chapter introduces the reader to the literature and research on DDDM. This literature review starts with conceptualizing the phenomena of data-driven decision making. After establishing the concept of DDDM, I provide an overview of the research on this practice. Coburn and Turners' (2011) review of the literature suggests that the research on DDDM includes (a) the educational outcomes associated with DDDM, (b) the components or activities associated with DDDM, and (c) the identification of conditions that support educators' engagement with data, like data warehouses. Using these three categories to organize the literature on DDDM, I provide a description of major studies and themes in each category. This chapter ends with a brief account of how this literature influenced the development of our research team's study and my dissertation.

The third chapter includes a description of the methods utilized to investigate the phenomena of data-driven decision making. As the methods utilized for my dissertation heavily overlap with the methods used by the Spencer research team, this chapter includes a rationale and a description of methods in both studies. This chapter begins with a rationale for the research team's investigation of the phenomena of data-driven decision making and the qualitative methods employed to study DDDM in-situ. Further, I describe the research team's selection process for identifying and recruiting school sites and grade-level teams to participate in this study. This chapter ends with a description of the methods employed for my individual

study. I specifically explain my rationale for selecting one school site, Greenbrook for my dissertation. I also describe my contribution to the data collected at this site, the type and quantity of data collected at this site, and my approach to data analysis.

The fourth chapter begins to tell the tale of data-driven decision making at Greenbrook. The information presented in this chapter is an analysis of the data collected from observing grade-level data-use meetings and from interviewing teachers who participated in these meetings. This chapter begins with an overview of the context of Greenbrook and important terms and concepts associated with data use at this school. Then I recount a typical data-use meeting at Greenbrook in order to describe the key actors and components of DDDM. Finally, I offer the perspectives of individual teachers who participated in the grade-level team meetings. The information presented in Chapter 4 is meant to provide an overview of the context of Greenbrook, the practice of data-driven decision making in grade-level team meetings, and teachers' perspective on the particular form of DDDM that happens in their meetings. This overview in Chapter 4 provides necessary background information for the three essays presented in Chapter 5.

The fifth and final chapter includes three essays that highlight particular policies or practices at Greenbrook that impacted teachers' data use. Each essay is related to and builds upon the preceding chapters in this dissertation, particularly Chapter 4. At the same time, each essay contains a distinct argument where I attempted to situate the findings from Greenbrook in relevant educational research and theories.

The first essay presented in the fifth chapter is titled "From Black and White to Red and Green: Color Still Impacts Students' Educational Reality." In this essay, I highlight the "stoplight" color-scheme (Love, 2004). The stoplight color-scheme is a data visualization tool

where data are color-coded in order to support teachers' interpretations of student performance data. Using evidence from the study of Greenbrook and literature on labeling theory, I argue that this color-scheme was primarily utilized to label and sort students at Greenbrook. These labels were associated with students' access to different educational avenues at Greenbrook, particularly the lowest performing students. I specifically raise the question about whether the stoplight color-scheme was beneficial for low-performing students at Greenbrook.

The second essay presented is titled "Beyond "Matchmaking": An Examination of the Aims of Data-Driven Decision Making." In this essay, I examine specific aims for data use. Borrowing the concept of "matchmaking" (Oakes & Guiton, 1995), I describe how Greenbrook educators' data use targeted matching students to pre-determined educational programs. I argue that matchmaking promoted particular data-use conversations and decisions while stifling inquiries into other issues that merited attention. Further, using teachers' perspectives and their individual data-use activities, I present teachers' alternatives to matchmaking.

The third and final essay is titled "The Decision Makers: Do Teachers Have the Authority to Make Decisions Based on Data?" In this issue, I identify a data-use support that is potentially missing from the existing literature: A political climate conducive to teachers using data to make decisions. Using a policy lens, I present the plethora of policies and mandates that mediate teachers' work at Greenbrook. As multiple policies prescribed teachers' instructional goals, methods, and assessment practices, teachers had little autonomy to make instructional decisions. Without the autonomy to make instructional decisions, teachers had little flexibility to respond to students' data in meaningful ways.

Chapter 2: Literature Review

What is Data-Driven Decision Making?

Data-driven decision making (DDDM) is a practice currently emphasized in educational policy, practice and research. Data-driven decision making is defined as educators engaging with students' performance data in order to inform educational decisions (Coburn & Turner, 2012; Mandinach, 2012). Yet, this definition fails to distinguish data-driven decision making from the historical practice of educators making decisions based on assessment data. In the U.S., student performance data has consistently served as a valued indicator in educators' instructional decision making. A prominent, longstanding example is university admissions where educators have often relied on students' performance data from the ACT or SAT to make entrance decisions. In high schools, educators often use student performance data to identify appropriate courses and tracks for secondary students (Oakes & Guiton, 1995). And at the elementary level, teachers have often relied upon performance data to assign students' to reading groups. These and other examples are meant to illustrate that teachers collected, analyzed, and used data to inform their decisions far before the practice of data-driven decision making became so prominent.

Data Regime

What makes DDDM different from what educators have done for decades? Data-driven decision making is a practice situated in what Henig (2012) calls a "data regime" or a political, ideological, and technical system (p. 4). The phenomena of DDDM is a summation of policies, values, and tools that shape educators engagement with data (Henig, 2012). The following section provides a brief overview of the data-use technologies, policies, and ideologies that undergird the practices of data-driven decision making.

Technical infrastructures of DDDM. Data-driven decision making is bolstered by an

industry of assessment systems, data warehouses, and other technological tools for educators.

The federal government and states have made a hefty financial investment in technological

infrastructure for data use (Burch, Hayes, Kowalski, & Lasley, 2009; Mandinach & Gummer,

2013); Mandinach and Gummer (2013) cite over a 600 million dollar investment by the federal

government in state longitudinal databases alone (p. 31). A portion of the technologies

associated with DDDM stemmed from the era of NCLB. The more punitive nature of NCLB

encouraged states, schools, and districts to purchase benchmark assessment systems that helped

predict students' end-of-year performance on annual, consequential standardized tests. These

benchmark systems were supposed to help educators identify students at risk of failing early on

in the school year (Burch et al., 2009; Carlson, Borman, & Robinson, 2011). These systems and

annual standardized assessments fostered an influx of data into schools, which encouraged

educators to access, analyze, and use these data to inform their practice. Meaning before the

data-use policies of RTTT, many states, districts, and schools were using available data to make

decisions (Carlson et al., 2011). Researchers documented that local efforts to use data were often

thwarted by a lack of timeliness of data and accessibility to all students' data. This is part of the

rationale for why the RTTT competition required the creation of longitudinal data bases as these

systems were supposed to enhance teachers' timely access to all students' data (Mandinach &

Gummer, 2013). RTTT policies and funds spurred the creation of longitudinal, statewide

databases across most of the U.S. (Gottfried, Ikemoto, Orr, & Lemke, 2011; Iorio & Adler,

2013). Across states, the nature, content, and features of databases and data management

systems vary, with some areas purchasing systems and others working with technology

companies to create custom systems (Burch et al., 2009). For the district-wide data management

systems, Burch et al., (2009) found that wealthier districts were more likely to create custom data management systems while under-resourced districts were more likely to purchase packages. For longitudinal, statewide databases, Mandinach and Gummer (2013) report that these systems are typically built, implemented, and then educators are taught how to use the system.

DDDM policies. Over the past 40 years, a variety of federal, state, and school district policies set an explicit expectation for educators to use data (Dunn, Airola, Lo, & Garrison, 2013; Ikemoto & Marsh, 2007; Mandinach, 2012; Marsh, Pane, & Hamilton, 2006). Marsh, Pane, and Hamiliton (2006) argue that data-driven policies date back to the 1970's with reform efforts such as "measurement-driven instruction" and school-improvement plans (p. 2). More recently, federal policies like No Child Left Behind (NCLB) and Race to the Top (RTTT) have further propelled standardized data and data-driven decision making to the forefront of educational reform (Hargreaves & Braun, 2013; Ikemoto & Marsh, 2007). No Child Left Behind and Race to the Top put muscle behind the movement of educators using data to inform their instruction. Specifically, NCLB sanctioned educators, schools, and districts that did not raise students' test scores, thereby making test scores a primary concern to all educators. The RTTT competition moved away from sanctions but instead offered states a heavy financial incentive to implement data-use policies and invest in data-use infrastructure (Fletcher, 2010). Almost every aspect of the RTTT competition guidelines required states and educators to use data to make instructional decisions. From teacher evaluations to the creation of longitudinal state-wide data bases to evaluating colleges of education, RTTT pushed all sectors of education to incorporate DDDM (U.S. Department of Education [USDOE], 2009b).

The federal emphasis on standardized test scores and data use pushed states and local districts to implement data-use policies (Hargreaves & Braun, 2013; Means et al., 2010). Local

data-use policies vary widely amongst states and districts (Carlson et al., 2011; Moody & Dede, 2008). However, a common theme across states and districts data-use policies is the requirement of teachers to regularly analyze student performance data in order to make and *justify* instructional decisions (Carlson et al., 2011; Mandinach, 2012). Accompanying this expectation for teachers to use data are new school-based policies that are intended to foster teachers' data use. For example, many schools now have an official time block set aside for educators to collaborate around data (Earl, 2009; Gallimore, Ermeling, Saunders, & Goldenberg, 2009; Little, 2012).

Beyond NCLB and RTTT, another major set of data-use policies stem from the federal Individuals with Disabilities Act (Jacobs, Gregory, Hoppey, & Yendol-Hoppey, 2009; Zirkel, 2012). To justify students' placement in special education, educators need specific data sources to provide evidence of students having a disability. One approach for monitoring students' performance data and verifying if students have a disability is the Response to Intervention framework (RTI), which has been adopted by multiple states (Fuchs & Fuchs, 2006; Fuchs, Mock, Morgan, & Young, 2003; Jacobs et al., 2009). Although RTI policies vary from state to state, across states this framework requires the regular assessment and analysis of student data to inform general and special education decisions. Meaning, even if states and local districts were not encouraged to adopt data-use policies via the RTTT competition, all schools and educators will have to engage with students' performance data to comply with RTI policies and the federal Individuals with Disabilities Act (Jacobs et al., 2009).

Theory of change. The educational policies that promote DDDM and the stakeholders invested in this practice are based upon particular beliefs. The belief that student performance data can offer an objective, measurable indicator of students' mastery of academic content

10

underpins data-driven decision making. As data "doesn't lie" (Duncan, 2009, p. 24), this is a

trusted source of information upon which to base critical decisions. Diverse stakeholders in

education embrace this belief that data (often quantitative data) can provide an objective,

accurate indicator of students' learning. From ideals based on social justice to ideals based on

free markets, data are appealing to many group of scholars, policy makers, and educators

(Sunderman & Kim, 2007).

Proponents of DDDM also believe that data offers guidance or directives for making

important decisions (Biesta, 2007; Henig, 2012). Proponents of DDDM adhere to this belief

across a continuum, with some asserting that data are "value-free" and it embodies answers to

critical educational questions (Henig, 2012; Mandinach, 2012). Others critique this idea that

data *alone* provides evidence for teachers to make decisions. Multiple scholars argue that data

provides suggestive evidence that educators may or may not draw upon to *support,* not drive

their decisions (Coburn & Turner, 2011; Dowd, 2005; Johnson & La Salle, 2010). Although the

extent to which data drives or supports educators' decisions is debated, stakeholders generally

agree that data are informative and can help facilitate better decisions.

Overall, proponents of DDDM believe that the decision-making process is more accurate

and effective when decisions are based on data, as opposed to educators' judgment or

professional wisdom (Mandinach, 2012). The theory of change for data-driven decision making

is that data enhances educators' decision making process, therefore, educators will make better

decisions that enhance the quality of education students receive (Carlson et al., 2011; Means et

al., 2010). Proponents of DDDM adhere to this theory of change for different reasons

(Hargreaves & Braun, 2013; Sunderman & Kim, 2007).

For some, data-driven decision making offers students of color, students living in poverty, students with disabilities, and other historically marginalized groups of students in public education an opportunity to have objective decisions made about their needs that are derived from data, as opposed to stereotypes or prejudice. Interest groups committed to social justice and equity in education value the notion that critical decisions made about students would stem from students' data as opposed to educators' anecdotal information, which is vulnerable to bias and deficit thinking (Dillon, 2010; Johnson & La Salle, 2010; Koschoreck, Skrla, & Scheurich, 2001). Further, those who strive for educational equity and social justice recognize the social value of standardized tests scores on students' lives, access to higher education, and employment opportunities (Ladson-Billings, 1995). Knowing that students need particular test scores to access important opportunities in our society, educators and scholars value the inquiry into achievement gaps and low performance that accompanies particular forms of DDDM (Bernhardt, 2009; Moody & Dede, 2008).

For others, data-driven decision making is described as an appealing alternative to the status quo in educational practices (Biesta, 2007; Henig, 2012). As Secretary Duncan states in his speech titled *Robust Data Gives Us the Roadmap to Reform*, "the status quo today is simply not good enough. No one should be satisfied." In this speech, Secretary Duncan emphasized how the status quo, i.e., the achievement gap, current graduation rates, and low-performing schools is transformed via data-driven decisions (Duncan, 2009). He asserted that data are the solution to solving a number of intractable problems in public education. Similarly, other proponents of DDDM assert that this practice will alter the status quo of the teaching profession. The idea is that educators should engage with data in order to become an "evidence-based" profession, like business and medical professionals (Biesta, 2007, p. 3; Ingram, Louis, &

Schroeder, 2004). An implicit notion here is that educators have based decisions on their "gut feelings or opinions" (Mandinach, 2012, p. 71) and these decisions have not yielded a rigorous, high achieving educational system. Overall, a portion of supporters believe data-driven decision making will spur a new reality in education where practice is based on evidence and therefore, educational practices will be better and yield better educational outcomes.

A third group of supporters believe data-driven decision making can empower local educators. Based on a teaching philosophy similar to John Dewey, data-driven decision making is conceptualized as a process of experimentation and reflection (Gallimore et al., 2009; Moody & Dede, 2008). The process is not data-driven; it is teacher-driven and data plays a supporting role in teachers' inquiry related to students' needs and interests. Proponents in this camp argue that data-driven decision making fosters change because it promotes "collaboration and reflection" amongst teachers (Moody & Dede, 2008, p. 239). This theory of change for DDDM is the least discussed in the literature (Moody & Dede, 2008).

DDDM regime summary. The distinction between individual teacher data use and teachers practicing DDDM is important. Previously, when educators relied upon assessment data to make, for example, a determination of students' reading group placement, these decisions and criteria were locally developed and implemented. Educators in individual classrooms and schools typically selected the type of data and criterion used for placing students into different reading groups. With DDDM, teachers' engagement with data is a formal, policy-driven endeavor that is supported by millions of public and private dollars and new technologies created for DDDM (Coburn & Turner, 2012; Henig, 2012).

DDDM regime critique. As described above, the practice of data-driven decision making is supported by particular technologies, policies, and ideologies (Henig, 2012). Yet, it is

important to briefly consider the critique of these technologies, policies, and ideologies. For instance, multiple scholars argue that DDDM policies erroneously emphasize quantitative data from standardized assessments (Hargreaves & Braun, 2013; Iorio & Adler, 2013; Shirley & Hargreaves, 2006). While proponents of DDDM value quantitative data as this type of data are perceived as "objective" and "doesn't lie" (Duncan, 2009; Mandinach, 2012), opponents argue that quantitative data from standardized test is fallible and/or an inappropriate indicator of student learning (Henig, 2012; Jorgenson, 2012; Mislevy et al., 2013). Essentially, the core tenet of DDDM—students' performance data are objective is disputed by scholars. Scholars argue that these data are often derived from standardized assessments that are potentially biased towards students of color and students living in poverty (Mislevy et al., 2013). Further, for all students, scholars argue that many standardized tests are limited in scope and do not appropriately measure students' knowledge and capacity to think (Goe, Bell, & Little, 2008; Jorgenson, 2012; Labaree, 2014; Popham, 1999).

Another critique of DDDM is related to the notion that particular data sources provide evidence of how educators should instructionally respond to students' data. In the practice of data-driven decision making, educators are supposed to examine data, make sense of it, and then translate their understanding of data into action, such as instruction (Mandinach & Gummer, 2013; Means et al., 2010). A group of scholars question this "derivation view" or the assertion educators can derive specific instructional next steps/actions directly from data (Biesta, 2007; Kvernbekk, 2011, p. 523).

Specifically, Kvernbekk (2011) argues that the starting point in educators' decision-making process is their hypotheses for teaching and learning, not data. Given that students' performance data are not a direct indicator of teachers' specific instructional techniques, data

may be used as evidence to support diverse hypothesis or theories of effective instruction. For example, educators may interpret positive student performance data as an indicator that a new reading curriculum is effective. Alternatively, these educators may interpret positive student performance data as an indicator that offering students breakfast in the morning helps enhance students' test scores. The point is that data itself does not offer directives for teaching and learning; students' performance data becomes meaningful in light of educators' hypotheses for teaching and learning. In other words, students' performance data are only informative to the extent that it offers evidence in support of educators' specific hypotheses for teaching and learning (Kvernbekk, 2011).

Finally, multiple researchers argue that the practices and policies associated with DDDM can have detrimental effects on teaching and learning (Booher-Jennings, 2005; Hargreaves & Braun, 2013; Iorio & Adler, 2013; Moody & Dede, 2008). For example, Iorio & Adler (2013) argue that the emphasis on educators making decisions from students' quantitative performance data simplifies students' academic needs to a number, which devalues the unique identities and needs of diverse students. Hargreaves and Braun assert that specific policies and technologies associated with DDDM are driving educators to "distraction by narrowly defining data that compel [educators] to analyze grids, dashboards, and spreadsheets in order to bring about short-term improvements in results" (2013, p. 25). In other words, particular data management systems and accountability policies are fostering a situation where DDDM means educators are trying to satisfy accountability demands instead of thoughtfully implementing long-term plans for educational improvement (Hargreaves & Braun, 2013).

Overall, most critiques of data-driven decision making are not arguments against educators' using data to make decisions. Instead, these are critiques of the ways in which data-

driven decision making is conceptualized and/or required in educational policy and practice (Biesta, 2007; Hargreaves & Braun, 2013; Jorgenson, 2012; Kvernbekk, 2011). For example, Kvernbekk and Hargreaves and Braun specifically discuss the value in practitioners collecting and analyzing evidence to make decisions, but these scholars critique particular DDDM policies that narrowly define evidence as standardized test scores. When data are defined exclusively as standardized test scores, other key sources of evidence for instructional decisions, such as teachers' professional judgment and contextual considerations are erroneously de-valued in DDDM policies and practices (Biesta, 2007; Hargreaves & Braun, 2013; Iorio & Adler, 2013).

What is the Data on Data-Driven Decision Making?

Currently, the research on data-driven decision making is often described as limited, particularly in comparison to the proliferation of this practice in public schools and policy (Burch et al., 2009; Coburn & Turner, 2011; Raths, Kotch, & Carrino-Gorowara, 2009). According to Coburn and Turner (2012), the research on data-driven decision making often explores three aspects of DDDM. One body of research focuses upon the outcomes of DDDM by investigating if data-driven decision making enhances educational outcomes. A second, growing body of research is attempting to understand the practice of data-driven decision in-situ by studying how teachers engage with data in school settings. Finally, a third type DDDM research aims to identify the political, technical, and contextual conditions that support teachers' data use. The following section provides an overview of these three categories of research on data use.

DDDM Outcomes

The research on data-driven decision making indicates that this practice can enhance students' educational outcomes (Bernhardt, 2009; Dillon, 2010; Lachat & Smith, 2005; Marsh, 2012). Yet, data-driven decision making can also maintain the status quo and/or negatively

impact students' educational outcomes (Barrett, 2009; Booher-Jennings, 2005; Johnson & La Salle, 2010). As Coburn and Turner (2011) assert, "one of the central lessons from research on data use in schools and school districts is that assessments, students' tests, and other forms of data are only as good as how they are used" (p. 173). The research on data-use supports this assertion that in schools, educators use data in diverse ways and for various purposes and this yields a variety of outcomes, some positive and some negative.

The research that highlights success stories of DDDM transforming schools or districts suggests a common theme: DDDM yields a positive outcome when educators use data with the aim of creating a more equitable learning environment for students (Burch et al., 2009; Dillon, 2010; Koschoreck et al., 2001; Lachat & Smith, 2005; Park, Daly, & Guerra, 2013). The studies that report positive outcomes from data use often cite values of equity and/or social justice as key ingredients in the data-driven decision making process.

In one example, Koschoreck et al. (2001) observed a superintendent who implemented DDDM across the district with an "ideological predilection for equity" (p. 286). From the data management system to protocols for data-driven conversations, the superintendent strategically attempted to ensure that all aspects of data-driven decision making aligned with his commitment to equity. On the district, school, and individual level, educators were encouraged through specific institutional norms and practices to make data-driven decisions that promoted equity amongst both students *and* the staff. For example, at the district level, one of the superintendent's data-driven decisions was that certain policies marginalized teachers and he therefore created new practices that enabled teachers to influence both school-wide and district initiatives. At the school level, a team of teachers capitalized on this enhanced power when they determined that their local curriculum was not meeting the needs of historically marginalized

17

students. One of the team's data-driven decisions was to abandon their current curriculum and create a new one that was more relevant to their students.

In other studies, Park et al., (2013) and Slavin et al., (2013) observed districts where leaders recognized inequities in the distribution of educational opportunities to students. In Park et al., (2013), school leaders recognized that the current course offerings created a scarce resource of college-tracked courses. Therefore, the school leaders redesigned the curriculum and de-tracked the school. Local schools no longer needed to utilize data to place some students in college-track and others in vocational courses as the entire curriculum became college-track. In another similar example, leaders of a large district recognized through their own engagement with data that the district had major disparities in student achievement that corresponded to major disparities in school funding and resources. Recognizing this issue via data, the district leaders decided to redistribute resources across the district with a bias towards the lowest performing schools (Slavin, Cheung, Holmes, Madden, & Chamberlain, 2013).

While data-use aims of equity and social justice seem to help facilitate positive outcomes, other types of data use potentially have little impact or even negative influences. Jennings (2012) argues that educators may interpret data as confirmatory evidence of their existing practices. This can potentially facilitate negative outcomes if the current practices are detrimental to students. For example, multiple studies document instances where educators interpreted data as confirmatory evidence that particular students were unable to achieve academically (Barrett, 2009; Booher-Jennings, 2005; Burch et al., 2009; Earl, 2009; Johnson & La Salle, 2010). In one example, Earl (2009) documented instances where teachers attributed low academic performance data to students or their families. Teachers referenced students' behavior or parents not reading with students at home as the justification for *not* offering these

struggling students after-school tutoring. Teachers reasoned that these students would not "benefit" from after-school tutoring (p. 46). In a similar example, Barrett (2009) observed teachers attribute low student achievement data to students' "sleeping often," being "smart but choosing not to complete work," and the perception that school was not important to certain students (Barrett, 2009, p. 117, 130, and 134). These statements were not only used to locate the source of student achievement but were also regularly utilized to justify teachers' decisions to not provide low performing students with supplemental service. These examples illustrate a theme in the literature: educators' engagement with data can fail to alter existing educational practices and undesirable perceptions of students.

Another theme in the literature is that accountability measures often facilitate lackluster data-use routines and outcomes (Booher-Jennings, 2005; Hargreaves & Braun, 2013; Moody & Dede, 2008; Park et al., 2013). Multiple scholars argue that data-driven decision making is often driven by schools and districts to meet top-down accountability expectations (Booher-Jennings, 2005; Hargreaves & Braun, 2013; Jennings, 2012; Moody & Dede, 2008). Moody and Dede (2008) assert that data use aimed at accountability "supports teaching to the test, creates a culture of blame focused on "weaknesses" uncovered in the data" (p. 236). Hargreaves and Braun (2013) argue that when accountability trumps improvement educators are "driven to distraction by narrowly defined data" rather than informed by meaningful evidence of students' performance.

Overall, research suggests that when educators engage with data for the purpose of complying with top-down accountability measures, this often facilitates superficial or even negative uses of data. For example, Booher-Jennings (2005) documents how teachers' aim for data use was to become "data-driven" as this was a major expectation for schools in the study's

district (p. 239). The goal of data use was not to improve teaching or even educational outcomes; the goal was to become data-driven in order to comply with district-wide policy (Booher-Jennings, 2005). Moody and Dede (2008) observed how accountability measures encouraged data use where educators often only analyzed data from one assessment and this data source provided little insight into teachers' daily teaching strategies. When probing this observation data, educators indicated that data use was "not meaningful" and was viewed as "a burden grudgingly fulfilled" (Moody & Dede, 2008, p. 237).

The Practice of DDDM

Studies of DDDM in-situ indicate that DDDM is a very general term that is consistently utilized to describe a diverse set of practices, ideologies, and policies (Coburn & Turner, 2011; Ikemoto & Marsh, 2007; Johnson & La Salle, 2010; Little, 2012; Moody & Dede, 2008; Park, Daly, & Guerra, 2013). Across contexts, educators practice data-driven decision making in significantly different ways and for diverse purposes. The following section summarizes the research on DDDM, highlighting the key components and influential factors that facilitate educators' engagement with data in diverse ways.

Key components of data use. Collectively, the research on DDDM indicates that this practice has consistent components across contexts. These components may vary in content, form, and/or operate differently based upon a particular context. Yet, typically DDDM in schools includes the following:

- Political, contextual, and technological factors that impact the nature of data use
- Data sources that vary in content, quantity, and complexity
- A set of data-use activities or a process of data use employed by educators
- A decision-making process that varies in complexity

20

- Purposes for data use that vary in aim

The research on the practice of data-driven decision making offers multiple frameworks to characterize the nature of these components across school contexts. Coburn and Turner (2011) and Mandinach (2012) offer data-use frameworks that attend to the key components of the *process* of data use. These frameworks present a similar list of activities that educators employ when practicing DDDM. Although variations exist, these frameworks include the follow data-use activities:

- Educators *collect* and *attend to* particular sources of data.

- Educators *analyze* these data sources using various methods.

- Educators *make interpretations* about how these data inform their practice and their understandings of students.

- Educators *decide* if they want to make changes to their practice, policies, or other aspects of school based on what they learned through this process.

- Educators *revisit* their decisions when analyzing new data (Coburn & Turner, 2011; Mandinach, 2012)

These frameworks describe similar data-use activities and the assertion that the nature of these activities is shaped by data-use tools, educational policies, and local school contexts. These frameworks differ as Coburn and Turner (2011) emphasize the role of interpretation in the data-use process where Mandinach (2012) proposes a more positivist approach to data use. Specifically, Mandinach (2012) proposes a cyclical data-use process where the systematic analysis of data will yield a rationale course of action that when implemented can be monitored and evaluated with further data collection (p. 79). Coburn and Turner (2011) present a more interpretive data-use process where educators' ideologies, school norms, and social interactions

bring meaning to data, the data-use process, and the lessons learned from this process (p. 177).

Together, these frameworks demonstrate that DDDM often includes similar activities but the

nature and overriding data-use process may differ from school to school.

Other approaches to characterizing data-driven decision making emphasize the role of

DDDM leadership. In practice, data-driven decision making may be led by school leaders,

teachers, or protocols (Earl, 2009; Gallimore et al., 2009; Little & Curry, 2009; Little, 2012).

Data-driven decision making may be practiced by professional learning communities, meaning

the practice is often led collaboratively by a team of educators invested in particular topics of

inquiry (Barrett, 2009; Gallimore et al., 2009). The practice of DDDM may also be a top-down

initiative that is led by school leadership such as principals or superintendents (Earl, 2009; Park

et al., 2013). Whether teacher-led or school leader-led, educators may also rely on DDDM

protocols that range from suggestive to prescriptive and delineate particular activities and topics

of conversation (Boudett, City, & Murnane, 2005; Little & Curry, 2009; Little, 2012).

Collectively, the literature suggests that data-driven decision making differs in structure and

content due to the person or protocol leading the practice of DDDM.

Ikemoto and Marsh (2007) propose a different type of framework that attends to two

main components of data use—data and the complexity of the decision-making process. This

framework places data along a continua of "simple versus complex data" with examples of

simple data being data from one source or point in time and complex data being multiple sources

or data that was collected over time (Ikemoto & Marsh, 2007, p. 110). Further, this framework

takes into account the nature of the decision-making process and positions these across a

continuum of simple to complex, an example of complex would be the use of sophisticated

statistical models like value-added modeling (Ikemoto & Marsh, 2007, p. 111). Overall, this

22

framework helps illustrate that the practice of data use varies in terms of the type of data examined and the ways in which these data were analyzed, interpreted, and utilized to support instructional decisions.

Another framework by Moody and Dede (2008) characterizes data use by its purpose. In studying data use across school contexts, Moody and Dede (2008) found that schools' focus for data use was (a) to comply with accountability policies, (b) to improve educational offerings or, (c) to reflect on educators' practices. For each purpose of data use, educators examined different sources of data with different aims, which led to varying outcomes. Schools that examined data use for accountability purposes often examined standardized assessment data and typically made data-driven decisions aimed at complying with external, accountability policies. Schools that targeted data use at school-improvement often engaged with multiple data-sources for the purposes of clarifying root causes of particular issues and to guide the creation of solutions for these problems. Finally, schools that targeted reflection conceptualized data in a broad sense, including information like teachers' perspectives and used this data to guide teacher-led inquiries into their own practices. This framework attends to educators' primary purpose for data use but also highlights that data-use purposes often facilitate particular outcomes and engagement with particular types of data.

Each of the abovementioned frameworks emphasizes different defining components of DDDM, yet, collectively they demonstrate that across contexts DDDM is practiced in diverse ways. In some settings, educators may rely upon a protocol that focuses teachers' attention on students' formative assessments and leads teachers to discuss instructional next steps (Little & Curry, 2009). In other settings, teachers may collaborate to determine how standardized test data informs their understanding of students' needs for supplemental tutoring services (Barrett, 2009).

The overall lesson here is that DDDM activities, data sources, conversations, and outcomes are quite different across contexts and the literature offers various frameworks to explain and describe these differences.

Educators in DDDM. While the last section explains the diversity of key components of DDDM, this section describes how the diversity of educators who practice DDDM influences the process, interpretations, and outcomes of DDDM. Studies suggest that educators' knowledge, ideologies, and philosophies of teaching impact their engagement with data (Burch et al., 2009; Coburn & Turner, 2011; Dunn et al., 2013; Johnson & La Salle, 2010; Mandinach & Gummer, 2013; Means et al., 2011). The following section specifically describes the research that highlights the role of teachers in shaping the practice and outcomes of data-driven decision making.

One body of research emphasizes educators' knowledge of "data literacy" or teachers' understanding of the mathematical and technical aspects of data collection and analysis (Dunn et al., 2013; Mandinach & Gummer, 2013, p. 30; Means et al., 2011). Mandinach and Gummer (2013) provide a broad definition of data literacy that includes teachers' capacity to "identify, collect, organize, analyze, summarize, and prioritize data" (p. 30). To appropriately analyze and make decisions with data, the findings from these studies suggest educators need a certain level of competency in data literacy (Jacobs et al., 2009; Mandinach, 2012; Means et al., 2011). Most literature on this topic advocates for colleges of education and teacher training programs to incorporate data literacy into their programs (Jacobs et al., 2009; Mandinach & Gummer, 2013). A limited number of studies actually investigated teachers' knowledge of data literacy and how this impacted the data-driven decision making process. Jacobs et al., (2009) found that teachers with more experience and knowledge around assessment and data use were more likely to (a)

make decisions based upon multiple data sources and (b) understand how to translate lessons learned from data into instructional decisions. Means et al., (2011) found that educators who worked in teams were more likely to yield "accurate conclusions" than educators who worked individually (p. 58).

A second body of work emphasizes the role of educators' ideologies on DDDM. Studies suggest that ideologies held by the individual teachers and school leaders who engage in DDDM shapes the lens with which educators view, analyze, and make decisions with data (Coburn & Turner, 2011; Dillon, 2010; Marsh, 2012; Park et al., 2013; Slavit, Nelson, & Deuel, 2013; Spillane, 2012). For example, Coburn and Turner (2011) observed that when two groups of teachers analyzed the same student achievement data, they came to very different decisions about students' needs. One group determined that students' needed a remedial math class. Another group determined that the students needed teachers with a different set of skills; therefore, they decided teachers should attend additional professional development. The authors argued that educators' perceptions of themselves and students influenced how they interpreted students' performance data.

In a similar example, Burch et al., (2009) observed that educators interpreted student performance data differently. When making interpretations on low student performance, one group of educators interpreted this data as confirmatory evidence of their belief that this content was too difficult for particular groups of students. In contrast, district administrators interpreted this low student achievement data as confirmatory evidence that particular groups of students were being denied the opportunity to learn by teachers (p. 58). Burch et al., (2009) concluded that teachers access to data "appear to have little effect on deeply entrenched race and class biases about who can achieve" (p. 59).

Educators' beliefs about students potentially influence multiple aspects of data-driven decision making. Coburn and Turner (2011) argue that educators' beliefs can sway them to attend to data that confirms their beliefs and ignore data that challenges them (p. 178). Lachat and Smith (2005) found that teachers' beliefs influenced the type of inquiry educators pursued when engaging with student performance data. Fuchs et al., (2001) and Park et al., (2013) suggest that educators' ideologies impact the selection of data-use aims and corresponding principles for data analysis.

Specifically, Fuchs et al., (2001) illustrates how educators' beliefs can impact data analysis. Fuchs et al., (2001) explored options for how educators can set criteria to assess academic growth for students with special needs. One option is for educators to calculate the average rate of growth for students with special needs across a school district. In this study, the district's average rate of growth for students with special needs was half the rate of growth of general education students; meaning that using data from the district, educators would expect students with special needs to master academic material over the course of 1 year at half the rate of students' without special needs. Alternatively, educators can derive a norm from exemplary schools that have a track record of achievement for students with special needs. In this study, the average rate of growth for students with special needs in exemplary schools was on par with the rate of growth of general education students. The norm from exemplary schools is the same norm for general education students. Depending upon which norm is selected, educators can expect and aim for very different levels of achievement for students with special needs. This study illustrates how educators' data literacy coupled with their expectations for students can impact specific, important aspects of DDDM.

Collectively, this literature indicates that educators' beliefs and knowledge of students mediate the ways in which they engage with students' performance data. The literature asserts that educators do not and cannot objectively analyze, interpret, and make decisions from data (Coburn & Turner, 2011; Dillon, 2010; Little, 2012; Marsh, 2012; Moody & Dede, 2008; Park et al., 2013; Slavit et al., 2013; Spillane, 2012). Educators' selection of data, the type of analysis they pursue, their interpretations of data, and the types of decisions they make are influenced by their beliefs and knowledge of data literacy.

Conditions for Data Use

The third category of research on DDDM aims to identify the technical structures and conditions that facilitate teacher data use. Although some variation exists, the literature describes a relatively consistent list of conditions that foster data use:

- Teachers need timely access to data.

- Teachers require the technical capacity to interpret and analyze raw data.

- Teachers should receive professional development and ongoing support for analyzing, interpreting, and utilizing data.

- Teachers are more inclined to 'use' data if the data are presented in a non-threatening environment.

- School leaders and teachers need time in their schedules that are allocated to collecting, analyzing, and interpreting data.

- School leaders have to establish a need for data use and model data use consistently.

- Schools and districts need data systems that assist teachers in organizing and interpreting data.

- Districts and states can encourage DDDM in schools through offering resources like professional development and maintaining data management systems (Choppin, 2002; Coburn & Turner, 2012; Gottfried et al., 2011; Hamilton et al., 2009; Kerr, Marsh, Ikemoto, Darilek, & Barney, 2006; Lachat & Smith, 2005; Love, 2004; Mason, 2002; Means et al., 2010; Simmons, 2012).

The findings from this research identify particular conditions that bolster teacher data use by offering teachers new supports specifically targeted at data use. For example, teachers may receive time in the school day to analyze data, timely access to data that is easily accessed in an online database, resources for data-analysis including professional development and data-interpretation supports, and added resources from district leadership to implement data-use routines and practices. The overall theme is that schools and districts require particular policies, resources, and technological infrastructure to support the practice of data-driven decision making.

At the same time, this research often lacks an understanding of the impact of various data-use supports on data use or the interaction amongst data-use supports (Coburn & Turner, 2011). For example, research calls for data management systems. Yet as Burch et al., (2009) points out, data management systems are quite diverse in content, features, and analytic tools. Further, data management systems are a costly investment for many districts. Yet, the literature offers school districts little guidance on the usefulness of various data management systems or on meaningful ways for educators to use these tools. In general, the research offers little insight into how particular supports or a constellation of particular supports bolster *meaningful* data use.

Summary and Relevance of DDDM Literature

The research presented in this chapters helps inform and situate my dissertation work. As stated above, the research on DDDM often examines (a) the educational outcomes associated with the practice of DDDM (b) the diverse ways in which educators practice DDDM in school settings and (c) particular conditions that support the practice of DDDM. My study draws from and contributes to the research that offers insights into how DDDM operates in school settings. Further, my research most closely aligns with the literature on the *conditions of data use* presented in this chapter. As stated above, the literature offers a general list of tools, school-based practices, and policies that correlate with teachers data use but beyond this list, it lacks information on the nature of these data-use conditions and/or how these data-use conditions facilitate data use in school settings (Coburn & Turner, 2012; Little, 2012). In Chapter 4 and 5 of this dissertation, I offer a unique look at the nature of particular data-use conditions that were present at the elementary school featured in this study.

The literature presented in this chapter also shaped our research team's understandings and approach to investigating DDDM. For instance, the literature indicates that the ways in which teachers practice DDDM is mediated by particular educational policies, technologies, and ideologies. This provided our research team a lens on DDDM that is multi-faceted and led us to investigate the myriad of factors that contributed to local data use at our school sites. Further, the varying frameworks for understanding differences in DDDM across contexts pointed us towards particular components of DDDM. For example, we were specifically looking to identify educators' data-use activities, the type of data evident at meetings, and the guiding leader or protocol of DDDM conversations. Further, we were attuned to the idea that the particular educators present at these meetings and their values might play a critical role in the interpretation

of data and the types of decisions educators were making with data. These and other aspects of the literature helped shaped our investigation of DDDM, which is described in further detail in the next chapter

Chapter 3: Methods

This study was conducted in coordination with a larger research project titled, *The Role of Student Characteristics in Teachers' Formative Interpretation and Use of Student Performance Data*. Dr. Jennifer Greene (principal investigator) and Dr. Thomas Schwandt (co-principal investigator) conducted this study with the assistance of a small team of graduate students[2]. The primary aim of this study was to investigate how teachers' knowledge and perceptions of students impacted teachers' analysis and interpretations of student performance data. Using a case-study approach, the research team investigated the role of student characteristics in data-driven decision making in three school-sites and six grade-level teams of educators (two per school site). The research team studied data use by observing teams of educators who analyzed and interpreted student performance data in naturally occurring, weekly or bi-weekly data-use meetings. Further, the team interviewed key stakeholders, observed within classrooms and at professional development sessions, and analyzed relevant secondary sources of information such as statewide policies and publically accessible school performance data.

As a member of the research team, I conducted a sub-study where I investigated the role of particular school-based conditions on teachers' engagement with data. Specifically, the research questions for my sub-study were:

1. In what ways do grade-level teams of teachers at Greenbrook Elementary analyze, interpret, and make instructional decisions with data?

2. In what ways do particular data-use practices or policies support (or limit) teachers' use of data to make instructional decisions?

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[2] The graduate students involved on this project were Hope Crenshaw, Dr. Nora Gannon-Slater, Priya La Londe, and Rebecca Teasdale.

To investigate these questions, I focused upon one school site and two grade-level educator teams. I utilized the same case study approach, the same participants, and the same data as the broader project to investigate my questions. However, I conducted an independent analysis and write-up. The following chapter is a more detailed description of the methods utilized in both the broader project and my own work.

Research Design for the Spencer Research Team

Over a period of six months, our research team met weekly to design this study of data use. We read current literature on data use, qualitative methods, and deliberated the nature and intended outcomes of this study. Entering this project, we recognized that this research was complex. One major source of complexity is that the literature indicated that data-driven decision making is a vague term that describes a variety of activities, ideologies, and outcomes (Coburn & Turner, 2012; Moody & Dede, 2008; Simmons, 2012), meaning that we were not clear on the nature of the phenomena we wished to study. The lack of clarity around the content of data-driven decision making signaled a need to employ qualitative methods where we had the flexibility to adjust our methods and our research questions as we learned about the phenomena of data-driven decision making.

Further, we found that the research on data-driven decision making often lacked an examination of this practice as it naturally occurs in schools. The majority of research on data-driven decision making was theoretical or employed interview and survey methods (see Dunn et al., 2013 & Gottfried et al., 2012 as examples). As the majority of research on data-driven decision making has occurred outside of schools (Little, 2012), the literature contains "shockingly little research" on how educators engage with data in their workplace (Coburn & Turner, 2012, p. 99).

To address this issue, researchers are studying data-driven decision making in-situ (see Kallemeyn, 2014 as example). Our research team is a part of the larger effort to understand data-driven decision making as it functions in educational settings. This study employed a case-study approach to identify and clarify the phenomena of data-driven decision making. As Stake (1995) argues, case study is not a method but rather a selection of what to study. Given the lack of clarity on data-driven decision making, we sought out to "thoroughly understand" the *case* of data-driven decision making (Stake, 1995, p. 9). Our unit of analysis was the phenomena of data-driven decision making, as opposed to the teachers who participated in DDDM. The teachers were our primary "informants through whom the case can be known" (Stake, 1994, p. 234). Further, other data sources like the research teams' observations of data use, local educational policies, district leadership, and the content of assessments utilized in schools also provided insights into the case of data use.

Knowing our aim was to study the case of DDDM, we then had to deliberate the boundaries of a case of data use. According to Stake (1994), researchers have flexibility in defining a case but we should aim to have a case that is a "specific, unique, bounded system." The literature suggested that DDDM is composed of practitioners (and their ideologies) (Burch et al., 2009; Slavit et al., 2013), school-based organizational routines (Coburn & Turner, 2011; Kallemeyn, 2014), and local state and district leadership (Koschoreck et al., 2001; Park et al., 2013). As the literature highlighted these components, we bound our case of data use in this way. We sought to understand how school-based routines, state and local leadership, and practitioners with particular ideologies contributed to the phenomena of data-driven decision making.

Spencer Research Team's Case Selection

Our research team ultimately selected three case studies of data use. These cases were selected according to four key selection criteria. First, according to the project's funding proposal, this study aimed to investigate data use in K-5 settings, as students' performance in their early educational career is often predictive of their lifelong educational outcomes. As K-5 is a critical time in a students' life, the data-driven decisions educators make about students' instruction and educational pathways during this time are also particularly important. Thus, the first criteria is that the educators taught in a K-5 setting and we further narrowed that to educators who worked with students in grades 3-5. Second, in order to primarily observe data use (as opposed to the implementation of data use), we selected school sites that had implemented data-use routines at least 2 years prior to our study. Further, one of the data-use routines needed to be educators meeting at least twice a month to analyze and interpret data, as we needed school sites that would provide us with multiple opportunities to observe DDDM. Third, as we were interested in how various student characteristics influenced the DDDM process, we sought out schools that had diverse student populations. We examined a number of indicators of diversity including demographic data on students' race, free and reduced lunch status, and primary home language. We were also interested in what one participant called an "academically diverse" student population or a student body that achieved at various levels according to standardized tests.

Finally, we sought out schools where data-driven decision making occurred in grade-level teams of teachers. Research indicated that data-driven decision making often occurs within teams of educators, meaning data-driven decision making is typically a group activity (Gallimore et al., 2009; Little, 2012; Means et al., 2011). In addition, the group activity of analyzing and

interpreting data allowed us some insights into teachers' thought-process and the nature of the DDDM process. As we required grade-level teams of educators, our fourth selection criterion stemmed from the logistical consideration that we could only include school-sites where at least one entire team of teachers consented to participate in this study.

After selecting school sites based upon the abovementioned criteria, we then invited grade-level teams of teachers to participate in the study based upon the recommendation of school leadership. Members of our research team met with the principal of each school, described the nature of our study, and if they were willing to have their school participate, then we requested that they recommend two grade-level teams of educators for our study. We started by inviting the two grade-level teams of teachers nominated by the principal. In two cases, all members of the nominated teams consented to participate in the study. In one case, we did not receive consent from one team and instead successfully recruited a different team to participate in the study.

Each case included a unique school site and two grade-level teams of educators. All three cases took place in the same school district, meaning these cases shared an important component of DDDM—district leadership and district-wide data-use policies. Beyond these characteristics, schools varied in terms of school-based data-use policies, aims of data use, data-use routines, and the nature of data-use conversations. The cases also varied in terms of student demographics, the school members who attended grade-level data-use meetings, the schools' performance on publically available accountability indicators, and local reputation. The grade-level teams varied in membership across cases but often included school administrators, instructional coaches, and always included 2-3 teachers who taught the same grade-level.

Spencer Research Team's Methods

To capture each case of teacher data use, the research team employed multiple, qualitative methods. In order to gather insights into the practice of data use and how data-use routines, individual actors, school norms, and more shape it, we observed grade-level teams in their naturally occurring data-use meetings. All grade-level teams in this study had regularly scheduled weekly or bi-weekly meetings that lasted approximately thirty minutes. Via district and union policy, these meetings were *intended* to provide educators with a collaborative time to analyze and make decisions with data. On top of the regularly scheduled thirty-minute data-use meetings, each school site also had "data days" where teachers met quarterly for approximately 90 minutes to analyze student performance data and make decisions based on this analysis. Research team members observed almost all data-use meetings and data-days for two of our school sites in the 2013-14 school year, including the case of Greenbrook that is highlighted in this study. The third case of data use is currently in-progress during the 2014-15 school year.

When observing data-use meetings, we audio recorded the duration of each meeting to have a full record of the dialogue. However, we did not transcribe the full account of each meeting. Instead, each research team member wrote field notes documenting the nature of the meetings observed. The field notes provided an overview of the grade-level teams' conversations including nuances of the meetings, non-verbal and critical exchanges amongst team members, and our analytic comments. The field notes also documented aspects of DDDM that were highlighted in the literature, including the type of data present at the meeting, the data-use activities that occurred, and evidence of teachers' knowledge of data literacy and their perceptions of students. All research team members used the same field note guide to hone-in on consistent aspects of the meeting.

Observation of data-use meetings was the primary method utilized for this research. To supplement our understanding of what occurred in data-use meetings, we also interviewed key stakeholders, including district leaders, school leaders, all teachers in the study, and other members of grade-level teams like instructional coaches. Further, to gain an understanding of the schools' contexts, we observed teachers teaching within their classrooms, attended at least one professional development session with teachers, and generally 'hung out' at the schools. We also analyzed secondary sources of information such as publically accessible climate survey data and student performance data.

After completing the bulk of data collection activities, we facilitated a "data interpretation meeting" with our grade-level teams of teachers. We intentionally invited and facilitated these meetings just for teachers, as opposed to also including the administrators and instructional coaches who often led the meetings. We aimed to facilitate these meetings in a manner where the teachers in this study had an opportunity to voice their perspective on the research team's interpretations of data-use at their school site. These data interpretation meetings offered participants a voice in our research and offered the research team an opportunity to clarify our understandings and interpretations with our participants. These meetings lasted approximately two hours and offered rich insights into teachers' perspectives on data and DDDM as it happened at their schools. For the sake of clarity, I will refer to these data interpretation meetings as group interviews throughout the rest of this paper.

By gathering information from multiple stakeholders and sources, our research team aimed to understand our observation of teachers' data-use meetings in the broader socio-political context. Qualitative methods offered a lens for identifying the various factors, stakeholders, and interactions amongst them (Anderson & Scott, 2012; Newman & Chin, 2003) that facilitated the

particular phenomenon of data-driven decision making. We purposefully employed multiple

qualitative methods and sought out diverse perspectives in order to investigate data-use in its

broader, complex setting. We aimed to identify what was intentional, what was unintentional,

what confirmed the existing research on DDDM, and what offered new insights on data-driven

decision making.

Dissertation Research

As a member of the research team, I contributed to the design of this research study and

to the data collection activities described in the section above. My particular study is based upon

the same approach, methods, and cases with a few variations. For example, I specifically

focused on one case of data use at the school Greenbrook. This section describes my rational for

selecting this case and the particular data I collected from this school site. Further, I conducted

an independent analysis of the data collected at Greenbrook and this analysis is also described in

this section.

Dissertation Case Selection

I selected one case of data use, the case of Greenbrook to investigate my particular

research questions because this case offered particular advantages for my study. First, prior to

my work on this research project, I had previously worked in this school site as a part of a

different university-school partnership. Due to my familiarity with the school site and a portion

of the teachers, I was charged with recruitment and most of the subsequent data-collection

activities at this school site. Including my prior work in this school, I spent almost three entire

semesters visiting the school, at times for just an hour and at other times, a few hours

approximately every other week. The concentrated time I spent observing in this educational

setting and interacting with the educators at this building afforded me a vantage point to study the particular conditions that impacted data use at this site.

Second, the case of data use at Greenbrook offered insights into a "typical case" (Seawright & Gerring, 2008, p. 297) of data use. Seawright and Gerring (2008) use the term typical case to describe people or sites that are representative of a phenomenon. Greenbrook is representative of the type of school targeted by educational reforms like data-driven decision. Data-driven decision making is described as a tool to reform; as Secretary Duncan states "data gives us the roadmap to reform" (Duncan, 2009). Implicit in the concept of reform is that there is a problem that needs addressing; in the context of U.S. public schools, *the problem* is a consistent, intractable achievement gap. Like many schools in the U.S., Greenbrook has a history of low scores on standardized tests, specifically with longstanding achievement differences between white, more affluent students and students of color from under-resourced neighborhoods. Further, as data-driven decision making is at times impacted by accountability measures and policies (Hargreaves & Braun, 2013; Ingram et al., 2004), Greenbrook offers a typical case for investigating the nature of DDDM in schools that face heightened levels of pressure to meet state and federal accountability standards. The case of data use at Greenbrook offers insights into how this practice operates in schools that historically struggle and therefore encounter additional scrutiny to implement reforms and enhance educational outcomes. For further details about the context of Greenbrook, please see Chapter 4, "The Case of Data-Driven Decision Making at Greenbrook."

Dissertation Methods

I utilized the same methods as the broader research project and consequently, the same data yielded from these methods. Specifically, for this dissertation, my data includes individual

interviews with all 6 classroom teachers, 23 field notes from observing grade-level team meetings, and two end of the year group interviews, where classroom teachers offered their perspectives on findings presented by our research team. All of these data were collected specifically for the broader research project.

Further, for my dissertation, I conducted additional interviews with two teachers at Greenbrook. One teacher from each grade-level team, Charlie [pseudonym] from grade 4 and Kim [pseudonym] from grade 3 indicated in their initial interviews that they had independently analyzed data outside of grade-level meetings. Further, in separate occurrences, they had both used these data to advocate for changes in students' learning environment, but this advocacy had occurred outside of grade-level meetings. In addition, both of these teachers had experiences with data analysis and data-driven decision making outside of Greenbrook. For instance, Charlie had previously worked in a different school and district where he had practiced DDDM in a different way. Wanting to know more about Kim and Charlie's background and their data use that had occurred outside of grade-level meetings, I interviewed these teachers more than once to probe their conceptions of DDDM further. The following chart indicates the additional interviews with Charlie and Kim and provides a description of all of the data collection activities that occurred at Greenbrook and were included in this research.

Table 1		
Data Collection Activities at Greenbrook		
Participant(s)[3]	Data Source and Method	Approximate time spent collecting data
Grade Level 3 Team	Observation of 9 grade-level meetings, 3 extended grade-level meetings (data days), and 1 group interview	10 hours

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[3] The names of teachers listed on this chart are pseudonyms to maintain the confidentiality of participants.

Table 1 (cont.)		
Grade Level 4 Team	Observation of 8 grade-level meetings, 3 extended grade-level meetings (data days), and 1 group interview	9. 5 hours
Kim (GL3 teacher)	1 classroom observation and 3 individual interviews	5 hours
Haley (GL3 teacher)	1 individual interview	1 hour
Noah (GL3 teacher)	1 classroom observation, and 1 individual interview	3 hours
Charlie (GL4 teacher)	1 classroom observation and 2 individual interviews	4 hours
Lily (GL4 teacher)	1 Classroom observation and 1 individual interview	3 hours
Devin (GL4 teacher)	1 classroom observation and 1 individual interview	3 hours
Instructional Coach (GL 3 and 4 team member)	1 individual interview	1 hour
School Administrator (GL 3 and 4 team member)	1 individual interview	1 hour
District Administrator	1 individual interview	1 hour
Total	13 interviews with 9 participants; 23 observations of data-use meetings; 5 classroom observations; and 2 data interpretation meetings	37 hours and 10 minutes
Table 1 Data Collection Activities		

I was present for most of the data collection activities described in Table 1. As a part of my responsibilities on the research team, I conducted all 6 individual interviews of classroom teachers and was present for the interviews with the district administrator and Greenbrook's instructional coach. In addition, I facilitated the data interpretation meetings for both grade-level teams and observed the majority of data-use meetings, data-days, and classroom observations that occurred at this school site. This is relevant in light of criteria for quality standards and

credibility in qualitative research. Becker (1996) asserts that qualitative researchers are concerned with issues of data accuracy and data precision, as opposed to validity and reliability. Data accuracy is briefly defined as data "being based on close observation" and data precision is data "being close to the thing discussed" (Becker, 1996, p. 67). The data presented in this dissertation is based on close, sustained observations of data-driven decision making and repeated interactions with the teachers who practiced DDDM.

Dissertation Data Analysis

The research design, methods, and data collection presented in this study were a product of collaboration amongst a team of researchers. Data analysis is where I diverged from the team and conducted an independent analysis and write-up of the data. I simultaneously worked as part of the team to analyze data from the broader project but my personal analysis is distinct due to my research questions.

For my personal analysis of the data collected at Greenbrook, I was guided by a framework for uses of assessment data developed by Darling-Hammond (1994). In this framework, the uses of assessment data are divided into two categories. The first category includes the use of assessment data for "sorting and selecting" students (Darling-Hammond, 1994, p. 9). In this category, assessment data are often utilized to sort students into hierarchical educational tracks. Historically marginalized groups of students are often sorted into less rigorous educational tracks, reproducing the longstanding achievement gap amongst particular groups of students. Darling-Hammond (1994) articulates a second category where data are used to identify and rectify inequities in the learning environment and to identify students' individual, academic strengths. The defining difference between these two categories is the use of

assessment data to group students into pre-determined categories versus using assessment data to understand students' unique needs and adjust the learning environment accordingly.

This framework drew my attention to the ways in which teachers utilized assessment data to make instructional decisions about students and to consider students' learning environment. Therefore, I initially honed in on teachers' instructional decisions and analyzed these decisions using the Darling-Hammond (1994) distinctions for data use. I identified instances where the data-driven decision included labeling students and placing them into pre-existing tracks. I also identified instances where educators tweaked the learning environment based on lessons learned from students' data. I then returned to each set of instructional decisions attempting to identify patterns in the conditions that shaped teachers' uses of assessment data. I coded for factors that were influential in data-use conversations, such as the data-use routine, resources available at the school, and teacher advocacy.

In this data analysis process, I started with the types of decisions made with data and then worked outwards to identify patterns of conditions that were associated with certain types of decisions to develop my coding scheme. I coded data-use meeting field notes, teacher interviews, and data interpretation meetings for decisions made with data and particular conditions associated with these decisions. Codes were derived from two major sources. One source was the participants and the data itself. For example, I coded for particular labels like "red students" or "yellow students" that educators often utilized in data-use meetings to refer to specific groups of students. The second source was literature on data-driven decision making. For example, I coded for teachers' description of professional development on DDDM as the literature indicated this is an influential condition for data use (Gallimore et al., 2009). Using

codes derived from both the data and the literature offered analytic tools to see which aspects of my data confirmed or contradicted what was present in the literature.

After coding, I attempted to identify themes in my data. I approached this analysis with a framework that most closely resembles suggestions found in Bazeley (2009). Bazeley (2009) suggests a "describe-compare-relate" framework for data-analysis (p. 4). The first goal is to provide a descriptive account of the data collected, which I did in coordination with the research project and my advisor. The second wave of analysis was to compare data sources and to seek out confirmatory and contradictory information. I specifically compared three data sources—field notes from grade-level team observations, teacher interviews, and literature on data-driven decision making (See Appendix for example).

When analyzing different data-sources, I identified ways in which DDDM at Greenbrook confirmed or challenged the literature on DDDM. This type of analysis facilitated particular lines of inquiry or what Bazeley (2009) refers to as third step of data analysis "relate" (p. 4). For example, I was struck by how the process of data use at Greenbrook differed significantly from the types of data-use process described in the literature. The literature often portrayed a data-use process where teachers were active participants who systematically collected data, interpreted these data, formulated action plans, and continuously evaluated and adjusted their plans based on further data. At Greenbrook, teachers were typically passive participants who did not collect data, interpret data, or use data to evaluate their work. This stark difference between what was described in the literature and what was observed at Greenbrook led me to explore explanations or generate arguments for why DDDM operated in a particular way at Greenbrook.

Bazeley (2009) states "effective reporting . . . requires your having used data, and the ideas generated from the data, to build an argument that establishes the point or points you wish

to make" (p. 2). In line with this sentiment, I determined that my data was best reported in the form of three essays that each contains an argument based on the findings of my data analysis. In Chapter 5, I present these three essays, where the data from Greenbrook are situated in relevant educational research and theories. By reporting my data in three separate essays, I aimed to present an argument with my findings that was supported by the literature and the data collected from Greenbrook (as suggested by Bazeley, 2009).

Before turning to these essays, I will first present the case of DDDM at Greenbrook. Specifically, in the next chapter, I will offer an overview of the context of Greenbrook and define key terms associated with DDDM at this school site. Then, I will describe a typical grade-level meeting where educators engaged with data to make decisions. Finally, I will describe the teachers who participated in grade-level meetings and their perspectives on DDDM. This overview of DDDM at Greenbrook presented in the next chapter is meant to foreground the three essays presented in Chapter 5.

Chapter 4: The Case of Data-Driven Decision Making at Greenbrook

Greenbrook's Context

Multiple scholars argue that the socio-political context of a school mediate the ways in which educators engage with student performance data (Booher-Jennings, 2005; Marsh, 2012; Moody & Dede, 2008). This assertion holds true for Greenbrook where policies and contextual factors influenced educators' engagement with data. The following is a description of key aspects of Greenbrook's context that impacted educators' data use.

Greenbrook Elementary was situated within a K-12 district that had historically struggled with an achievement gap. As one district administrator stated, this district had a history of "uneven academic achievement" amongst particular populations of students. According to multiple academic measures, students of color within this district, particularly African American students have had less academic success compared to their white counterparts.

District leadership characterized Greenbrook Elementary as "racially identifiable." A racially identifiable school is one whose racial demographics differ significantly from the district's population. In comparison to the district's racial makeup, Greenbrook had a significantly larger proportion of African American and Latino(a) students. This school faced pressure from the district to diversify their student body and attract students from other schools and neighborhoods. In response to this pressure, the school hosted a variety of special programs, mainly funded by grant money.

During this study, in an effort to diversify the student body at Greenbrook, the district mandated a major change in the school's instructional program. In order to maintain confidentiality, this paper will not include specific details about the district's mandate. After learning about the mandate, other initiatives at the school, such as data use became secondary to

this mandated transition. For example, multiple grade-level collaboration times allocated to data use were repurposed for planning for this new transition. Further, educators had to make time after-school for collaborations and forums related to this transition. Overall, educators at Greenbrook had to devote scarce resources and time to this new endeavor.

Beyond this school-specific change, Greenbrook was simultaneously implementing new federal and state policies. This school resided in a state that had recently won Race to the Top funds; the funding served as a catalyst for a variety of new educational and evaluative practices. The following is a limited list of new practices that Greenbrook was in the process of implementing.

- The school was piloting a new reading curriculum.

- The district adopted a new report card that was based on standards-based grading.

- The state and the district had mandates related to Response to Intervention (RTI), which is discussed further in the next section.

- The state required that all districts adopt a standardized way of evaluating teachers; the year of this study, Greenbrook piloted the Danielson Framework as the new, standardized evaluation protocol for evaluating teachers.

- The state required that all school districts prepare for the transition to the new Common Core standards and the corresponding, computer-based PARCC assessment.

This incomplete list of policy-mandates illustrates that data use was one of many new practices that educators were adjusting to at Greenbrook. Further, educators at the school struggled to implement all of the new policies which meant data-use practices were often superseded by more pressing issues.

Educators at Greenbrook also faced challenges in the classroom. For example, general education classroom teachers (as opposed to the teachers for the gifted program) regularly received new students and lost students throughout the year. During the year of this study, the school had a mobility rate of 22%, which is almost twice the state average (State Report Card, 2013). In addition to gaining new students, general education teachers often had more than one student who knew no English at all *and* whose native language was unknown by anyone in the building. In addition to these unique challenges, according to student performance data, teachers had what two teachers described as "academically diverse" students or students with a wide range of academic abilities. Teachers in the 3rd and 4th grade had students ranging from non-readers to phenomenal readers who tested above grade level.

Further, these teachers often held other roles in the building. Two held official, leadership roles for at least half of the school year and others were basketball coaches, liaisons for special programs, and more. The teachers' day-to-day existence in the building was stressful, filled with tasks, and often unpredictable.

In summary, Greenbrook's student population consisted of a large proportion of low-performing, low-income, African American students. The political emphasis on raising the achievement of this particular student population fostered a variety of mandates on this school. Educators at the school struggled to implement all of these mandates while meeting the diverse needs of their students and fulfilling their responsibilities as coaches and school-leaders. Data use existed in this messy, busy, difficult context. Like many endeavors at this school, educators' data use was quick and completed out of necessity.

Overall, the context of Greenbrook was not well suited for data use. Although the nature of Greenbrook's context often posed challenges to data use, these challenges are commonplace

in low-performing, struggling schools. As low-performing schools are often the target of data-use policies, Greenbrook provides an apt context to study data use. This context provides an understanding of the particular challenges low-performing schools might face in implementing data-use policies.

Data-Use Jargon

Educators at Greenbrook had a shared language for data use. The terms utilized in data-use meetings often related to state and/or district policies that mediated data use. The following is a description of frequently used terms related to data.

Response to Intervention (RTI)

Greenbrook employed an RTI model or a Response to Intervention model. Response to Intervention was a state-mandated practice for Greenbrook. The State Board of Education (SBE) describes the aim of RTI as the following.

> Improve the learning and performance of all students in grades K-12 by building the capacity of (state name) public school districts and schools to develop, use, and sustain a multi-tiered system of research-based curricula, instruction, intervention, and assessment (SBE, 2008).

Often, teachers spoke of the RTI framework as the rules and policies that governed data use at this school. Observations of teachers engaging with student performance data resembled practices promoted in the RTI framework. The following is an overview of the RTI framework and then the features of the RTI framework present in educators' data use at Greenbrook.

Response to Intervention is a framework for instructional decision-making. The overarching aim of RTI is to provide students' with "high quality instruction" that meets students' individual needs (SBE, 2008, p. 1). To reach this aim, educators examine a spectrum

of instructional services students' receive in a school, from general education to special education services. The first tier of RTI includes an examination of the instruction all students receive in a general education room (SBE, 2008, p. 1). Per the expectation of the U.S. Department of Education, general education means that all students will receive access to the same curriculum but instruction will be "differentiated" (USDOE, 2009a, p. 12). If students continue to struggle, after the teacher has differentiated instruction, then students receive an added level of academic support. This added level of support is called tier 2 in the RTI model (USDOE, 2009a; SBE, 2008). Students in tier 2 receive an "intervention" or an instructional technique that is supposed to be researched-based and offer struggling students high quality remediation. The third tier involves individualized supports for students who continued to struggle after receiving both core instruction and an intervention. The RTI model suggests that 80-90% of students receive tier 1 instruction, 5-10% of students receive tier 2 instruction, and 1-5% of students receive tier 3 instruction. At each tier, students are supposed to receive research-based instruction that meets students' needs (SBE, 2008). It is important to note that state and federal policies state that students' instruction is supposed to be researched-based or evidenced-based but these terms are not specifically described in RTI policy. Further, at Greenbrook, the research or evidence that supported their instructional techniques was never discussed in grade-level meetings.

Although all schools in the state must follow an RTI model, each district implements this framework in unique ways. Greenbrook, per district mandates implemented RTI in two distinct ways that intersected with data use. First, Greenbrook primarily utilized RTI to target literacy instruction and students' performance data on literacy assessments (as opposed to math, science, etc.). Second, the school had an RTI block or a daily instructional time period. During this time

period, on Mondays-Thursdays, students identified by data as tier 2 and tier 3 (struggling students) received academic interventions. Every Friday, the RTI block was reserved for progress monitoring students or assessing struggling students on a standardized, district-wide assessment. This weekly test was not directly assessing the skills or content that students were taught during the week. On Fridays, teachers or specialists administered a 1-minute fluency test to students that assessed speed and accuracy of students' oral reading skills. This assessment is referred to as GOALS [pseudonym] and it is described in more depth below.

GOALS

According to RTI policy, as explained above, educators use assessment data for multiple purposes, including identifying low-performing students. In the RTI framework, the assessment recommended to identify struggling students is called a "screener" (RTI Action Network, 2014). At Greenbrook, educators assessed students using the screener GOALS. GOALS is a computer-based assessment system that is intended to "identify at-risk students early." GOALS has many features; the following features were discussed at least once in either teacher interviews or observation of grade-level meetings at Greenbrook.

- GOALS fluency test is used as a screener for RTI, meaning students are assessed 4 times per year to see if they are on grade-level.
- GOALS fluency test is administered weekly to a small portion of the student population that is perceived as at-risk or well below grade level.
- GOALS has two math assessments that were administered by teachers.
- GOALS has an online data-base that contains students' performance data and tools for analyzing student-performance data

Often, when the term GOALS was utilized in grade-level meeting, educators were referring to students' performance on the 1-minute fluency test. This assessment measured the number of words' students read correctly in one minute. Each time this test was administered, students read a different passage and as the year went on, the passages became more difficult. The idea being that students' reading skills are expected to improve over the course of the year, so the assessments should also become more rigorous. All students were assessed on this 1-minute fluency test quarterly to monitor their growth. Students in Tier 3 or the lowest-performing students were also assessed on this 1-minute fluency test almost every Friday. In grade-level meetings, the team typically only looked at and discussed students' performance on the quarterly 1-minute fluency test.

To summarize, according to RTI policy, general education students were assessed quarterly on a 1-minute fluency test to monitor their performance. Low-performing students were assessed both quarterly and most Fridays on a 1-minute fluency test. In addition, all students took other GOALS assessments like a mathematical computation assessment and a reading comprehension assessment. Yet, in grade-level meetings, the team typically only discussed students' performance on the 1-minute fluency test that was administered quarterly.

Green Means Go, Red Means Stop

At Greenbrook, educators primarily engaged with GOALS fluency data in order to make data-driven decisions. As described further in the next section, educators typically examined a GOALS data-report that color-coded the student population according to their performance. Technically, the data was color-coded according to students' percentile ranking. Students whose score was in the 90th percentile were color-coded white; students in the 75th-90th percentile were purple; students in the 25th-75th percentile were green; students in the 10th-25th percentile were

yellow; and students below the 10th percentile were red. Students at Greenbrook had scores that typically situated them within or below the 75th percentile so students' data was commonly color-coded red, yellow, or green.

Interviews with teachers indicated that they had a shared understanding of the color-scheme yet this understanding was not characterized by percentile ranking. As one teacher described in an interview, "red means stop"; "yellow means gun it, you are almost there"; and "green means go." According to interview data, if a student's name and score was in red on the data printout, this signaled to educators that the student was struggling and needed an intervention. If a student's name and score was in green on the data printout, this meant students were "fine." If a student's name and score was in "yellow," then the student was "almost there."

Reference List of Data-Use Jargon

The following list provides a concise definition for terms associated with DDDM described in this section.

- Response to Intervention (RTI)- a policy-driven framework for evaluating students' academic performance and identifying appropriate instructional supports for struggling students

- Intervention--an "evidenced-based" instructional support for students who are struggling academically

- Progress Monitoring--a weekly assessment administered to struggling students in order to monitor their academic progress

- GOALS is a package of assessments that measures students' level of proficiency on grade-level skills and contents.

- Red--a color utilized in the assessment system GOALS to indicate that students are struggling academically

- Yellow--a color utilized in the assessment system GOALS to indicate that students are not having major academic struggles but they are also not on-grade level

- Green--a color utilized in the assessment system GOALS to indicate that students are on grade-level

DDDM at Greenbrook

As stipulated in the teachers' union contract, teachers were expected to attend grade-level meetings every other week over the course of the school year. So twice a month for approximately 35 minutes, all grade-level teachers were to attend a meeting. Often these meetings included classroom teachers, the principal and/or the instructional coach, and occasionally specialists like ESL teachers or the school's interventionist. According to information told to the research team during the recruitment phase, the purpose of these meetings was to provide teachers a time to collaborate on instruction and students' performance data. In addition to these bi-weekly grade-level meetings, each team had extended grade-level meetings called "data-days" where they had a 90-minute block to collaborate and make decisions based on students' performance data.

Over the 2013-14 school year, the research team observed 9 grade-level meetings and 3 data-days for the third grade team. In addition, we observed 8 grade-level meetings and 3 data-days for the fourth grade team. Overall, grade-level team meetings were regularly cancelled and when they did occur, they did not always contain conversations about data. Approximately half

of the grade-level meetings observed in the 2013-14 school year contained no mention of students' performance data[4].

When grade-level teams did discuss students' performance data, educators in both grade-level teams followed a predictable pattern of data-driven decision making. This pattern persisted over the course of the school year and across grade-level teams. In other words, in both grade-level teams over the course of the school year, teachers viewed, interpreted, and used data in almost identical ways. This predictable, consistent pattern of DDDM is described next.

Typical Data Use Meeting

A group of people assembled at a conference table. This group included three, grade-level teachers, the principal, an ELL teacher, and one instructional coach. After assembling, either the principal or the instructional coach distributed printed, hard copies of student performance data for all students in a particular grade. The print out contained a chart (example below), which listed data on each student's performance on the GOALS fluency assessment. The students were listed from highest to lowest scorer, i.e., the student with the highest score was in the first row of the chart and the student with the lowest score was in the last row of the chart.

Student Name	Corrects	Errors	Accuracy	Performance Summary	Potential Instructional Action
Student A	125	10	92%	Average	Continue Current Program
Student B	115	2	98%	Average	Continue Current Program
Student C	100	5	95%	Below Average	Further Assess & Consider Individualizing Program
Student D	75	10	87%	Below Average	Further Assess & Consider Individualizing Program

Figure 1. **Example of GOALS Color-Coded Data with Fictitious Student Data.**

[4] A special thanks to Dr. Nora Gannon-Slater who calculated the time teachers spent on data.

Figure 1 (cont.)					
Student E	35	12	66%	Well Below Average	Begin Immediate Problem Solving
Student F	40	4	90%	Well Below Average	Begin Immediate Problem Solving

Figure 1. **Example of GOALS Color-Coded Data with Fictitious Student Data.**

After each member of this meeting received the data chart, the principal or the

instructional coach directed the team's attention to students in the red or students whose score

landed them below the 10th percentile. The instructional coach started calling out the name of

the student who was listed at the very bottom of the chart that displayed students' scores, or the

student with the lowest score. After a student's name was called, teachers were to respond if this

student had a particular label like ESL (a student who receives English as a second language

services), SPED (a student who receives special education services), Speech & Hearing, and/or

GT (gifted). Although teachers were told to respond with these labels, SPED, GT, SPED, etc.,

the principal often answered for them. Below is an excerpt of the instructional coach facilitating

a "call and response" dialogue around students' performance data. Please note that students'

names are not included to protect their identities. Also, I utilized numbers along with the general

title of student or teacher to denote different teachers and students.

Instructional Coach: So [Student 1] is ESL?

Principal: Right

Instructional Coach: [Student 2]?

Principal: SPED

Instructional Coach: [Student 3], [Student 4], and [Student 5] are all ESL.

Instructional Coach: Is [Student 6] ESL?"

Teacher 1: no

Instructional Coach: [Student 7]?

Principal: SPED

Instructional Coach: [Student 8]?

Principal and Teacher 2 in unison: SPED

Instructional Coach: [Student 9]?

Principal: SPED

Teacher 1: No

Principal: He is not SPED?

Teacher 1: No

Principal: He is not speech and language?

Teacher 1: No

Principal: I'll check him but skip him for now.

Instructional Coach: [Student 10]?

Teacher 3: That is mine. She is GT but also ESL.

Instructional Coach: [Student 11]?

Teacher 3: He is IEP, autism, FLS. (GL4, team meeting[5])

During this call and response, the instructional coach has placed labels like "ESL", "SPED", etc.
next to students' names. If students were red and SPED, then the team did not discuss them
further. In other words, if students were in the bottom 10th percentile according to GOALS
fluency data and they were members of the special education program at Greenbrook, then the
team did not discuss these students and their data during grade-level meetings. If students were
red with no additional label of ESL or SPED, the team discussed these students.

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[5] The citation "GL4, team meeting" means that this is grade-level meeting of 4th grade teachers.

Without any verbal directives, the team knew that at this point in the meeting, they would now sort red, non-labeled students into instructional groups. The team spent 10 minutes or less determining an educational intervention for all students in red. Students in red were sorted into three different types of groups: a group that works with an interventionist, a group that works on a computer-based software program, or a group that remains within the classroom of their homeroom teacher. The conversation around sorting students usually included a discussion of (a) the number of slots available in each placement, (b) the teacher's perspective on the student's placement, and (c) the student's history in different placements, as characterized in the conversation below.

> Instructional Coach: Like do you think [student 1] would make progress in [intervention group]?
>
> Teacher 1: yes.
>
> Instructional Coach: with [the interventionist]?
>
> Teacher 1: yes.
>
> Instructional Coach: What about [student 2]? Has [the interventionist] had him before?
>
> Teacher 2: I don't know about before this year but I know she didn't have him this year.
>
> Instructional Coach: Ok let's put him in there. (GL4, team meeting)

This dialogue is representative of the extent to which the team deliberated the placement of students into instructional groups. The team rarely (if ever) discussed students' strengths/weaknesses; the nature of the intervention; and/or their rational for placing a student in a particular intervention.

After the team placed all students in red into an instructional group, the principal and/or instructional coach identified a specific person who is supposed to progress monitoring all red

students. Progress monitoring included assessing students weekly on a 1-minute fluency test and entering these data into the GOALS database. Teachers or specialists maybe charged with progress monitoring students; when the progress monitor was identified, his/her name was written down next to the students' names and the conversation continued. It is important to note that at subsequent meetings, students' progress monitoring data was rarely discussed. In data-use meetings, the aim was to ensure students *were being* progress monitored, not to see if students were making progress.

After the team identified placements and progress monitors for students in red, they identified a group of students for enrichment. A small portion of students who scored in the green (green= above the 25th percentile) could attend enrichment with an enrichment teacher. The instructional coach called out students whose score made them eligible for enrichment. Teachers either responded "yes" and the student was placed in enrichment or they spent a few minutes discussing if a particular student should attend enrichment. Similar to the placement of students in red, this conversation was very brief, typically less than 2-3 minutes.

Other students—ones who scored in the yellow and most of the students who scored in the green or higher—were typically not discussed at all. Usually, less than half of students in a given grade were even mentioned at a data-use meeting. Therefore, at this point in the meeting, the team often stopped discussing students' performance data and moved onto other school issues.

In summary, the above description of a typical data-use meeting is meant to illustrate the key components of DDDM at Greenbrook. In grade-level meetings, the teams followed a predictable set of steps when making decisions on students' performance data. These steps were not discussed at the meeting, as the team was familiar with this process.

Step 1: Teachers received data from principal or the instructional coach.

Step 2: The team identified students who are ESL, SPED, and/or Gifted.

Step 3: The team sorted students who were red but not ESL or SPED into one of three

interventions.

Step 4: Teachers identified a small group of 4-5 students for enrichment.

Step 5: The principal/instructional coach moved onto other issues that may or may not

include data.

The time spent on steps 1-4 in these meetings decreased over the course of the school year. For

example, in September, one grade level team spent 44 minutes on this process and by April, they

went through all 4 steps in 12 minutes.

Teachers' Viewpoint on Data and Appropriate Uses of Data

As described above, the data-use meetings at Greenbrook were quite predictable and

routinized. When teams discussed data, they consistently examined one source of data,

identified the lowest performing students according to this single data source, and responded to

these data by sorting students into instructional groups. Teachers' actions at grade-level

meetings gave the impression that teachers were invested in or at least agreed with this data-use

routine, particularly as teachers rarely voiced opposition during the meetings. Yet, individual

and group interviews[6] suggested otherwise. Individual teachers often critiqued the data-use

routine employed at grade-level meetings and the data examined at these meetings.

It is important to note that teachers' critique of GOALS data and the data-use routine

employed in their grade-level meetings was primarily expressed in teachers' individual and

group interviews. Teachers rarely challenged GOALS data or the data-use routine in grade-level

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[6] In the methods section, I explained that at the end of the school year, our research team met with the classroom teachers in grade-level 3 and 4 for approximately two hours. These group interviews were intended to offer teachers a time to voice their perspectives on data, DDDM, and our research teams' initial findings.

meetings where administrators were present. Further, in grade-level meetings, they were rarely, if ever, asked to share their personal perspectives on students' performance data or the data-use routine. Therefore, the description of teachers' viewpoints I present in this section came primarily from teachers' individual and group interviews.

The Teachers

To appreciate teachers' viewpoints, I will first offer a bit of background information about each teacher. Each grade-level team consisted of 3 teachers. The third grade team included Kim, Noah, and Haley [pseudonyms]. The fourth grade team included Charlie, Devin, and Lily [pseudonyms]. These teams were similar as each team had two general education teachers and one gifted teacher. The teams were also similar as each grade-level teacher had a similar counterpart on the other grade-level team. For example, Haley from the 3rd grade team and Lily from the 4th grade team were similar as they both taught in the gifted program, had the most experience in the classroom, and had the least amount of involvement in data-driven decision making. Devin from the 4th grade team and Noah from the 3rd grade team were similar as they were both new teachers in general education classrooms who were just learning about data-driven decision making. Kim from the 3rd grade team and Charlie from the 4th grade team were both general education teachers with a moderate amount of experience in the classroom and compared to their teammates, the most amount of experience with data-driven decision making. The following is a more in-depth description of these pairs of teachers who shared similar characteristics.

Haley from the 3rd grade team and Lily from the 4th grade team both had over twenty years of teaching experience. Further, they both taught in the gifted program. The students and

teachers in the gifted program were often perceived as significantly different than the teachers

and students in the general education program, as Haley describes below.

> My kids are very different; my needs are different. We have different needs and
> different populations. They [the other third grade teachers] do a lot of collaborating with
> each other because they do a lot of sharing of kids. I love their approach but I don't fit in.
> I would do better collaborating with a second grade gifted teacher or the fourth grade
> gifted teacher. (Haley, GL3[7], II[8])

Haley expresses above that the general education teacher and the gifted teachers teach "different

populations." As a consequence of teaching gifted students, Haley and Lily also experienced

data use similarly. Mainly, as these teachers had students with high scores, they were often free

from the pressure and policies related to data use. As Lily stated, her classroom was a "data-free

zone." In data-use grade-level meetings, Lily and Haley often had little to contribute as their

students and their students' data were rarely examined.

In contrast, Charlie from grade 4 and Kim from grade level 3 faced similar pressures and

policy mandates related to data use. Both teachers had a number of low performing students in

their classrooms, which meant their students' data was often discussed at meetings. Further,

these teachers both had experience with data-driven decision making that occurred outside of

Greenbrook. For example, Charlie had practiced DDDM at a different school in a different

district. Kim had a strong special education background, which made her very familiar with

data-driven decision making. These prior experiences with data use sets these two teachers apart

from the rest of the sample as Charlie and Kim had a sense of possibility when it came to data

use. They had specific ideas for enhancing data driven decision making at their school that was

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[7] GL3 is an acronym to denote that this is a third grade teacher (GL=grade-level).
[8] II is an acronym to denote that this quote came from a particular teacher's individual interview.

inspired by their outside knowledge of the practice. Further, these teachers had both taught for over five years and held leadership roles in the building. These teachers were often influential and vocal members of their respective grade-level teams.

With less than five years of experience, Noah and Devin were newcomers to teaching. Further, the vast majority of their knowledge of data-driven decision making stemmed from their experiences at Greenbrook. These two teachers had unique, individualistic perspectives on DDDM that were expressed in individual interviews but were often not voiced to their peers. Noah and Devin were often the least vocal in team meetings.

By each grade-level teacher having a similar counterpart on the other grade-level team, each team had similar characteristics. Each grade-level team was made up of an experienced teacher, a teacher with moderate experience, and a teacher with less than five years of experience. Further, each team had a member who was not expected to use data, a teacher with prior data use experience, and a newer teacher who only experienced data use at Greenbrook. In this way, the make-up of each grade-level team was similar.

To appropriately represent the participants in this study, it is important to demonstrate how teachers individually and collectively questioned the nature of data-driven decision making at their school. Individual and group interviews with teachers revealed that teachers shared certain concerns about aspects of DDDM at Greenbrook. The following section describes teachers' perspective in more depth.

Teachers' Perspective on GOALS

In grade-level meetings, teachers rarely critiqued the data examined at this meeting—GOALS fluency data. In individual interviews, teachers repeatedly critiqued GOALS. Specifically, in individual interviews, 5 out of 6 teachers questioned the value of GOALS

fluency data and if this data source was the most appropriate assessment for making data-driven decisions. Across these five interviews, teachers expressed two major concerns with GOALS data. First, the GOALS data utilized in data-use meetings were based upon a fluency assessment. Essentially, students read a passage for 1 minute and their score was based upon the number of words they read correctly. As illustrated in the excerpts below, teachers were concerned that reading fluency data was an incomplete picture of students' capacity to read, particularly as this data did not measure students' reading comprehension or other related skills.

> Well, I mean GOALS is really, it only tests fluency. Basically, is she getting the words right, how fast is she getting the words right? You know there are a lot of things that aren't in this data, all it tells me is she made a mistake and this is where she is supposed to be and here's where her trend is, and if she continues on this trend, by the end of the year, she's going to be this far away from where she's supposed to be. (Devin, GL4, II)

In another example, Lily also expressed her concern at only assessing students' fluency.

> Having assessments to inform instruction makes sense, otherwise why are you doing it? For the GOALS, I don't really understand because it's all fluency so I don't know what they [other teachers] do to get these kids [up to grade-level]. I mean, just reading out loud and helping kids read out loud, memorizing sight words can help, but I don't know if you're going to make huge gains. (Lily, GL4, II)

In a third example, Haley too questions the narrow scope of GOALS data.

> Interviewer: Do you think that the information that you get from GOALS is accurate about your students?
>
> Respondent: No, because one of my kids has a stuttering problem so he doesn't perform well on it. I have this very multicultural class, I probably have 10 kids who speak a

different language at home and they can word call but they don't understand what they're

reading.

Interviewer: So it's never about comprehension?

Respondent: It's not about comprehension at all. (Haley, GL3, II)

Here, Haley touches upon teachers' second concern with GOALS, the accuracy of this data. To

expand a bit on teachers' perception that GOALS was inaccurate, it is important to understand

that teachers' were questioning the ways in which GOALS fluency data represented students'

capacity to read. Teachers were given student performance data from GOALS that essentially

indicated if students were able to read (i.e., students in the green) or not able to read (i.e.,

students in the red). At times, like in Haley's example above, GOALS would indicate that

students could not read and in interviews, teachers expressed that they questioned this claim. In

Haley's example, she explains that one of her student stutters, so he doesn't perform well on

GOALS, which is a fluency test but she doesn't believe this means he is a poor reader. She

specifically uses the term "word caller" to describe how students could read the words, which

gave them a high score on GOALS, but she did not perceive that they could comprehend what

they were reading. This term "word caller" was a part of the data use jargon and it was utilized

to describe students who were fluent readers but not able to comprehend the text.

For example, in a rare occurrence at a grade-level team meeting, a teacher challenged

GOALS data. In this instance, the interventionist excitedly said to the instructional coach, "Look

at this" and pointed at a particular student's score. The instructional coach responded "He is a

good reader" and Kim interjected, "He doesn't understand anything he is reading." The

instructional coach responded, "Yes, he is a word caller." While this was a rare instance of a

teacher challenging a student's data, no further conversation followed.

In a similar example, in his individual interview, Devin from the 4th grade team described how one of his students can read words but cannot comprehend what she reads.

I would actually say that her [pause] like she gets almost nothing from the reading.

So she'll read a whole passage and you'll ask her questions about it and it's like she

didn't even read it so I mean she's the same way. Yeah, I have a few students like that.

(Devin, GL4, II)

Like Devin, Kim, and Haley, all 6 teachers discussed in either individual or group interviews that GOALS data was at times inaccurate. Due to teachers' knowledge of students like if a student "stuttered," had a learning disability, or were English Language Learners, teachers asserted that GOALS was an inaccurate measure of particular students' capacity to read. Overall, teachers perceived GOALS as limited as it only assessed fluency and because it only assessed fluency; teachers perceived that at times it was an inaccurate indicator of students' capacity to read.

Out of all of the classroom teachers, in her individual interviews, Kim was the sole teacher who expressed that she saw value in GOALS data. However, as Kim described she was also one of the only teacher who received any training on the purpose and meaning of the GOALS assessment. Kim stated the following.

I think it [GOALS data] can be very beneficial if the teacher knows what it is and how to

read it but it was just kind of thrown at us. . . . The training that leads into that never

occurred so a lot of teachers ask, what is fluency telling me? . . . If the training never

occurs and teachers aren't aware of what they are looking at, it is really hard to analyze

that data in a productive way. (Kim, GL3, II)

Kim's assertion that teachers were not trained on this assessment tool or provided with the necessary background information to interpret this data was confirmed by two separate sources. First, in individual teacher interviews, most of the teachers reported that they had received no training on GOALS. Second, in a district administrator interview, s/he stated that teachers had no training on analyzing GOALS data.

Although most teachers questioned GOALS data, they still often believed that GOALS did accurately identify the lowest performing students. GOALS was designed to identify students who were in the bottom 10th percentile nationally and teachers believed the assessment was relatively successful in doing this. However, half of the teachers questioned the need for an assessment to identify the lowest performing students, as characterized in the two quotes below.

> I think the thing that teachers feel with all of the assessments is if we're assessing and assessing, what do we do with it? I mean we use to, in the district, give benchmarks to all of the third and fourth and fifth grade kids in the fall. It would be like a mini- [annual high stakes test] in the fall so that we could look at it and say like: Oh, these 5 kids aren't going to pass [the annual high stakes test]." I could have told you that. I can tell you who my strong kids are and who isn't. I don't need to spend 3 hours of instructional time giving them an assessment for that . . . We're using it to determine who our low kids are and I think by and large, if you ask the teachers to rank the kids or ask who are the kids that are struggling readers that you want to provide support to then they could have told you that without the assessment. (Haley, GL4, II)

Noah describes a similar sentiment in his individual interview.

> It's an interesting question because I could probably guess pretty well before I even passed a test out how each student would do on it. I mean I bet, kind of like you step

outside and guess the temperature, I bet I could get it plus or minus 3 degrees, I bet I

could do the same with my students, so is it [GOALS data] really telling me anything that

I don't already know? Maybe not…that sounds kind of weird to say that. It makes me

think maybe I shouldn't even give them [the assessments], because I don't know…maybe

I'm speaking too highly of my own knowledge of them possibly. (Noah, GL3, II)

It is important to note that all teachers stated that they were not opposed to other sources

of data that they found informative and accurate. As one teacher stated, "any data helps" and

across interviews, teachers often cited particular data sources that helped guide their instruction.

In particular, four teachers referenced the value of the Developmental Reading Assessment

(DRA). This assessment was utilized in previous years across the district and teachers spoke of

the value of the DRA data.

If its [an assessment] used like an instructional springboard, like this is what we need to

do, then it's really good. I mean the DRA was actually a good assessment because it

gave you a pretty well rounded picture of where to go. GOALS [pseudonym] I don't see

as that, just because like I said the nature of the test, it's so black and white and it doesn't

give you anything other than how fast they are reading and how many errors they made

while reading…But what I like about the DRA is it's instant feedback, you know exactly

how the kids are doing and it gives you a good idea of where to go with them from there.

(Devin, GL4, II)

Lily offered a similar perspective on the DRA.

To me, there are other measures, for example, a DRA test. This is the first year we

haven't had to do them. I learned a lot. You actually listen to a child read, it's not about

speed and time. Then you actually have them answer a series of questions. You figure

out: Do they understand what they read and are they able to speak about it? That seems to me much more significant. That whole ability to comprehend text as opposed to just reading. I find them [DRA assessments] more informative for informing instruction because I can see right away, especially since you have to write, this child is struggling on (a) understanding, and (b) explaining to me what happened in the story. To me, I can see that kid needs some support. They definitely couldn't be in circle and writing a summary because they clearly can't. So for me it's like a guide. (Lily, GL4, II)

As indicated in these quotes from teachers' individual and group interviews, teachers were not opposed to data or the idea that student performance data was informative. Teachers specifically questioned GOALS fluency data. Teachers perceived GOALS data as (a) limited as the assessment only tested fluency, and (b) inaccurate for particular students, such as English Language Learners. Further, teachers viewed GOALS as unnecessary as the only useful outcome was to identify the lowest performing students, which teachers believed they could already do accurately.

Teachers' Critique on the Content of DDDM Conversations

The data-use routine in grade-level meetings heavily focused upon identifying and responding to the lowest reading test scores Grade level 4 teachers described this emphasis in a group interview.

Lily stated: That [reading test scores] is kind of what we are pushed on, that is what we are monitored on. Does anyone ever ask us about our math scores?

Devin and Charlie responded: No

Lily goes on to say: "Never, literally never. The onus is on us to get kids reading at grade-level . . . what is measured is what we work on. (GL4, group interview)

In a group interview with grade-level 3 teachers, they had the following dialogue related to this emphasis on reading data.

> Haley: What jumped out to me is that we rarely discuss math data, science, or social studies data…I don't know what I want to say about that.
>
> Kim: I think it is unfortunate. We collect math data, why do we not use it? We have access to tools to evaluate writing; we aren't using those. That to me is frustrating, when we either are using something that we are not looking at or we have something available to us that we are not using. Why is it just literacy? That has been an ongoing frustration for me personally to just look at literacy. (GL3, group interview)

In individual interviews, Charlie and Kim expressed that the team should be analyzing and responding to students' math data. Charlie stated the following.

> Same thing for math, and I think math kind of gets pushed away, because I think our focus is on reading, but we struggle just as bad on math. But the focus is always on reading, how are we going to become better readers. But we've got kids that can't multiply. (Charlie, GL4, II)

Kim too discussed the need to monitor and discuss students' performance in math.

> I have asked that we have a math intervention group for [students] as long as the students are average or above average in reading so keeping that reading as a first priority. But then those students that really don't have any reading problems but are struggling in math, can we get them an intervention? I had a couple of students who were getting enrichment during our intervention block but are failing math. Why are they getting extra reading when they're already above grade level in reading but are really struggling in math? (Kim, GL3, II)

In addition to wanting to respond to students who had low math scores, some teachers also expressed interest in discussing more than just the lowest performing students. Across individual and group interviews, teachers asserted that the exclusive emphasis on the lowest performing students according to reading data was an important but too narrow of a scope. The third grade teachers expressed this sentiment in the following dialogue.

> Kim: It would be nice to have conversations about the other ones. Students who in the fall were in the red and it's the winter benchmark and they are now in the yellow. That conversation doesn't occur; it is still just who is in the red now.
>
> Noah: At the last collaboration, I had the same thought. Immediately, we just scrolled down [to the bottom of the data display to the lowest performers]. Boy, it would have been nice to scroll up and just celebrate a couple of accomplishments as opposed to just focusing in the red.
>
> Haley: You feel a bit beat down.
>
> Noah: I feel more disappointed by not helping my top quarter. Who do you teach to in a classroom of 20 plus kids? If you look at that data, I think it is realistic to focus your attention on the largest percentage of kids . . . but I also feel bad. I am so happy some of my kids are going into gifted next year because they need that, I didn't do them any favors. I just hope I didn't hurt them that bad, seriously, I didn't challenge them, nowhere near what they could have, but that is the nature of this. You teach to the largest percentage . . . sometimes [that is] the red. (GL3, group interview)

As indicated in Noah's statements, general education teachers often expressed that they felt a tension between this top-down emphasis on enhancing the outcomes of the lowest performing

students and teachers' personal commitment to all of their students. Devin expressed another example of this sentiment in the following quote.

> I'm constantly aware of her [student in the lowest performance bracket] and trying to keep her on the same page and she's just so far off… at the end of the day I still have 21 other students that are expected to be successful. (Devin, GL 4, II)

Teacher interviews also expressed a disconnect between the way students were discussed in grade-level meetings and the way teachers thought about their students more generally. When discussing students in grade-level meetings, the conversations were narrowly focused upon red students and the placement of these students into intervention groups. Yet, in individual and group interviews, teachers discussed a wide range of students and students' needs. Rather than discussing students' needs in relation to reading scores, teachers often discussed students' personality and their perception of students as learners. The following examples illustrate the diversity of academic needs identified by teachers.

Haley, the third grade teacher of gifted students asserted that although her students' performance data was very high, her students still had academic needs. She explained:

> So I have four very bright, I mean if I had to rank my kids, these are my most brilliant kids. They're all boys and they're all really high flyers. They're very unusual. I have one boy who paces the whole day and flaps his arms. I have one who can't be with the group because he is too distracted by them. I have another one who goes out for stress breaks like every half hour. He can just walk out of my room and go do sensory things. And one who has speech issues and talks a thousand miles a minute and it's really hard to understand him because he's speaking so fast. But these are my three really top kids. (Haley, GL3, II)

Noah, the third grade general education teacher described a very thoughtful desk arrangement where he identified students' needs and then attempted to place them by supportive peers, such as placing two students with the same native language next to each other so they could support each other in translating their school-work. The following is an excerpt from this interview.

> These desks, these table groups are strategically arranged, I mean it isn't just a random pick of kids, they are seated by people who can help them with their work. Like over here, I have two kids that are from Korea, so they help each other out talking. (Noah, GL3, II)

Charlie, the fourth grade general education teacher discussed the importance of teachers recognizing and addressing students' socio-emotional needs in the following excerpt.

> Last year towards the end of the year, like around the time of [annual high-stakes standardized test], things were just falling apart [for a specific student]. She didn't care and didn't want to do anything. I already knew she was low, I already knew she was struggling. I was talking to her knowing mom was in the hospital, things like this, so when talking to her, she finally she let it out. Now, I know I can back off. . . . I am a little more lenient. Now, I'm having more in-depth conversations with a nine-year-old about life [pause] and it just really puts things in perspective. (Charlie, GL4, II)

A fourth grade teacher indicated that students needed educators to communicate with one another consistently. He described that teachers in the building did not regularly communicate around students' progress and the ways in which they were collectively attempting to address students' needs.

> So, and I feel like that's a school-wide sort of problem. That's been the problem with this school for a long time. We don't have communication when it comes to this. . . . I

mean that's kind of the point, we're trying to help the kids, I want to know what you are

doing so that way either we're not doing the same thing or they are getting something that

they need. (Devin, GL4, II)

These interview excerpts illustrate that teachers identified a wide-array of academic needs for

students. From school norms to seating arrangements, teachers indicated their sense of

responsibility to address students' unique needs. Overall, the emphasis on the lowest performing

readers in data-use meetings did not characterize the breadth of their responsibilities as teachers.

They felt responsible for addressing a wide range of students needs like their achievement in

math, their well being, and multiple other considerations that were absent from data-use

meetings discussions.

Summary

In grade-level meetings, teachers in both teams harmoniously participated in the data-use

routine. They examined GOALS data, identified the lowest performing students, and offered

their perspective on the placement of these students in an intervention. Yet, outside these

meetings, in individual and group interviews, teachers generally critiqued both GOALS data and

the narrow scope of the data-use routine. Teachers' critique of GOALS data and particular

aspect of the data-use routine employed in their grade-level meetings is an important part of the

tale of Greenbrook. Teachers at Greenbrook were participants in the data-driven decision

making process, but they did not endorse it.

Chapter 5: Findings from the Case of Greenbrook

This chapter is meant to be an extension of Chapter 4, the "Case of DDDM at Greenbrook." In the previous chapter, I offered an overview of the context of Greenbrook, background information about teachers and their perspectives, and a description of the typical ways grade-level teams engaged with student performance data. In this chapter, I hone in on specific aspects of DDDM at Greenbrook.

More specifically, this chapter contains three essays that focus upon distinct conditions of data use at Greenbrook. I decided to write-up my findings in three separate essays so that I could present an analysis of particular practices and policies present at Greenbrook that were supported by the data and relevant educational research and theories. These essays are intended to be stand-alone pieces but at the same time depend on the earlier discussions of DDDM literature, methods, context, and findings of this study.

The first essay presented in the fifth chapter is titled "From Black and White to Red and Green: Color Still Impacts Students' Educational Reality." In this essay, I highlight the "stoplight" color-scheme (Love, 2004). The stoplight color-scheme is a data visualization tool where data are color-coded in order to support teachers' interpretations of student performance data. Using evidence from the study of Greenbrook and literature on labeling theory, I argue that this color-scheme was utilized primarily to label and sort students at Greenbrook. These labels were associated with students' access to different educational avenues at Greenbrook, particularly the lowest performing students. I specifically raise the question about whether the stoplight color-scheme was beneficial for low-performing students at Greenbrook.

The second essay presented is titled "Beyond "Matchmaking: An Examination of the Aims of Data-Driven Decision Making." In this essay, I examine specific aims for data use.

Borrowing the concept of "matchmaking" (Oakes & Guiton, 1995), I describe how educators' data use targeted matching students to pre-determined educational programs. I argue that matchmaking promoted particular data-use conversations and decisions while stifling inquiries into other issues that merited attention. Further, using teachers' perspectives and their individual data-use activities, I present teachers' alternatives to matchmaking.

The third and final essay is titled "The Decision Makers: Do Teachers Have the Authority to Make Decisions Based on Data?" In this issue, I identify a data-use support that is potentially missing from the existing literature: A political climate conducive to teachers using data to make decisions. Using a policy lens, I present the plethora of policies and mandates that mediate teachers' work at Greenbrook. As multiple policies prescribed teachers' instructional goals, methods, and assessment practices, teachers had little autonomy to make instructional decisions. Without the autonomy to make instructional decisions, teachers had little flexibility to respond to students' data in meaningful ways.

Essay 1: From Black and White to Red and Green:
Color Still Impacts Students' Instructional Reality

Students' skin color matters in U.S. public schools. Students of color receive a sub-par education in comparison to their white counterparts according to almost every indicator of educational quality. If examining educational outcomes, white students are more likely to graduate, have higher ACT and SAT scores, and read at or above grade level (Darling-Hammond, 2010; Vanneman, Hamilton, Anderson, & Rahman, 2009). If examining educational settings, white students are more likely to attend schools with adequate funding and ample resources (Baker & Corcoran, 2012; Mathis, 2003). If examining the classroom setting, white students are more likely to sit before teachers with a track record of success and hold high

expectations for their students (Darling-Hammond, 2010; DeAngelis, Presley, & White, 2005; Llamas, 2012). Research heavily supports the stance that students of color in this nation receive a lower quality education than white students.

The disparities between students of color and their white counterparts are well-documented. Yet, this study investigates a new relationship between educational opportunities and students' "color." In the practice of data-driven decision making, at times, students' performance data are color-coded to support educators' interpretations of raw data (Herman & Gribbons, 2001; Marsh, 2012; van Harmelen & Workman, 2012). The color-coding of student performance data is intended to support educators in interpreting student performance data. Researchers documented a gap between educators' knowledge of data analysis and the type of knowledge needed to effectively make instructional decisions based on data. To close this gap, data management systems and stakeholders in DDDM created data visualizations like color-coded data that were easily interpreted by educators (Gottfried et al., 2011; Lachat & Smith, 2005; Marsh, 2012; Means et al., 2011).

One specific color scheme utilized in DDDM is the stoplight color-scheme—green, yellow, red. Test scores that meet or exceed a particular pre-determined threshold are marked green, the scores that fall below the threshold are yellow, and the scores that are far below are red (Fitzpatrick & Margolin, 2004; Love, 2004; van Harmelen & Workman, 2012). This stoplight color-scheme is shown to increase the likelihood that educators will use student performance data and was therefore deemed a successful support for teachers data use (Herman & Gribbons, 2001; van Harmelen & Workman, 2012).

Yet, what type of data use is facilitated by color-coded data? How does color-coded data impact teachers' analysis of student performance data and their impressions of students? The

case of Greenbrook provides insights into these questions. As described in Chapter 4, educators at Greenbrook viewed student performance data that was color-coded, specifically students' data was color-coded with the stoplight scheme—green, yellow, and red (see Figure 1, p. 61). I will argue in this essay that the stoplight color scheme at Greenbrook did not *support* teachers' efforts to interpret data. Instead, the stoplight color-scheme served as *the interpretation* of students' performance data in grade-level data-use meetings. Further, in the team meetings, the colors green, yellow, and red served as a proxy for both students' academic performance and teachers' instructional response to students.

Conceptual Framework

To analyze the ways in which educators' discussed and made instructional decisions from color-coded students' performance data, I drew from two interrelated frameworks. First, I considered the research on labeling theory, specifically, the process by which particular labels gain negative connotations and at times are detrimental to students. Second, I considered the frameworks for data use in educational policies, including the Response to Intervention framework. I end this section by arguing that students' performance data are utilized to label students, a phenomena I refer to as data-driven labels.

Labeling Theory

Kagan (1990) argues that all humans categorize and labels objects, people, and actions. Sorting and labeling is a naturally occurring psychological process present in humans, including teachers. Yet, natural or not, educators' instinct to label students has consequences for a vulnerable population, children. Researchers have documented how the classifications of students impacts teachers' instruction and students' quality of education. Briefly, students' labels can impact teachers' view of students, their academic potential, and teachers'

responsibility to educate students. Certain labels diminish students' educational opportunities while others enhance students' educational opportunities (McKown & Weinstein, 2008; Rubie-Davies, Hattie, & Hamilton, 2006).

The labeling of students is not inherently detrimental. The literature suggests problems arise when particular student-labels gain a negative connotation (Booher-Jennings, 2005; Kagan, 1990). One notable example is the student-label "at risk." Often determined by students' data, students were labeled at-risk if they were perceived as vulnerable to failing or dropping out of school. Boykin (2000) and Sanders and Jordan (2000) argue that this label fostered educators' attribution of students' academic troubles to the student and his/her home life. In turn, the at-risk label often served as a barrier to students accessing rigorous education, ironically further placing students at-risk for unfavorable academic outcomes (Martinez & Rury, 2012).

The at-risk label is one of many student-labels that carry a negative connotation in schools. The literature suggests that negative student-labels can be detrimental to students in multiple ways. Students with negative connoted labels often receive less attention, praise, and support in the classroom (Hughes, Gleason, & Zhang, 2005; McKown & Weinstein, 2008). Educators often hold lower expectations and feel less of a responsibility for the learning of students who have an unfavorable label (Booher-Jennings, 2005; Diamond & Spillane, 2004; Rubie-Davies et al., 2006). Further, students with negatively connoted labels are often aware that teachers treat them differently and expect less from them in the classroom (Kagan, 1990; McKown & Weinstein, 2008). In short, students' labels often translate into negative instructional realities for students. Students with unfavorable labels are particularly vulnerable to experiencing an alienating, low-quality education.
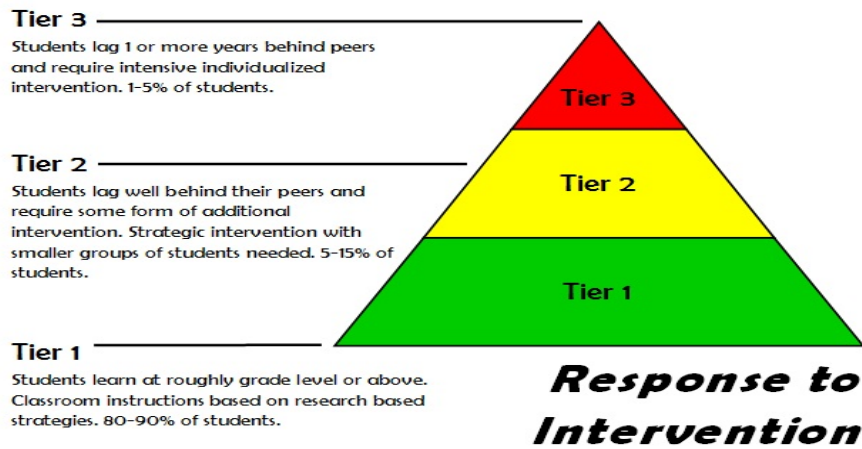
Data-Driven Labels

Students' labels are socially constructed through particular tools, rituals, and processes (Ball, 2012; Kagan, 1990). Of primary importance to this study is the construction of student-labels via student performance data or what I will refer to as *data-driven labels*. Data-driven labels are constructed through standardized tests, scoring criteria, and educational policy. Students receive a data-driven label based upon their test score, which is mediated by the assessment, its scoring criteria, and the educational policies that govern testing and cut-off scores.

According to No Child Left Behind and continuing with Race to the Top, students received specific data-driven labels associated with their test scores on standardized tests. Students test scores earned them the label 'above, at, or below-grade level' (Coburn & Turner, 2012). These data-driven labels effectively grouped students into three performance brackets. Starting in 2015 for most public schools, federally funded consortiums oversee the Common Core assessments and now regulate the assessments and the scoring criteria that determine if students are classified above, at, or below grade-level (Doorey, 2012; Fletcher, 2010).

The academic classification of students is pervasive in federal policy and this extends to policies that govern instruction. Response to Intervention (RTI) is a comprehensive framework for determining students' instruction. This framework furthers the practice of adorning students with one of three data-driven labels. In RTI policy, students are classified as tier 1, tier 2, or tier 3, with tier 1 being students who are at or above grade-level and tier 3 being students who are well below grade-level (Fuchs & Fuchs, 2006; Fuchs et al., 2003). Not coincidentally, these tiers are often presented visually with the stoplight color-scheme. Figure 2 is an example of a visual representation of RTI (St. Croix School District, 2015). The triangle is intended to illustrate (a)

the relationship between students' color and their instructional needs, and (b) the proportion of students who should be green, yellow, and red in each school.

Tier 3 ——————————————
Students lag 1 or more years behind peers and require intensive individualized intervention. 1-5% of students.

Tier 3

Tier 2 ——————————————
Students lag well behind their peers and require some form of additional intervention. Strategic intervention with smaller groups of students needed. 5-15% of students.

Tier 2

Tier 1 ——————————————
Students learn at roughly grade level or above. Classroom instructions based on research based strategies. 80-90% of students.

Tier 1

Response to Intervention

Figure 2. **A visual representation of the RTI framework.**

The RTI framework indicates that educators should provide students with instruction based upon their data-driven label. As illustrated in Figure 2, students who are green should receive "research based" instruction for students at grade-level. On the other end of the spectrum, students in "red" are well below grade-level and should receive an "intervention."

In summary, students receive data-driven labels through a policy-driven process. Students are tested, labeled according to their test score, and according to the RTI framework, provided with particular types of instruction based on those labels. In data management systems and data-use frameworks like RTI, academic labels may be represented by a stoplight color-scheme.

Finding 1: Data-Driven Labels at Greenbrook

Similar to the process described in the previous section, students at Greenbrook were assigned a color based upon their performance data. As described in Chapter 4, educators viewed data where students' names and raw data were color-coded green if students' scores were

at or above the 25th percentile. If students' scores placed them above the 10th percentile but below the 25th percentile, then students' names and scores were color-coded yellow. If students' scores were below the 10th percentile, then students were color-coded red.

As discussed in Chapter 4 but worth repeating here, teachers held conflicting views on the meaningfulness and accuracy of students' color. However, in the grade-level meetings, teachers rarely voiced opposition to students' color and would discuss students' according to their color. The content of data-use meetings centered on students' data-driven color—as opposed to students' raw data or teachers' understanding of students' academic needs.

At Greenbrook, grade-level teams rarely (if ever) discussed students' actual numerical scores on assessments. Instead, the conversation revolved around either (a) *individual* students' color or (b) discussions of color-coded *groups* of students, as illustrated in the excerpt below. In the following excerpt, a teacher and an interventionist debated which color-coded group of students needed an intervention.

Interventionist: Do we want to keep pounding on the reds [referring to students who scored in the red]?

The interventionist then listed the names of 11 students in yellow and suggested that they needed interventions and that perhaps these yellow students would benefit more from interventions then students in red. The third grade teacher, Kim disagreed and argued that their grade-level team should continue to focus on students in the red.

Kim: Looking at my list, [student name 1] is new to the country so the fact that he is in yellow.

Interventionist: Amazing.

Kim continued: [student name 2] and [student name 3] were in the red in the fall and are now in yellow.

Interventionist: Ok.

The other teachers do not chime in on this discussion and the team proceeded forward by sorting red students into intervention groups. This excerpt illustrates how grade-level teams literally discussed colors. The interventionist questioned the school norm to focus upon the "reds" or the group of students who scored in the bottom 10th percentile on a nationally normed fluency test. In an effort to maintain the emphasis on red students, Kim argued that certain yellow students were improving as they "were red in the fall and are now in yellow." This exchange between teachers is an example of how students' colors became a shared language for teachers to discuss students' performance in grade-level meetings.

Like the third grade-team, the fourth grade- team meetings also consisted of color-full conversations. Below is an excerpt from a fourth grade meeting where Lily, the gifted teacher is asking the fourth grade general education teachers about the RTI block. As Lily taught in the gifted program, she was unaware of the rules and norms related to the RTI block.

Lily: Do you have the lowest kids?

Charlie: I have the middle of the road kids, the yellows. I have low and then I have some that are doing Lexia.

Later, Lily inquired about what teachers do on Fridays for the RTI block.

Charlie: Friday is supposed to be a testing day but it is not consistent.

Devin: It is consistent for the kids in the red; they always get monitored. You don't have to monitor if they are in the yellow or the green.

This excerpt offers another example of how grade-level teams used students' colors as a shared language. As indicated in the two excerpts above, in both the third and the fourth grade team meetings, the colors from the GOALS data display represented more than students' percentile ranking, they became a label that grouped each individual student in with other students who shared the same color—red, yellow, or green. The next section describes how students' color was consequential for students' instructional reality.

Finding 2: Students' Color Mediated Their Access to Instruction

Students' color had an instructional reality at Greenbrook. It often determined the type of instruction students would receive during the RTI block. The following decision tree represents the particular avenues available to students for the RTI instructional block based on their color.
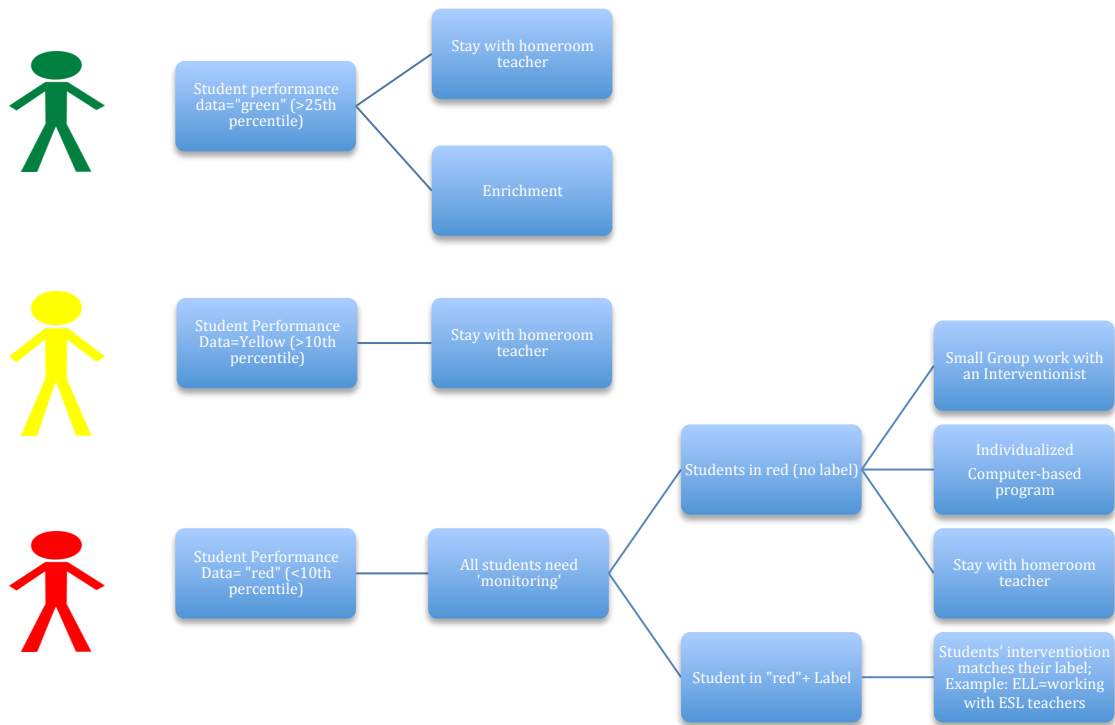

Figure 3. Greenbrook's RTI data-driven decision matrix.

The RTI block was a forty-minute instructional block, which occurred four days per week. Yet, beyond the RTI block, students' color still impacted their access to instruction. Multiple teachers described the use of students' color to place students into guided reading groups. So in the daily reading block, students in red were often grouped together and worked on skills that differed from students in green. Further, in grade-level meetings, teachers were advised to instruct red students with an alternate reading book, designed for students who were below grade-level.

The overriding ideology was that students of a particular color had similar needs. Red students needed specialized instruction from an interventionist and monitoring. Most green and yellow students needed general instruction from their homeroom teacher. The DDDM conversations over the course of the year reflected this ideology. Grade-level teams rarely discussed individual students' needs or strengths; students' needs were essentialized by their color. Even when faced with conflicting evidence, students' color could trump other indicators of students' needs. Meaning, if teachers advocated for students' admittance into an instructional group that was not corroborated by students' color, students could be denied access. The following examples illustrate this phenomenon.

Mary

Mary was a third grade student in the gifted program. Everyone agreed that Mary was a bright student but her teacher had multiple sources of evidence that demonstrated Mary was struggling academically. For starters, on the GOALS assessment, Mary was in the yellow, which was an anomaly for gifted students, who often scored above the green or in the highest percentiles. Second, Mary's second grade teacher and test scores provided evidence that Mary had struggled tremendously on particular learning objectives in the second grade. Third, on

classroom-based assessments, Mary excelled in particular areas and performed poorly in other areas.

Mary's teacher had a wealth of teaching experience and an admirable commitment to all of her students. She attempted multiple strategies in the classroom to support Mary, including one-on-one support, diverse teaching strategies, and supplemental resources. Her teacher also sought out the support of her colleagues.

Beyond receiving advice from others, Mary's teacher did not have access to additional supports for Mary because her test scores were not "low enough." Mary's teacher stated, "I am all of her support which is pretty bad because it's not my forte." As Mary was not in the red, she did not qualify for special education and correspondingly, specialized services.

Hugo

In a grade-level meeting, fourth grade teachers, a school administrator, and an instructional coach were using data to determine which students would receive enrichment. Enrichment consisted of a small group of 4-5 green students who work with a specialized, enrichment teacher for 40 minutes a day, four days per week. This instructional time is intended to challenge high-achieving, green students. The instructional coach, school administrator, and classroom teacher all believed Hugo belonged in an enrichment group. The problem is Hugo's was not a green student. Upon looking at Hugo's scores, the administrator stated, "he just seems so much higher to me." The instructional coach responded, "I know he is very smart." The classroom teacher then discussed his strengths on in-class assessments. Despite the team's judgment that Hugo was smart and a worthy candidate for enrichment, the team ultimately decided that Hugo needed an intervention. Interventions were reserved for low-performing, red students. In interventions, small groups of 4-5 students work with a reading specialist, typically

with materials and learning objectives that are below grade-level. Educators at the table wanted to place Hugo in a challenging, rigorous environment but his test scores suggested he needed remediation. Hugo received remediation.

In the case of Hugo and Mary, contrary to educators' judgment, students' color denied them access to specific educational avenues available at the school. Multiple experienced educators perceived Hugo as intelligent and believed he qualified for enrichment. They had witnessed his responses to questions, his performance on in-class assessments, and heard him think. Multiple experienced educators perceived Mary as a bright student who potentially had a learning disability. They also had in-class assessment data and teachers' observations to support this claim. Yet, one source of assessment data, GOALS fluency data conflicted with teachers' appraisal of students. This single source of assessment data trumped teachers' judgment—which according to the literature, this is the one of the purposes of DDDM. As Mandinach and Gummer (2012) state, "it is no longer acceptable" for educators to use "anecdotes, gut feelings, or opinions", educators should instead make decisions based upon data (p. 71). In this case, educators did not use their gut feelings, they used data. Test data drove Hugo straight to remediation and away from a rigorous, challenging learning opportunity. Data drove Mary away from specialized services and interventionists. Data from a single fluency tests was consider more correct than teachers' assessment based on classroom data and professional judgments based on their experience with the student.

Same Kids, Same Data, New Analysis

As described above, students' color was an influential factor in determining students' instructional program. An interesting example of this is that in three instances during grade-level meetings, students' color changed while everything else remained constant. Due to a switch in

analysis, the same student(s) with the same test score (s) on the exact same fluency assessment changed colors. In these instances, when the color changed but all else remained constant, educators' response to students changed in accordance with the color. This is illustrated in the examples below.

In a beginning of the year grade-level meeting, the instructional coach asked the fourth grade gifted teacher, Lily, if she had any students that she was "worried about."

Lily responded: I have four kids that I worry about [she lists all four students' names].

Instructional Coach: Ok hold on [she looks at the data display with color-coded data] I didn't know [student name] was on your list.

Lily: He is yellow. (GL4, team meeting)

After hearing and seeing that the student was in yellow, the instructional coach and Lily have no further discussion about this student. Lily is not expected to offer any anecdotal evidence, student work samples, or professional judgment to either confirm or deny the yellow status of this student. If the GOALS data display color-codes a student yellow, then the student is yellow. Lily even commented, "My poor kid is in the yellow" indicating that she felt bad that one of her gifted students was yellow.

Towards the end of this meeting, in a rare occurrence, the school psychologist, who floats between schools in the district, entered this grade-level team meeting. He showed Lily his IPAD where he had pulled up her students' performance data from the online GOALS database. He explained to her that the display on his IPAD was different than data display she had. He stated, "It is just a different way of visually displaying the data." Lily's printout had students' performance data that was color-coded according to students meeting a particular fluency threshold, i.e. hitting a pre-determined cut off score. The school psychologist ran the analysis

typically referred to in grade-level meetings where students' performance data was color-coded by percentiles, i.e. students' were ranked and sorted into performance brackets according to national averages. When examining percentile scores, Lily had no students in yellow. Looking at this analysis, Lily stated, "Oh that is much better. So there is no one in my room to worry about." He confirmed that she did not need to "worry" about any of her students. Her "poor kid" in the yellow was no longer a worry and the team did not discuss this student further.

In a similar example, at a third grade team meeting, the principal told each grade-level team that the GOALS assessment system had a specific analysis to be used for English language learners. The administrator stated to the grade-level team:

> And we really didn't know that we had that capability of doing that [a report for ELL students] on GOALS until we played around with some of the reports and we found it and so that was kind of neat for us. (GL4, team meeting)

The principal ran this analysis and explained that according to the new analysis, most English language learners were no longer red. With the push of a button, a group of English language learners went from red to yellow or green. As these students were no longer red, they no longer needed additional time with English language teachers and further, students were no longer progress monitored. The administrator stated how this new analysis of ELL students' data would decrease the ESL teachers' "case load."

This exact same conversation took place in a third grade team meeting. In this meeting, the administrator explained the new report and showed teachers that most ELL students were now yellow or green instead of red. The administrator also told teachers that these students no longer needed progress monitoring or interventions.

In these team meetings and in interviews, teachers indicated that they agreed that English language learners should be assessed in a different way than native English speakers. However, teachers differentiated between the process for assessing students and the need for English language learners to work with ESL teachers. Despite students' new color, in grade-level meetings, teachers still advocated for their students to work with ESL teachers. Teachers' advocacy was backed by the school's publicly accessible statistics, which indicated Greenbrook had a disproportionate number of English Language Learners in comparison to the state and the district. Greenbrook had a large proportion of recent immigrants, many students in the 3rd and 4th grade who were learning English for the first time. Throughout the grade-level team observations, teachers had to negotiate which of their students would receive English language services and which students would go without, as the limited number of ESL educators could not serve the entire ELL population. The switch in the analysis of ELL students' performance data alleviated the school's responsibility to respond to students, but did not ameliorate students' need.

Summary

These examples of Hugo, Mary, and students whose color changed were rare occurrences. Typically, in grade-level meetings, teachers did not challenge students' color and/or the corresponding placement of students' into instructional avenues. These examples of Mary, Hugo, and students whose color changed were meant to illustrate that when the grade-level team experienced a disruption in the DDDM routine, the team still relied on students' color to settle the matter. Disruptions in the grade-level team's DDDM routine did not foster inquiry, promote the consideration of other data sources, and/or enable teachers to contribute their professional judgment.

Finding 3: It's Not Easy Being Red

In the popular children's show, *Sesame Street*, Kermit the frog has mixed feelings about his green skin. He sings a beautiful song, "Bein' Green" about the complex reality of a life lived green. Similar to Kermit's plight, being red at Greenbrook had pros and cons. Their red color fostered instructional realities that were at times advantageous and at other times, potentially detrimental.

Beyond wanting to metaphorically draw from *Sesame Street*, I started this section with a reference to a children's show as a reminder that the students discussed in this section, this chapter, and this entire dissertation were very young children. The red students discussed in this section are as young as seven and no older than 11. Another important reminder is that students were labeled red due to their performance on a 1-minute oral fluency exam.

On the one hand, being red afforded students extra attention from teachers. At grade-level meetings, red students were by far the most frequently discussed group of students. The instructional coach or principal started every DDDM conversation by directing everyone's attention to the red students. Meaning at every conversation about data, each red student was at least briefly discussed by the grade-level team, as opposed to some yellow and green students who were never discussed at grade-level meeting.

Further, as indicated in interviews with teachers, teachers felt pressured to enhance the educational outcomes of red students. All teachers expressed in their interviews that they were concerned for students who were in the "red" and wanted to help these students. At times, this investment in red students was expressed as a matter of personal concern. For example, Kim stated, "The energy has to be on saving these students in the red. . . . I think it is the nature of teachers to want to help kids so if we see kids failing, the first thing we want to do is help them"

(Kim, GL3, group interview). At other times, this attention on red students was expressed as a need driven by external accountability policies. For example, Charlie stated in a group interview, "As a struggling school, this [students' red data] is what we have to worry about constantly" (Charlie, GL4, group interview). Regardless of teachers' rationale for focusing on red students' academic performance, teachers' conversations in interviews and grade-level meetings demonstrated that red students and their academic performance was a priority at this school.

Further, red students had access to resources that were only available to them. To comply with RTI policy, students in red were to receive "targeted group interventions" or instruction that was specifically designed to enhance the learning outcomes of students who struggled in general education environments (SBE, 2008, p. 2; Zirkel, 2012). As a consequence of RTI policy, red students qualified for small group instruction facilitated by an interventionist, who had extensive teaching experience as a reading specialist. Red students were also eligible for individualized instruction administered by a software program, Lexia.

On the other hand, it is unclear if the academic interventions were actually an advantage. The specific nature and qualify of instruction offered by the interventionist and Lexia are outside of the scope of this study. However, comments made by educators in grade-level meetings and individual interviews suggest that teachers had conflicting perceptions about the value of the interventions offered to red students. For example, at a third grade meeting, the interventionist advocated for certain red students to *not* receive an intervention. She argued that certain red students had received "tons" of interventions and had failed to make gains, indicating that the interventions had not helped red students improve. Similarly, in a fourth grade team meeting, the

instructional coach indicated that red students who worked with the interventionist last year were still red or under-performing this year.

> Principal: So [student name 1] is in with [the interventionist] so let's take [student 2].
>
> Instructional Coach: [Student 1] had [the interventionist] all last year too and he is still [she motions to the board and the student's data in red].

Charlie continued to list his students that were slotted to work with the interventionist.

> Instructional Coach: (in a weary voice) [Student name 3] had [the interventionist] all last year too, every round. [Student name 4] had the interventionist too. (GL4, team meeting)

> Educators also indicated that the other intervention, Lexia was also insufficient. In each grade-level, six of the lowest performing students were placed in the intervention Lexia. Lexia is a computer-program that is supposed to individualize instruction for students and enhance their capacity to read (WWC, 2009). When conducting interviews mid-way through the year, two teachers described how the school encountered licensing problems with Lexia and students lost access to this intervention. The fourth grade teacher, Devin explained how the loss of the intervention was detrimental to one of his red students.

> She [a red student] has a drop off here where she goes all the way down to 29 words. I mean first of all she's low, I mean and you can see that, like this is where she should be and she was close to it, and she was achieving it, and then all the sudden there is this big drop off. That was about the time that we stopped having her on Lexia, so you know she was still getting the help in the classroom, but not as much. She wasn't getting the intervention. (Devin, GL4, II)

On top of the concerns about the effectiveness or consistency of interventions for red students, the school also did not have enough resources to offer interventions to all red students. Meaning, grade-level 3 and 4 had more red students then available interventions. The excerpt below is from a 4th grade meeting where the instructional coach described the scarcity of available slots for an intervention.

Instructional Coach: So [the interventionist] is the only one who takes a 4th grade intervention group and we have 13 kids and she will take 5. So we need to figure out . . . looking at these names, all of these kids have been in intervention groups for years, all of them . . . I guess we just have to choose which 4 or 5 kids will make the most growth being in an intervention group. (GL4, team meeting)

In third and fourth grade meetings, teachers had to determine which red students would receive an available slot with the interventionist or for Lexia. The interventionist could only take 5 students and each grade-level could only place 6 students in Lexia, as the school only had 6 available computers in a lab for students. At times, these available slots did not cover the total number of red students; for example, at the beginning of the year, the third grade class had approximately 16 red students and only 11available interventions.

When determining who should receive which intervention, the decision was often made without much deliberation. The placement decisions were not based on data but rather according to anecdotal information and teachers' judgment, such as in the excerpt below.

Instructional Coach: Do you think [student name 1] will make progress with [the interventionist]?

Charlie: Yes.

Instructional Coach: Ok. [Student 1 is placed in a group with the interventionist.] What

about [student 2] has the interventionist had him before?

Devin: I am not sure about before this year but she hasn't had him this year.

Instructional Coach: Ok, lets put [student 2] in too. [Student 2 is placed in a group with

the interventionist too.]

Instructional Coach: Ok, so that's two seats. [Student 3] has he been in with the

interventionist?

Devin: He was in Lexia but I think he might do better with the interventionist.

Instructional Coach: Ok. [Student 3 is placed in Lexia.] (GL4, team meeting)

As long as slots were available, the teachers were typically able to select their red

students' placement in particular interventions. As illustrated in the excerpt above, teachers were

able to make these decisions without having to offer much explanation.

When there were more red students than available interventions, students received

preference for an intervention *if* they were "in-process" of being referred for special education,

as illustrated in the excerpt below.

Interventionist: Here is the question do you want me to take [student 1] or [student 2],

that is the call. . . . You two [referring to Kim and Noah] decide who you want me to

take.

Kim: [Student 2] has already been referred to the RTI team [for special education] and

my hope is that he will go to an evaluation.

Interventionist: So you prefer that I take him, so he is in-program?

Kim: I would prefer that, is that ok with you?

Noah: Yeah and in the meantime, I will start the paperwork on [Student 1]. (GL3, team

meeting)

Kim explained that students must receive interventions in order to qualify for special education.

Without documentation of an intervention, students will not qualify for SPED services,

according to RTI policy. Kim stated the following:

From special education law, if he is currently going through an evaluation, the RTI team

has to ask if he is going through an intervention. If the answer is no, we can't do

anything [qualify the student for SPED services]. From a special education standpoint,

we can put him through an evaluation, but if he is not receiving the highest level of

intervention we can give him, then the argument is going to be he is not receiving the

highest level of intervention [she is saying that he will not qualify for SPED services

without documentation of the intervention] (GL3, team meeting)

In this grade-level meeting and in teachers' interviews, teachers indicated that the primary

benefit of red students receiving an intervention is that this helped them qualify for SPED

services, as opposed to actually helping them academically.

Summary

Overall, being a red student at Greenbrook was not clearly a benefit or a draw back. On

the positive side, teachers felt either a personal or a policy-driven responsibility to focus

attention and resources on red students. On the negative side, the extra resources allocated to red

students were not necessarily effective and were potentially implemented to comply with RTI

policies, as opposed to helping the student.

Discussion

To support teachers' interpretation of data, data management systems and school leadership may color-code the data (Love, 2004; Marsh, 2012; van Harmelen & Workman, 2012). At Greenbrook, color-coded data went beyond *supporting* teachers' interpretations of numerical data. The color-coded data became a student label that represented students' academic performance *and* their membership to a group of students who should receive the same type of instruction. This label was particularly consequential for red students who were both the most frequently discussed and had the most number of rules or policies associated with their color.

This type of DDDM at Greenbrook, where the outcome is to group and label students, particularly the lowest performing students merits further attention. Research on DDDM suggests that the use of color-codes to emphasize the data of the lowest performing students in data management systems is utilized beyond Greenbrook, in educational contexts spanning from early elementary schools to universities (Gottfried et al., 2011; Iorio & Adler, 2013; Marsh, 2012; van Harmelen & Workman, 2012). For example, at Purdue University, professors can access a data management system where their college-level students' performance data are color-coded red, yellow, or green. Students are color-coded red according to an algorithm that identifies "those students who are at-risk of performing badly" (van Harmelen & Workman, 2012, pp. 9-10). Like Greenbrook, the rationale for color-coding Purdue students' data are to identify and intervene when students are in the red (van Harmelen & Workman, 2012). This same type of data management system exists across the state of Virginia. This state has a statewide "Early Warning System," where low-performing students receive an "off track" label in the data management system to signal to teachers that students need an intervention.

The practice of adorning low performing students with a particular label is meant to help students but the research on labeling theory suggests that these labels can be potentially detrimental. As indicated in Earl (2009) and Barrett (2009), student performance data that emphasizes students' deficits can confirm and/or promote negative perceptions of students. By providing evidence that students are "failures" or "low-achievers," low student performance data can actually facilitate educational barriers for students. Multiple studies document instances where educators decided not to provide supplemental resources or tutoring services to the lowest performing students because they believed students would not "benefit" (Barrett, 2009; Booher-Jennings, 2005; Earl, 2009, p. 46). The literature on the "at-risk" label further supports the stance that emphasizing low student performance does *not* translate into additional support or educational opportunities for students (Boykin, 2000; Kagan, 1990).

Of course, this isn't always the case. Some educators and districts have had success in identifying and then improving struggling students' educational outcomes (Bernhardt, 2009; Carlson et al., 2011; Lachat & Smith, 2005; Mack, 2014). These success stories typically share a common theme. Educators go beyond red, yellow, and green when engaging with student performance data.

As opposed to color-coding student performance data, some data management systems and schools employ more complex data-interpretation supports. For example, in 5 urban high schools, educators engaged with a data management system that enabled teachers to aggregate, disaggregate, and analyze student data from multiple sources (Lachat & Smith, 2005). This facilitated teachers' capacity to test hypothesis related to teaching and learning. For instance, teachers had a longstanding belief that low performance correlated with low attendance. The data management system analyzed these two data-sources—test scores and attendance and found

no significant correlation. In light of this finding, teachers pursued other inquiries and found a relationship between low-test scores and students who indicated on school-climate surveys that they felt uncomfortable in the school. Teachers then responded by attempting to enhance the school's climate (Lachat & Smith, 2005). These cases and others in the literature illustrate how students may benefits when schools employ data-interpretation supports that are more complex than color-codes (Burch et al., 2009; Gallimore et al., 2009; Lachat & Smith, 2005; Mandinach, 2012).

Further, more complex data-interpretation supports can better facilitate the engagement of educators in the data-use process. As indicated at Greenbrook, a color-code system may not *support* data-interpretation, but rather make the interpretations for teachers. The simplistic color-code scheme removed the agency of teachers because data-interpretations and instructional next steps were pre-determined. Teachers' essentially input raw data, the management system interpreted the data for them, and then particular policies prescribed how teachers should respond to the data management system's interpretation. Teachers were often the receivers of data and instructional decisions rather than active participants in data-driven decision making. In this way, the color-scheme served to reduce data-driven decision making to an oversimplified framework for assessment and data use.

Additional studies should further investigate the ways in which data-use supports position students and teachers in the practice of data-driven decision making. Additional research is needed to clarify how data-use supports can actually *support* rather than rule the data-driven decision making process. Further, if data-use supports play an influential role in instructional decisions, how can these supports inform teachers' understanding of students' struggles as opposed to just highlighting students who struggle?

Essay 2: Beyond "Matchmaking":

An Examination of the Aims of Data-Driven Decision Making

Simmons (2012) characterizes data-driven decision making as the "educational Swiss Army knife" (p. 1) as the practice is touted to target so many diverse educational aims. Yet, the literature lacks clarity on the nature of the actual aims educators target when engaging with data. Conceptually, researchers understand that DDDM involves educators making decisions with data (Coburn & Turner, 2012; Mandinach, 2012), but beyond that, the literature lacks a description of the diversity of aims with which this practice operates in schools (Little, 2012). Typically, the purpose of DDDM is described in research as either educational improvement and/or preventing educators from using their "gut" (Coburn & Turner, 2011; Duncan, 2009; Earl & Timperley, 2009; Mandinach, 2012). These aims are quite general and perhaps intentionally open-ended so local school leaders can tailor aims to their particular context, student body, and values. Researchers have confirmed that in-practice educators have diverse aims when engaging with data (Burch et al., 2009; Coburn & Turner, 2012; Gottfried et al., 2011; Moody & Dede, 2008). Yet, the literature also indicates that aims for data use are at times ambiguous and/or unknown to stakeholders (Booher-Jennings, 2005; Earl, 2009).

Research on data use suggests district and school leaders need an *explicit*, shared aim for data use (Hargreaves & Braun, 2013; Simmons, 2012). A clearly articulated data-use aim fosters a shared understanding for the desired outcomes of DDDM (Park et al., 2013) and avoids the pitfall that the aim is to merely become "data-driven" (Booher-Jennings, 2005, p. 240). Further, explicit aims for data use bring meaning to the practice. Without a clearly defined aim for which to target data-use practices and decisions, DDDM can become an "activity trap" where educators perform a set of acts out of compliance as opposed to acting with purpose (Timperley & Earl,

2009, p. 125). Also, with the abundance of student data available to educators, an aim for data use can bring clarity to deciding which data sources are the most informative (Timperley & Earl, 2009). Data-use aims could also support the careful consideration of data-use routines and frameworks employed in schools. Data-use aims can guide the selection of data sources, the types of decisions made from data, and ultimately, the extent to which data-driven decision making will influence educational practices and students' education (Coburn & Turner, 2011; Park et al., 2013).

As aims for data use impact the process and potential outcomes of data use, it is important to consider the nature of these aims. Moody and Dede (2008) describe three diverse data-use aims that they observed in the Milwaukee school district. A portion of schools in the district aimed data use at complying with accountability policies. This aim often fostered educators' analysis of standardized data, the identification of weaknesses, and produced "products" to prove their compliance to stakeholders (Moody & Dede, 2008, p. 236). The second type of aim was described as "school improvement" (Moody & Dede, 2008, p. 238). When aiming for school improvement, educators often analyzed multiple data sources to identify and rectify problems in the school. The third type of aim for data use was described as a "reflective process" (Moody & Dede, 2008, p. 239). When aiming to reflect on their teaching and students' learning, educators did not depend on data to direct their work. Instead, educators identified particular lines of inquiry that were important to them or their students and looked to diverse sources of data to explore their inquiries.

Other bodies of research on data use highlight the aim of equitable educational opportunities and outcomes for all students in a school or district (Bernhardt, 2009; Dillon, 2010; Johnson & La Salle, 2010; Koschoreck et al., 2001; Park et al., 2013). This research emphasizes

educators' values and school leaders' capacity to invest all teachers in the aim of equity. For example, in a case study of a historically low-performing, large urban district, a superintendent framed data use as a tool to evaluate students' opportunities to learn. Data use was one component of his reform plan that was characterized by the slogan "commitment over compliance." He defined commitment as "doing the right thing for students" and compliance as meeting federal regulations (Park et al., 2013, p. 656). In another example, a team of educators practiced DDDM with the goal of enhancing student outcomes for the school's growing population of students of color. At this school site, educators collected "perception data" from parents and students to ensure that their data-use aim of equity was guided by the voices of all-important stakeholders (Bernhardt, 2009, p. 25). These examples from research suggest that when educators aim for equity, they consider diverse data sources and analyze data in light of particular values and ideologies.

The literature indicates that data-use aims vary. Further, this research suggests that educators' aim for DDDM promotes particular inquiries and decisions while stifling other possibilities. In other words, data-use aims can help bound DDDM to particular data sources, inquiries, and decisions that are in-alignment with their aim.

This idea that data-use aims promote certain types of inquiries while stifling others is the theme of this essay. In this essay, I will present the data-use aim, referred to as "matchmaking" (Oakes & Guiton, 1995) that was observed in grade-level team meetings at Greenbrook. I will argue that matchmaking promoted particular data-use conversations and decisions while stifling inquiries into other issues that merited attention. Further, using teachers' perspectives and their individual data-use activities, I will present alternatives to matchmaking that were present at the school but not present at grade-level meetings.

Data to Sort Students Versus Data to Inform Teaching and Learning

To examine the data-use aim at Greenbrook, I drew from an assessment framework by Darling-Hammond (1994). As described in my methods section, Darling-Hammond (1994) asserts that educators use students' assessment data in two fundamentally different ways. First, educators use assessment data to sort students into pre-existing educational tracks. Meaning, the educational offerings at the school remain static and assessment data are used to determine which current educational offering best meets students' needs (as indicated by assessment data). Research offers examples of this data-use aim in practice. For example, educators use data to select tracks for high school students like a remedial track vs. a college-preparatory track (Barrett, 2009; Darling-Hammond, 1994; Oakes & Guiton, 1995). At the elementary level, educators may use assessment data to select students who qualify for a limited number of supplemental services, like after-school tutoring (Booher-Jennings, 2005; Earl, 2009).

Oakes and Guiton (1995) refer to this first aim as "matchmaking" (p. 3), as educators' aim is to match students to pre-determined curricula or educational tracks. For example, in Oakes and Guiton's (1995) study, high school teachers consulted new students' assessment data to identify which educational track—college-prep, general education, or vocational education was most appropriate for students. The underlying principle in matchmaking is that students' test scores indicate which course or educational track students' need. This data-use aim assumes that (a) the existing educational offerings and learning environment are sufficient, and (b) that test scores provide a valid indicator to match students to a curriculum (Ball, 2012; Bush, 2006; Oakes & Guiton, 1995).

In contrast to using assessment data to sort students into pre-existing educational offerings, educators may engage with data to inform the nature of educational offerings.

Darling-Hammond (1994) describes the second approach to data use as educators using data to create or adjust educational offerings. In this second approach, teachers may use students' performance data to inform adjustments in the curricula, their teaching strategies, the learning environment, and more. For example, Koschoreck et al. (2001) observed a team of teachers who abandoned their current reading curriculum in light of low-test scores and created a reading program tailored to their current students' strengths and needs. In another example, Park et al. (2013) observed a district where leaders recognized that high school offerings created a scarce resource of college-prep courses. Therefore, the school leaders redesigned the curriculum and de-tracked the school. Local schools no longer needed to utilize data to place some students in college-prep courses and others in vocational courses as the entire curriculum became college-track.

Each approach to data-use aims at a different target. In the matchmaking data-use aim, the target is matching a student to a pre-existing curriculum or educational avenue. Test scores are used as an indicator of the students' capacity to succeed in a particular educational avenue (Booher-Jennings, 2005; Oakes & Guiton, 1995). In the second approach to data use, educators examine data in order to refine or evaluate the current learning environment. Test scores are interpreted as an indicator of the extent to which the learning environment is meeting the needs of students (Dillon, 2010; Johnson & La Salle, 2010; Lachat & Smith, 2005). Positioning these two aims as a heuristic dichotomy, I analyzed the data at Greenbrook to examine how particular data-use practices and decisions aligned with one of these two aims. The following section describes this analysis.

Considering Matchmaking as a Data-Use Aim

The data-use aim at Greenbrook fell neatly into the matchmaking aim of data use described by Oakes and Guiton (1995). As described in the first essay "From Black and White to Red and Green," grade-level meetings consisted of educators using color-coded data to sort students into corresponding, pre-existing educational offerings (See Figure 3, p. 84). Similar to diagnosing patients in the medical profession, students were tested, diagnosed, and then placed into 'treatment' or an educational program or curriculum that matched their diagnosis. Educators diagnosed students as red, yellow, or green and then matched all students of a particular color to a corresponding curriculum and learning environment (See Figure 3, p. 84). Noah from grade-level 3 describes the grouping and sorting of kids in grade-level meetings.

> You know my low kids, they go to see a reading specialist based off the data. And if they fall within an approaching range then they will be with us in [general education classroom], and if their scores are at grade level or above then they meet with an enrichment teacher at that time. So the data that is collected and talked about in the meetings, kids are sorted and grouped according to skill level. (Noah, GL3, II)

The focus in grade-level meetings was on students and their particular test scores and corresponding placement. This aim of matching students to curriculum dominated the grade-level meetings.

On the one hand, this aim of matching students or diagnosing and then treating students of the same diagnosis with the same educational treatment has some support in research. Multiple evaluations of educational interventions have documented that students of similar abilities can benefit from receiving the same, empirically-based instruction or "standard-treatments" (Fuchs & Fuchs, 2006, p. 95; Fuchs et al., 2003; Marchand-Martella, Ruby, &

Martella, 2007; U.S. Department of Education, Institute of Education Sciences, What Works

Clearninghouse [WWC], 2009, 2013). Fuchs and Fuchs (2006) assert that matching students of

similar ability to a standardized, empirically-validated program can benefit students because (a)

teachers have a clear understanding of how to address students' needs because it is spelled out by

a protocol or educational program and (b) "the fidelity of implementation is easier to assess and

ensure" then a non-standardized program (p. 96). Marchand-Martella et al., (2007) observed that

a school's adoption of standardized educational programs enabled teachers to learn and

implement the same types of teaching skills and instructional strategies. They argued that

teachers were then able to offer a high quality education to all students as all teachers taught in a

manner that was empirically-based (Marchand-Martella et al., 2007).

The research on standard-treatments supports this aim of matchmaking exhibited in

Greenbrook's grade-level meetings (Fuchs & Fuchs, 2006; Fuchs et al., 2003; Marchand-

Martella et al., 2007; WWC, 2009, 2013). For example, the lowest performing students were

often matched to Lexia, a software-program that has research to support its effectiveness in

raising students' reading test scores (McMurray, 2013; WWC, 2009). In this way, the lowest

performing readers were offered a research-based intervention that was supposed to enhance

their reading scores.

While matchmaking has some empirical support, the case of Greenbrook offers insights

into why the matchmaking data-use aim is limited and potentially problematic. The case of

Greenbrook suggests that the data-use aim of matchmaking stifled valuable conversations around

teachers' instruction, trends in students' data, and potential barriers to student learning.

Lack of Conversation on Instruction

In grade-level meetings, students were matched to educational treatments but the instructional strategies and learning environments of these treatments were never discussed. The matchmaking aim at Greenbrook rarely, if ever, instigated data-use conversations around the nature and quality of instruction. Teachers' learning objectives and teaching strategies were rarely discussed in these meetings, regardless of whether students' performance improved, remained the same, or dropped. In a group interview with fourth grade teachers, the teachers describe how data-use meetings were limited to grouping.

Devin: What is frustrating is that when we go to collaboration, we are not talking about the data really besides when we are dividing the kids up.

Lily: We are not planning.

Perhaps not surprisingly, the lack of conversation around instruction in DDDM meetings corresponds with teachers stating that data-use meetings did not impact their instruction. In this group interview and most individual interviews, teachers indicated that data-use meetings and students' assessment data did not impact their instruction. For example, when asked how the GOALS data presented at DDDM meetings impacted their instruction, teachers responded in the following ways. Charlie stated, "I don't change my instruction much. Everything I do instruction wise is the same for everyone." Lily stated, "I teach the same way all year." Devin, Haley, and Noah also stated that the GOALS data did not impact their instruction; it only impacted the ways in which they grouped students.

Lack of Inquiry into Trends

This aim to match students to pre-established leveled groups potentially emphasized individual students' scores at the cost of conversations and inquiry into trends present in the data.

Even when trends were obvious in student performance data, the team did not discuss possible interpretations of or resolutions to troubling trends, such as indicators of an achievement gap. The following excerpt from a data-use meeting with grade level 4 teachers, a school administrator, and an instructional coach is representative of how trends like the achievement gap fell outside of the matchmaking data-use aim.

> School administrator: As part of my evaluation, I had to write SMART goals and most of my SMART goals are focused on my reading and math assessment. They are only attending to my African American and SPED students. So for fourth grade, currently **one out of seven students** [with special needs] made our target for RCBM [GOALS, a reading curriculum-based measure] and only **three out of our 25 African American students hit the goal**, so my goal is to increase that by at least 10 percent by the winter. In math, **only two of our seven sped students made our goal and only two of our 24 African American students.**
>
> Grade level 4 teacher, Lily whispers: That's scary!
>
> Instructional coach: 25 African American
>
> School Administrator: No, only 24 of our African American students took the test. So then on top of that, I picked out some students to keep an eye on for fourth grade. My SPED students are also African American, student 1, student 2, and student 3 are my SPED students. And my African American students are student 4, student 5, and student 6. So I may be coming in and checking in on those students periodically, following their GOALS and their benchmarking or progress monitoring.
>
> School Administrator turns to grade level 4 teacher, Devin [the least experienced teacher of the group]: You have student 4?

Devin: I have student 4, student 5, and student 6.

School Administrator: All right. Student 4 needs to come through the RTI process [begin the special education referral process]. (GL4, team meeting)

Almost the exact same conversation took place in the third-grade team meeting, where the school administrator also identified a large proportion of African American students and students with special needs who were below grade level.

In alignment with the matchmaking data-use aim, the focus of both of these grade-level data-use conversations was individual students and the most appropriate educational treatments for each individual student. After presenting glaring evidence of an achievement gap, the conversation never turned to discussing this trend.

In both grade level meetings, what is *not* discussed is the most revealing. The team did not question why students with special needs and African American students were much more likely to score below grade level than their white, non-labeled counterparts at this school. Also, the teams did not discuss how teachers, the school administrator, and the instructional coach could address these students' academic needs. No changes were proposed to the instruction students received, their learning environment, and/or school policy.

Throughout an entire school year of observations, the glaring achievement gap was *never* discussed in grade-level, data-use meetings. The data-use aim of focusing on individual students' scores and placements dominated data use to the extent that even flagrant patterns in achievement were excluded from the conversation. Like the district, Greenbrook had a "history of uneven academic achievement," which was evident across multiple indicators. For at least 5 years prior to this study, students with special needs and African American students scored well below their white counterparts on statewide assessments. In comparison to 5 years earlier,

according to publically available test scores for Greenbrook, the achievement gap had *grown*. Less than 1/3 of African American students met standards according to the state standardized test compared to over 70% of white students meeting (or exceeding) standards. Less than 1/10th of students with an IEP met standards while over 50% of students without IEPs met standards (State Report Card, 2014)

Lack of Discussion on Students' Opportunities to Learn

The root causes of the achievement gap at Greenbrook were not discussed in data-use meetings but teachers candidly discussed this issue in other settings. In interviews and classroom observations, teachers pointed out particular school-wide policies and norms that potentially created undue hardships for groups of students. For example, all of the grade level 4 teachers and one grade level 3 teacher discussed the discrepancy in educational opportunities between students in the gifted program and students in the general education room. Teachers explained that students and teachers in general education were far more likely to experience top-down mandates, like additional testing. Lily, the gifted teacher explains how the general education teachers had to test low-performing students every Friday.

> But there's a lot of pressure on teachers that kids need to improve and their scores need to go up and we better see growth. So what that looks like in **everyone's room is a little bit free but it feels like if you really have struggling kids then not that free**. Like for example, Devin [a general education teacher] really does have to do progress monitoring and timed readings and I don't know, is that how students grow? How is that helping children? They're not becoming more engaged learners, if anything they're bored out of their minds, like I got to one minute read. They do it every Friday. There's four days of instruction and one day of progress monitoring. (Lily, GL4, II)

In addition to teachers expressing that students and teachers in the gifted program had less mandates, teachers generally expressed that general education students would benefit from time in the gifted program.

> You know because both Devin [pseudonym] and I have kids that I think would flourish if they could go into Lily [pseudonym for the gifted teacher] class throughout the day. And not just during RTI but also during the reading block, they can go down there and work on extended projects. (Charlie, GL4, II)

It is important to note that the gifted program and the general education room were composed of different demographics. African American students were the primary demographic for general education classrooms and the minority in gifted classrooms. As one third grade teacher described, this difference in demographic was not accidental, she stated that the gifted program was "a response to upper middle class families not wanting their kids mixed in" (Haley, GL3, II). In the district, gifted students primarily remained in the gifted room and general education students remained in general education rooms without much interaction between the two groups.

In another example, teachers consistently asserted that they had insufficient instructional time to adequately educate students. The school day lasted 6 hours but students had multiple class periods away from their teachers, including a daily 1-hour block reserved for activities related to the school's magnet program. One teacher described how this time-crunch limited his capacity to differentiate instruction for his students.

> Well you teach the curriculum that's given to you, certainly the curriculum gives you some diversification options but it's one thing to say, you know, here's the curriculum this is what you can do for differentiation, but then to find the time to really implement

that . . . anything really outside of the core curriculum is quite challenging, I mean we

really aren't here that long, it's a short day really…my point is, you know there's not a

lot of time. (Noah, GL3, II)

A different teacher calculated that he had "2 hours and 45 minutes" of instructional time with his

students (Devin, GL4, II). Overall, every teacher described a lack of time as an obstacle to

providing a quality education to all students.

Another potential issue with the learning environment identified by teachers was related

to the treatment of students with special needs at Greenbrook. As described in Chapter 4, grade-

level teams did *not* discuss the data of low-performing students who were also classified as

special education students. Literally, students in special education were identified at the

beginning of data-use meetings as SPED and then never discussed again. In alignment with the

matchmaking data-use aim, the team did not need to discuss SPED students as these students had

a diagnosis and a corresponding treatment. In a group interview, the fourth grade teachers

explained the rationale for not discussing SPED students in DDDM conversations.

Devin: They are already getting SPED services so during the RTI block, they are working

with SPED teachers, so it is already decided on what they do. We don't necessarily have

to do anything more with them.

Lily: Someone is going to give them services.

Charlie: They already have those in their IEPs what they are doing. Again [said with a

sarcastic laugh], you get that feeling, well they are ESL, they are not my problem. SPED,

they are already being take care of. I am just being honest, you get that way. And then

when you get those tests back and they [students] don't do very well; well, they are

SPED. And it is looked at that way [referring to a school norm].

Lily: Um-huh. [in agreement with Charlie's previous statement]

Charlie: That is what the education system has put on . . . It gets those kids down; those SPED kids and those ESL kids are not held the same as the general ed kids [referring to a norm at this school]. Because it is easy to say well they didn't do well because they are SPED. (GL4, group interview)

As Charlie and Lily indicate in this conversation, these teachers associated the lack of outcomes for students with special needs in grade-level meetings to a potential school norm of low expectations for students with special needs. In the grade-level 3 group interview, teachers too were concerned about the lack of conversation around students with special needs yet, they perceived this as an unfortunate consequence of scarce resources.

The other thing that I think is really real, here at Greenbrook, we have a lot of kids in the red. You have to filter out, you have to weed through 20 red kids because we can't service all 20 red kids. If you are at another school in the district, they have 2 red kids, so they don't have to weed through. They just say these are our two red kids and we are going to provide services to them. They can even dig even into their yellows because they have the personnel to do that. When you are working in a school like where we are at and you have so many red kids, you have to filter. You have to say, "well this is a SPED kid and they are getting services here" and skip that child because there are a whole cluster of red kids. (Haley, GL3, group interview)

Whether due to scarce resources or a school norm of low expectations, teachers in both grade-level teams were concerned with the school's capacity to appropriately educate students with special needs.

Summary

The matchmaking aim employed at grade-level data-use meetings bounded teachers'
conversations to students' test scores and students' placement into pre-existing educational
avenues. This data-use aim has some support in research that indicates sorting students into
similar ability groups and then offering them an empirically validated treatment may foster better
educational outcomes for students (Fuchs & Fuchs, 2006; Marchand-Martella et al., 2007). At
the same time, observations of grade-level meetings and interviews with teachers suggest that
this data-use aim stifled teacher conversation around instruction, the glaring achievement gap
between white students and students of color, and particular policies or practices teachers
perceived as problematic.

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Teachers' Alternative to Matchmaking

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Particular teachers expressed interest in a fundamentally different aim for data use. As
opposed to matching students of a particular test scores to a learning environment, most teachers
expressed a desire to target data use towards adjusting instruction or the learning environment for
students. Haley, Devin, Charlie, and Kim all described ideal data use as identifying trends in the
data and then responding to that data by changing instruction or the learning environment. Haley
describes what this could like in grade-level meetings.

> What I don't get to participate in which I think would be fabulous to participate in is the
> kind of collaboration where you look at Unit 6 assessment together with your colleagues
> and you sit and you say: wow, look at this, half of my kids don't know how to measure
> angles but look all your kids can measure angles, how did you teach that and would you
> show me? Would you re-teach that with my kids? Just feeling like you can do those
> kinds of things, that would have never happened I don't think. (Haley, GL3, II)

Charlie and Kim went beyond describing possible alternatives to data use. Outside of grade-level meetings, Charlie and Kim independently engaged with student performance data to target disparities in students' learning environment. These were unique instances that they described in individual and group interviews, *but not in grade-level meetings*. Meaning, outside of grade-level meetings, these teachers analyzed and made sense of data in unique ways. These occurrences are described in more detail in the next two sections.

Kim's Unique Uses of Data

Teachers and administrators often looked to Kim for support. She seemed to be a trusted source of knowledge on matters of instruction and student performance data as teachers and school leadership often asked for her perspective in grade-level meetings. Meaning, in grade-level meetings, she was often vocal. At the same time, she did not question and/or attempt to change the matchmaking data-use aim that occurred in grade-level meetings. Kim did however believe that the current grade-level meetings and outcomes needed improvement and she attempted to make changes privately and in meetings with school leadership that occurred without the grade-level team.

In an initial interview, Kim expressed frustration with the lack of supplemental math services at the school. She explained that a group of students in the third grade were on grade-level in reading yet below grade-level in math. During the RTI block, these students were receiving additional minutes on literacy when the data indicated these students needed additional instructional time in math. Kim stated,

> I had a couple of students who were getting enrichment during our intervention block but are failing math. Why are they getting extra reading when they're already above grade level in reading but are really struggling in math? (Kim, GL3, II)

In a subsequent interview, Kim explained how she privately met with school leadership and successfully utilized student performance data to secure supplemental math services for students during the RTI block. She stated, "This last time I basically just put the data out there and said, I have students who are in enrichment but are failing math, why can't we give them the support?" Kim identified student performance data as a critical tool for both identifying this gap in educational supports and for convincing school leaders that the school needed supplemental math services and resources. She explained that for the last two years, she advocated for supplemental math services but when she "put the data out there," she convinced the administration that this was a worthy investment.

In a rare occurrence, Kim also utilized student performance data to more sufficiently target the instruction students received. Recognizing that yellow students were struggling readers, Kim utilized student performance data to successfully secure additional reading resources for their instruction. Further, Kim paired up with the second-year teacher in her grade-level and they co-taught all students in the yellow together. She noted that this teacher was new and believed he could use support when attempting to instruct struggling readers, a task that is quite complex and requires some experience. With Kim's advocacy, yellow students in third grade received both additional educational resources and access to two teachers, one who was quite experienced and talented. To ensure that the additional resources and the co-teaching were impacting students, Kim regularly collected and monitored students' performance data. She observed her students' scores go up and at the end of the school year, many of these students tested at grade-level.

Charlie's Unique Uses of Data

Charlie had previously practiced DDDM in a different school district. In his previous district, there was a different data-use aim, which was to identify school-wide strengths and weaknesses. With this background, Charlie engaged with data at Greenbrook in a novel way.

At Greenbrook, teachers collected behavior data in a systematic way using an online behavior management system that stored and analyzed data on students' behavior. In line with Charlie's experience in his previous district, he aimed to identify school-wide patterns in students' behavior data. Working with a team of teachers from multiple grade-levels, Charlie and his colleagues identified a trend—teachers most frequently documented misbehavior on "Tuesdays at 10 o'clock" (Charlie, GL4, group interview) and struggling readers, according to GOALS data, typically exhibited this behavior. In an individual interview, Charlie explained that this time and day corresponded to a particular learning activity that was prescribed to teachers as part of a mandated, new curriculum. Using behavior data and reading data, Charlie made the argument to school leadership that this spike in poor behavior on Tuesdays at 10 was related to the specific learning activity prescribed in the new curriculum. He further argued that the behavior data offered evidence that the learning activity prescribed by the new curriculum did not meet struggling readers' needs.

In a different example, in what he deemed a "social experiment," Charlie conspired with the gifted teacher to move one of his general education students into the gifted classroom. To be clear, this was not a data-driven decision. To gain admittance to the gifted program, the district-wide policy specified students needed to exceed a threshold on an entrance exam for the gifted program. Although not a data-driven decision, by experimenting, Charlie gained student performance data to support his hypothesis that his students would benefit from spending time in

117

the gifted classroom. With access to the gifted program, his student's test score rose significantly by the end of the school year. It is important to note that this student was African American. By the end of the school year, this student scored in the upper performance brackets on GOALS, making him one of the few African American students at Greenbrook whose scores were above grade-level.

In each of these examples, Charlie and Kim engaged with student performance data to target disparities in students' learning environment. These teachers engaged with student performance data both to advocate for changes in students' learning environment and to evaluate whether particular teaching strategies and learning environments would enhance students' educational outcomes. Further, these teachers had data that they interpreted as evidence that their adjustments to students learning environment were impactful, as students' scores increased. Charlie had data that showed one of his student's educational outcomes were enhanced by the gifted program. Kim had data to support that her math intervention and her instructional tactics for yellow students enhanced the educational outcomes of students.

These cases of Charlie and Kim were unique and stood out when I analyzed my own data from Greenbrook. Thus, I returned to Greenbrook at the beginning of the next school year to see if they had continued to use data in unique ways and/or if their previous efforts to change students' learning environment had carried over to the new school year. What I found were two highly discouraged teachers. Their previous efforts had not carried over to the new school year. Kim had specifically tried again to advocate for supplemental math services for students who struggled in math and was told that she could not provide these services; per district mandate the school was only offering supplemental reading services. Further, despite her students increase in

reading scores from the previous year, she was also no longer able to offer a reading program that she had identified and implemented the previous year.

Discussion

To characterize the data-use aim at Greenbrook, I drew from a data-use framework by Darling-Hammond (1994). This framework differentiates between educators' aim to use data to sort students into pre-existing learning avenues and educators aim to use data to evaluate and adjust the type of learning opportunities offered at a school. At Greenbrook, I observed both types of data use. In grade-level meetings, educators used data with the goal of matching students with a particular test to a pre-determined educational placement. Yet, outside of data-use meetings, two teachers independently engaged with data with the aim of adjusting student(s) learning environment and creating new educational opportunities to students.

These examples from Greenbrook illustrate how data-use aims can limit or expand the ways in which educators use data to inform instructional decisions. In grade-level meetings, the aim to match students limited data use to informing students' placement. This is in contrast with Kim and Charlie who independently analyzed and used data to consider a variety of issues such as (a) correlations between students' behavior and particular instructional strategies (b) the need to support students who struggled in math, and (c) the educational outcomes of a general education student who gained access to the gifted program.

These different goals for data use raise questions about what or who should be the aim of data use, i.e. students and their placements or a variety of factors that shape teaching and learning. Similar to the findings in previous studies (Dillon, 2010; Koschorek; 2001; Park et al., 2012), Charlie and Kim offer examples of what is possible when data use has a broader aim than matchmaking; educators may use data to identify and rectify systemic issues in the learning

environment. This need at Greenbrook for educators to address structural inequities in the learning environment is supported by evidence collected in this study and publically accessible data. For example, approximately 80% of African American students at this school did not meet standards, while over 70% of white students at this school met or exceeded standards (State Report Card, 2014). These data further suggest that the overall learning environment at Greenbrook was specifically not addressing the needs of African American students.

Bodies of research on students' opportunities to learn, culturally relevant teaching, and inequities in educational settings have strong empirical evidence to suggest that if a concentrated number of students in a school has low performance data, then this data reflects a structural inequity, not the capabilities of students (Anderson, 2004; Johnson & La Salle, 2010). Schools may lack the basic conditions necessary for students to learn, which can facilitate large numbers of students' low performance. For example, public schools may lack the type of funds and resources necessary to facilitate a learning environment (Anderson, 2004; Baker, 2012). Alternatively, a school may not have quality teachers and/or teachers with high expectations for all students (Diamond & Spillane, 2004; Kagan, 1990). Another key ingredient for student learning is strong, supportive school and district leadership (Hargreaves & Braun, 2013; Tozer, Senese, & Violas, 1995). Ample empirical research supports the assertion that without particular prerequisites like adequate funding, effective teachers, and school and district leadership, students will not academically achieve at the same rate as students who have access to a high quality learning environment (Anderson, 2004; Hargreaves & Braun, 2013; Tozer, Senese, & Violas, 1995).

The literature on students' opportunities to learn suggests that in particular schools, the data-use aim of matchmaking is not likely to enhance students' educational outcomes. If the

overall learning environment is deficient, than students' placement into different educational tracks is unlikely to foster enhanced learning outcomes. This idea that matchmaking may not yield educational improvement in under-resourced and/or low quality learning environments becomes an important consideration. Given that DDDM is intended to reform schools and enhance the learning outcomes of students (Coburn & Turner, 2011; Duncan, 2009), matchmaking may be an inappropriate data-use aim in particular contexts.

In considering the data-use aim of matchmaking in under-resourced and/or low quality learning environments, it is important to discuss how this relates to broader educational reform efforts. In educational research and policy, the emphasis is often on students and their test scores as opposed to the quality of students' learning environment and their access to equitable learning environments. This is evident in particular federal endeavors, such as the What Works Clearinghouse (WWC), which is a database facilitated by the Institute of Education Sciences (WWC, 2015). The federally funded WWC offers an analysis of the research on the effectiveness of standardized, instructional programs. For example, on the WWC website, under the title "Find What Works," educators can select a category like "Children and Youth with Disabilities" and then view what type of programs have "evidence of improvement" (WWC, 2015).

Similar to the data-use aim at Greenbrook, the What Works Clearinghouse collects and analyzes data in order to identify effective educational treatments or standardized curricula for students. The WWC primarily offers evidence of the effectiveness of standardized programs. A key criticism of this emphasis on identifying which standardized programs "work" is the lack of consideration of the diversity of educational contexts (Biesta, 2007; Kvernbekk, 2011, p. 523). Biesta (2007) and Kvernbekk (2011) argue that this notion that an educational program can work

in the same way and produce the same positive educational outcomes across diverse contexts with completely different students is highly problematic. This is a particularly relevant concern for under-resourced and/or low quality schools. Again, this emphasis on students and their placement into a standardized curriculum neglects other important considerations for teaching and learning, like inequities in school funding and students' access to high quality teachers.

Across federal, state, district, and school-based efforts to reform education using data, it is important to consider educators' aim for data use. A particular consideration that merits further attention in research is the extent to which specific data-use aims promote or stifle important considerations for teaching and learning, like the quality of students' learning environment.

Essay 3: The Decision Makers:

Do Teachers Have the Authority to Make Decisions Based on Data?

Policy research often neglects to examine how social policies intermix and merge within the context of individuals' lives (Newman & Chin, 2003). Individuals often are subject to policies originating from various entities that govern their day-to-day existence, socially and professionally. Newman and Chin (2003) argue that the combined effects of multiple policies on people's lives are an important policy consideration.

Similarly, Coburn (2001) argues that educational research often studies a singular policy input to a school or district, as opposed to the totality of educational policies. She argues that this single-policy lens for educational research neglects the magnitude of expectations and endeavors with which educators engage on a daily basis. Further, the potential tensions that arise when policies converge elicit important considerations for how practitioners will make sense of and ultimately implement the totality of policies.

In educational settings, where practitioners are the targets of a conglomeration of local, state, and federal policies, educators may face a number of political predicaments. In other words, educators may experience conflicting directives from different policies. For example, one study explored a conflict educators faced when one educational policy promoted teachers use of scripted-curricula and another policy promoted differentiating the curricula to meet individual students needs (Demko & Hedrick, 2010). Teachers in this study faced moral issues, as they personally believed in differentiating the curriculum to meet the cultural and academic needs of students. Further, they faced power issues when determining which policy carried greater weight or consequences. In negotiating these moral and power issues, teachers had to decide if they should implement the scripted curriculum with fidelity or discard it in order to differentiate instruction. In another example, Robertson (2008) explored the tensions raised when public, higher education institutions receive funds from private corporations. Robertson (2008) specifically questioned how university policies or mission statements are diminished when universities accept funds from corporations with missions that conflict with the traditional purposes of universities. These examples demonstrate how educators face political predicaments where they must make sense of policies that conflict with one another or with value-systems embraced by individual and/or groups of educators.

In this essay, I examine how teachers' data use can potentially conflict with other educational policies and expectations. The findings from this study demonstrates how teachers are often restricted in their capacity to respond to students' data by educational policies that govern their educational objectives, instruction, and their schedules. Without the autonomy to make instructional decisions, teachers have little authority to respond to students' data.

I examined the practice of data-driven decision making at Greenbrook to determine how it aligns or conflicts with other educational policies targeted at Greenbrook. This idea stemmed from interviews with teachers at Greenbrook where they described data-driven decision making as one part of a larger political whole. Teachers did not think about data-driven decision making in isolation. For example, my attempts to interview teachers directly about data use yielded conversations describing RTI policies, mandated curricula, and other school, district, and federal policies and expectations.

Teachers as Policy Implementers

At Greenbrook, teachers' work involved implementing instructional decisions required by school, district, state, and federal policies. Major decisions around teaching and learning were often prescribed for teachers by authority figures. Teachers' daily activities often consisted of following rules and implementing mandates.

Instructional Objectives

Instructional objectives are specific skills and knowledge that teachers expect students to learn and stakeholders expect teachers to teach. Recently, instructional objectives became the subject of federal policy. Since the adoption of No Child Left Behind in 2001, educators were held accountable for instructional objectives specified by federal policies (Hanushek & Raymond, 2004; Sunderman & Kim, 2007). This trend continued with Race to the Top, which required states that were funded to adopt Common Core standards (Doorey, 2012).

The Common Core standards delineate skills and content for each grade level, K-12. Meaning, for example, all 3rd grade students in the 43 states and 4 territories that adopted Common Core standards should exit 3rd grade knowing the same skills and content as their peers (National Governors Association, 2014). This expectation that teachers at Greenbrook should

know and teach the Common Core standards was illustrated in a grade-level meeting where the principal quizzed teachers on if they could list the math facts all third grade students should know by the end of the year. She first asked generally if teachers knew the math facts students should master by the end of third grade. She then specifically directed this question to the newest teacher, Devin. His colleagues, Haley and Kim responded for him by listing off specific math facts students should know.

Like most schools across the nation, Greenbrook switched to Common Core standards in the 2013-14 school year. During grade-level meetings and a professional development session, teachers received resources, directives, and strategies for transitioning their curriculum to the Common Core. At the beginning of the school year, teachers were provided with "Common Core Guides" that listed the instructional objectives teachers should teach each month over the course of the school year. Teachers were instructed to use this guide as a "checklist" and to check off each instructional objective as they taught it in the specified timeframe. Later, teachers received a similar guide with instructional objectives emphasized in the new PARCC assessments, which were created to assess students' knowledge of Common Core standards. Teachers were also told to "get rid of lessons that are not aligned with Common Core" as the school's math program was created prior to the Common Core.

To comply with federal and state policy, teachers at Greenbrook were to teach the skills and content delineated in the Common Core. To comply with district and school leadership, teachers were to teach specific learning objectives from the Common Core in particular time frames. The instructional objectives teachers were to teach and to some extent the order in which they were taught were determined by federal, state, and local policies.

Instructional Delivery

At Greenbrook, teachers were directed to use particular resources and techniques to teach students Common Core standards. Mainly, the district mandated the use of particular educational programs. For example, this year, the school was told to pilot a new reading program that was aligned with the Common Core. This reading program specified the instructional techniques, content, and daily activities for teachers. For example, teachers knew on Mondays they would introduce a new story to students, using interactive PowerPoint slides created by the reading program's manufacturer. On Tuesdays, students were to read the story independently and then respond to guided questions. These daily activities examples illustrate how this program was a package and teachers were supposed to implement as directed. Teachers didn't need to select stories, create instructional materials, or lesson plan; the reading program included all of this. One teacher describes this reading program:

> It has it even scripted to the part of- I don't do this but my colleagues tell me you can print out your lesson plans… All scripted. There's no teacher choice. You just keep on moving along. It's all set up. When you first set up, you have to type in all the dates for the school year. What days were off? I don't know what happens with a snow day!
> (Lily, GL4, II).

Similar to the reading program, teachers administered math and science programs that contained pre-made lesson plans, resources, and assessments. In the following exchange between the principal and a teacher, Kim expresses how she wants written approval to veer from the prescribed curricula for social studies and science.

In a grade-level team meeting, Kim stated how she "would love" to do project-based social studies and science like she observed in another school. The principal immediately stated,

"Just do it!" Kim responded, "Can I get this in writing?" The principal smiled and responded while pretending to write, "Yes, per [principal name], we taught…." [Kim interjected] "What the kids wanted to learn."

Overall, the majority of the teachers' instructional program was pre-determined and teachers were expected to follow it. They were expected to implement lesson plans from curricula used district-wide. Meaning, teachers were rarely expected to design content, the instructional techniques to deliver content, and/or the overall learning experience for students.

Assessment

Multiple aspects of the assessment process were also prescribed. First, the mandated curricula contained assessments for teachers to administer. For example, the new reading curriculum included weekly reading assessments that teachers were supposed to administer. Second, as a part of the data-use process, educators were required to assess struggling students weekly using GOALS, a reading fluency test. Third, in data-use meetings, teachers were provided with specific dates or a time period in which they needed to assess students on a district-wide or school-wide, mandated assessment. Overall, teachers had assessments prescribed for them from mandated curricula, data-use policies, and from school and district leadership.

The process for administering the assessments was often defined by rules and policies. For example, teachers were often provided with a scripted instruction sheet for each assessment. Noah from grade-level 3 described this process, "There is an instruction sheet that, you know, it's a very formal test where, similar to [state standardized test], where it's scripted, you will now pick up your pencil and turn your paper over and you will have 30 minutes, you know, very scripted." As Noah and other teachers described, then assessments were either scored

automatically by a computer or with a prescriptive grading sheet. As the type of assessment, the

process for administering it, and the evaluation of results were typically standardized and

scripted, teachers often had little agency in the assessment process.

Instructional Response

When students' assessment data indicated they were struggling academically, educators'

attempts to help these students were also mediated by state and local policy. First, teachers were

directed to respond to particular groups of students with specific struggles. State policies for

Response to Intervention (RTI) promoted teachers' response to students with special needs,

English Language Learners, and students who scored below the 10th percentile on a nationally

normed test (SBE, 2008). Second, as described in Chapter 4, teachers were directed to

specifically focus on these groups of students' capacity to read, other academic struggles were

not a priority. As described in the previous issue "Beyond Matchmaking," a teacher literally had

to fight to provide supplemental services to students struggling in math. Third, the district

defined which instructional supports were eligible for these groups of students. Teachers had a

short menu of district-approved educational interventions for struggling students. Fourth, the

school specified the time period when teachers should address struggling students' needs. The

school had a 40 minute, 4 day per week RTI block where resources and attention were mainly

directed at ensuring students moved from 'below' to 'at' grade-level in reading.

Instructional Time

The administration at Greenbrook provided teachers with an instructional schedule that

specified when these learning objectives and educational programs were to take place each day.

The administration, guided by district policies, specified the amount of time teachers should

spend teaching content areas as well as the exact time each academic area was taught each day. Teachers and students' daily activities were part of a standardized, daily schedule.

Summary

The adoption of Common Core standards delineated the content and skills teachers should teach throughout the school year. District policies prescribed educational programs to teach Common Core standards so teaching strategies, lesson plans, and resources were implemented by teachers but often not determined by them. School leadership determined the schedule and the amount of time teachers taught Common Core standards and the district-selected educational programs. Assessments were also selected and mandated by both state and district policy. Finally, local and state policy further mediated the ways in which teachers responded to assessment data. In summary, policy makers or school leaders decided most of teachers instructional program and day-to-day activities.

Data-Driven Decision Making in a Plethora of Mandates

Any given policy described above was not necessarily problematic or overly restrictive. These policies in isolation often had sound reason and even research to support their existence. For example, the Response to Intervention (RTI) policy present at Greenbrook was grounded in peer-reviewed research. The restrictive nature of these RTI policies were shown to provide a protocol and adequate resources for helping struggling readers, which is a very complex, difficult process (Fuchs & Fuchs, 2006; Fuchs, Marston, & Shin, 2001). Like the RTI policy, an examination of each individual policy at Greenbrook may demonstrate policies with a clear and rational aim.

However, when examining the conglomerate of educational policies present at Greenbrook, these policies were quite restrictive in the sense that most of teachers' work was

governed by policies. As the primary recipient of the policies, teachers lived these policies in

totality. As one teacher described, "We have a strict program that we have to stick to with

limited resources and limited time" (Kim, GL3, II). In this environment, teachers were quite

limited in their capacity to respond to students' data as almost every aspect of their instruction

was prescribed. Yet, these teachers still faced an expectation to adjust their instruction based on

students' data, as they describe below.

> So the truth, you're always supposed to be using assessments to guide instruction,
>
> especially with struggling students. So my boss [the principal] will say in meetings,
>
> where are we having trouble? She does expect practitioners to look at the data and
>
> absolutely understand what they're supposed to be teaching and why we would then
>
> reteach or fix our teaching. (Lily, GL4, II)

Similarly, Noah describes his perception of the principal's expectation for teachers to use data.

> The initiative comes from administrators. I mean they want the data. . . . I think it kind
>
> of goes without saying that you know, our groupings and stuff should based off of a
>
> focused attention to progress, you know, but I don't think it's [data-use expectation]
>
> anything in writing that…anything that formal. (Noah, GL3, II)

Teachers' perceptions that they were expected to use students' data to inform their instruction

was corroborated by interviews with district leadership. When asked about the expectations of

teachers to use data, a district administrator stated the following.

> One of the things we really try to focus on with our RTI framework is what is happening
>
> at the Tier I level, the classroom level. A lot of the research points to if you [meaning
>
> teachers] have less than 80% of your students successful in the classroom, then you need
>
> to start looking at maybe it is the instructional practices in the classroom? Are you

missing something curricular-wise? We have asked [grade-level] teams to ask these questions of themselves. What are some of the things that we are seeing here [indicating student data] that maybe instructive of what we need to do or change within our practices. (District administrator interview)

This expectation for teachers to use data to guide their instruction seemed to conflict with the plethora of policies that governed teachers' instruction. On the one hand, the content of teacher's instruction, the delivery of their instruction, the assessment of students, and their daily scheduled was prescribed to teachers via school, district, and state policies. On the other hand, teachers were to offer students' instruction that was informed by students' data. Teachers experienced two conflicting expectations—they were to use data to guide their instruction, at the same time, almost every aspect of their instruction was prescribed.

Discussion

The political environment at Greenbrook seemed in conflict with the data-use policies heavily emphasized in the current educational reform movement. The current research and policies on teacher data use emphasized that teachers should use student data in order to adjust instruction and/or the learning environment (Hamilton et al., 2009; Mandinach, 2012; Means et al., 2010). Further, current research suggests that particular data-use supports will foster teachers' data use and teachers' capacity to respond to data (Choppin, 2002; Means et al., 2011; Simmons, 2012). The case of Greenbrook suggests the research on data use and data-supports are falsely grounded on the assumption that teachers are the instructional decision-makers.

This insight gathered from this study at Greenbrook challenges the logic of data-use policies directed at low-performing schools. Like Greenbrook, many struggling schools are governed by a conglomerate of federal, state, and local policies. Unlike higher-achieving,

wealthier schools, schools that have low test scores, a large population of students of color, and less resources are much more likely to be the target of educational mandates that govern teaching and learning (Boykin, 2000; Burch et al., 2009; Milner, 2013; Sleeter, 2008). Teachers in the very schools our current federal administration wants to "turn-around" (USDOE, 2009b) often have the least amount of autonomy to alter their practices.

When examining our lowest performing schools, researchers and policy makers should consider whether the political and financial investments in data use make sense. Data-use policies directed at teachers can only succeed in a political environment where teachers make decisions about teaching and learning. If teachers do not have the autonomy to adjust instruction or the learning environment in light of what can be learned from students' performance data, perhaps we should not invest so heavily in teacher data use in these contexts. Instead, we should direct professional development, data-warehouses, and other data use supports at the people who make most of the teaching and learning decisions, i.e. school administrators and policy makers. Alternatively, to actually facilitate teacher data use, policy makers and administrators will have to alter or remove prescriptive educational mandates in order to enable educators to make decisions based on data.

Chapter 6: Dissertation Conclusion

In the previous chapter, I offered a discussion on specific conditions of data use present at Greenbrook—the stoplight color-scheme, the aim of data use, and data-use policies. In my concluding remarks, I will attempt to offer a more macro-level discussion of the case of DDDM at Greenbrook. I will start with a discussion of how this case contrasted with my personal conception of DDDM.

Before starting this project, I taught at a school similar to Greenbrook. I was a middle-school teacher in an under-resourced, low performing school. When teaching 6th grade in Chicago Public Schools [CPS], every year, I had *at least* one student who could not read. Literally, I had sixth grade students who could not read or write their own contact information. Beyond these extreme cases, the majority of my students were far behind their wealthier peers at higher achieving schools. Essentially, low student performance was the norm at this public school.

During my time at this school, No Child Left Behind accountability policies were enacted. The school I worked in consistently "failed" and was at risk of being shut down. One positive outcome of these threats and policies was that educators in my school became attuned to student achievement data and students' struggles. The conversation quickly went from bemoaning kids for being "lazy" and "not caring" to collectively considering how we as a staff could improve students' educational outcomes. Although far from ideal, as a staff, we started to make changes and take responsibility for student learning.

From my experiences in CPS, I perceived educators data use as a practice in social justice or a practice that pushed teachers and schools to address low-performance rather than to attribute it to students. Yet, when I started to study educators' data use, I found that the literature

contradicted my understanding. Few studies indicated that teachers' data use fosters enhanced

learning outcomes for students and/or changes in teachers' instructional habits (Barrett, 2009;

Bernhardt, 2009; Coburn & Turner, 2012; Hargreaves & Braun, 2013; Slavit et al., 2013).

Multiple studies suggested that teachers may interpret data with the purpose of "legitimizing"

their current stances and practices (Coburn & Turner, 2011; Jennings, 2012, p. 4; Slavit et al.,

2013). Further, this use of data to confirm educators' existing beliefs and practices potentially

perpetuates inequities within schools (Barrett, 2009; Johnson & La Salle, 2010). Alternatively, a

limited number of studies suggest that educators can utilize data to address structural inequities

within schools, confront low expectations of students, and foster enhanced learning outcomes for

historically marginalized students (Dillon, 2010; Koschoreck et al., 2001; Park et al., 2013).

Overall, the literature suggested that when educators engage with data, they might do so in a

ways that limit or enhance students' educational opportunities.

The case of DDDM at Greenbrook offers a different perspective on data use than what I

learned from the literature and my experiences in CPS. In the literature and in my own

perspective, the nature of data use depended upon teachers and the ways in which they choose to

engage with data. Yet, the case of Greenbrook demonstrated that DDDM is at times heavily

influenced by particular policies and practices that shape the ways in which teachers engage with

data.

For example, multiple scholars portray teachers as active participants in DDDM who

select, interpret, and analyze students' performance data (Coburn & Turner, 2011; Jacobs et al.,

2009; Mandinach & Gummer, 2013). In contrast, teachers at Greenbrook did not interpret data

as they engaged with color-coded data that was interpreted for them. In a second example from

the literature, DDDM is often described as a process where data illuminates novel solutions to

school or district-based problems (Mandinach, 2012; Park et al., 2013). Where at Greenbrook, data was not used to identify or generate solutions to school-wide problems. Teachers were restricted in responding to students' data to a pre-determined list of instructional placements (i.e., matchmaking). In a third and final example, DDDM is described as a "social justice tool" where educators' engagement with data resolves intractable inequities in schools and fosters positive academic outcomes for all students (Bernhardt, 2009; Dillon, 2010, p. 32; Park et al., 2013). Yet, at Greenbrook, despite particular teachers' commitment to rectifying inequities at the school, the glaring achievement gap among the student population was *never* discussed at a DDDM meeting. And, according to publically accessible data the school's achievement gap *widened* the year of this study, with over 70% of white students meeting or exceeding reading standards while only 20% of African American students did the same. Issues like the achievement gap at Greenbrook were outside the scope of how DDDM was practiced at this school.

In this particular case of DDDM, what lessons can be learned? I propose that one particularly interesting takeaway from the case of Greenbrook relates to educators' roles in DDDM. To illustrate this point, I will use Kim and Charlie's unique uses of data presented in the essay titled, "Beyond Matchmaking." Briefly, Kim and Charlie interpreted students' performance data as indicators of school-wide gaps in students' opportunities to learn. Kim argued for math supports to address the proportion of students who underperformed in math, a subject never discussed in grade-level meetings. Charlie analyzed multiple data sources to argue that the lowest performing students across grade-levels were most likely to exhibit poor behavior during a particular instructional technique that teachers were using weekly in accordance with a mandated curriculum.

Charlie and Kim made arguments grounded in data that students lacked particular

opportunities to learn due to specific, seemingly adaptable learning conditions at the school.

This type of data use, where educators engaged with data to evaluate and adjust students'

instruction is exactly what I had anticipated finding when this study started. I anticipated finding

this type of data use—where educators engaged with data to identify and rectify potential

obstacles for students' learning or at the very least, where teachers generated decisions and next

steps based on data—as the literature often conceptualizes data use in this way (see examples in

Coburn & Turner, 2011; Mandinach, 2012; Means et al., 2010). One highly interesting takeaway

from the case of Greenbrook is that a substantially different form of DDDM exists, one where

the data-use process and outcomes are pre-determined and prescribed to teachers. In this form of

DDDM, teachers like Kim and Charlie who performed their own analysis of data and generated

new approaches to educating students based on this analysis were an anomaly, not the norm.

Yet, in retrospect, considering the context of Greenbrook, this is not that surprising.

Similar to the argument made in the third essay in this chapter, Greenbrook had a history of poor

performance and like many schools that fail to meet accountability expectations, this fostered a

plethora of policy mandates that governed teachers' work (Boykin, 2000; Milner, 2013; Sleeter,

2008). In this environment, where teachers often lacked autonomy to make instructional

decisions, this particular form of DDDM might be expected. Like most of teachers' work at

Greenbrook, the data-driven decision making process was prescribed. The aim of data use, the

interpretations of data, and the possible decisions made with data were mainly determined for

teachers, not by teachers. Further, teachers' insights about students and their recommendation

for instruction were never part of the data-driven decision making meetings. Teachers' primary

role in DDDM meetings was to help determine the placement of students' into an instructional

group, not to offer input into the nature of that instruction. The DDDM process never included a time for teachers' to offer suggestions for improving the instruction of students or a time for teachers to offer their perspective on students' abilities or instructional needs.

The case of Greenbrook demonstrates the importance of looking beyond teachers' role in DDDM to other key factors that shape this practice. As opposed to positioning teachers as the unit of analysis in studies on DDDM, researchers should also consider data management systems, data-use routines, and school context. These types of considerations—inputs to DDDM are examined in the research but they are framed as conditions that *support* data use. Yet, in addition to considering the conditions that support data use, the literature needs a better understanding of what *stifles* teacher data use. The case of DDDM at Greenbrook clearly indicated that particular policies and practices restricted the ways in which teachers could use data. At Greenbrook, educators were restricted to (a) one specific data source, (b) a limited list of decisions they could make from this data, and (c) a particular set of DDDM activities. These restrictions on data use heavily influenced the ways in which DDDM was practiced at this school site.

Further, researchers can more broadly engage with the idea that the practice of DDDM *always* occurs within particular political and contextual constraints. Across school sites, educators can only examine data they have access to, make decisions that they have the power and resources to make, and engage with data in ways that are possible given particular school norms and policies. From a research agenda, this means studying DDDM from a lens that considers what is possible for teacher data use in particular contexts. By asking what is feasible for DDDM given the resources, human capital, and political climate in particular contexts, researchers may challenge the claim that DDDM alone can reform education. Further, by

examining the broader contexts that enhance or constrain teachers' use of data, researchers will better represent the diversity of DDDM, teaching, and learning across school sites.

The case of DDDM at Greenbrook also raises another consideration for future research. Although rarely explicitly discussed in the literature or policies on DDDM (Kvernbekk, 2011), the proliferation of DDDM in educational settings is based heavily on the notion that data constitutes evidence of students' academic performance *and* teachers' future instructional response for students. As Kvernbekk (2011) asserts, students' data are actually not evidence in itself; students' data becomes evidence in light of particular assumptions related to teaching and learning. Meaning, data are typically examined for a particular purpose or in alignment with a particular theory of change that shapes the data-use process and the type of interpretations educators can make with data (Moody & Dede, 2008; Park et al., 2013). Educators generally examine data with a particular lens (that is often policy-driven) that structures the ways in which they make meaning of data.

For example, at Greenbrook, DDDM operated according to an assumption that a particular source of data (GOALS fluency data) could accurately determine students' placement into specific learning environments (i.e., enrichment, interventions, general education). In turn, these placements were to enhance students' educational outcomes. In other words, DDDM at Greenbrook operated according to the idea that if teachers match students with similar test scores to a particular curriculum, then all students' test scores will go up. When explaining this underlying principle of DDDM at Greenbrook at an academic conference, one of my audience members described this data-use process as "algorithmic." In many ways, DDDM at Greenbrook was similar to an algorithm, where the same set of steps was taken in the attempt to solve a specific problem. At Greenbrook, the problem was students' low achievement and the

same set of specific DDDM steps were repeatedly taken to attempt to solve this problem. This assumption that a particular set of steps could solve the problem of low student achievement undergirded DDDM at Greenbrook.

Research suggests that at other school sites, different assumptions guide DDDM. For example, Gallimore et al. (2009) described a school where grade-level teams of teachers were encouraged to inquire into trends in student learning and experiment with new instructional techniques and teacher practices. As a part of their inquiry, teachers were also expected to analyze students' performance data, student work samples, and common assessments (Gallimore et al., 2009, p. 504). In this study, school leaders offered teachers (a) time to collaborate (b) professional development on teacher inquiry into student learning (c) the freedom to analyze data that educators found meaningful and (d) the autonomy and resources to experiment with new instructional techniques and curricula. The underlying theory of change for teacher data use at this school site was something like—if teachers consider data when reflecting on their practices and their instruction, then teachers may gain meaningful insights on their work, which will enhance the quality of students' education.

The case of Greenbrook and the school featured in Gallimore et al. (2009) illustrate how adopting different principles to guide DDDM can lead to different outcomes for students and teachers. Yet, these principles are relatively untested. The literature offers little insight into if and how specific principles for DDDM influence educators' engagement with data. This area of DDDM merits further attention in research. Researchers can offer insights on how and if these assumptions are (a) feasible and (b) in alignment with particular data-use tools, policies, and practices. Further, by investigating the underlying principles for how DDDM is intended to operate in particular schools and contexts, researchers can better speak to specific audiences of

practitioners.

A third and final important consideration for future research on DDDM relates to the question posed in the title of this study: I asked "data use for what and for whom?" The case of Greenbrook demonstrates the importance of these questions. At Greenbrook, data-driven decision making was essentially a "sort and treat" model where students were adorned with data driven labels and offered pre-determined educational treatments that corresponded to their label. Is this "sort and treat" model an appropriate way to practice DDDM, particularly in a low performing school? What are other possibilities for DDDM?

The policies and the literature on DDDM offer limited insights on what constitutes ideal or even appropriate data use. Beyond stating desired outcomes like "continuous improvement" or "reform," the policy and research on DDDM fails to explicitly articulate a vision for data use (Duncan 2009, 2010; Coburn & Turner, 2011, p. 99; Mandinach & Gummer, 2013, p. 31). Due to the diversity of school contexts, policy mandates, teaching conditions, and students, perhaps neither researchers nor policy makers can or should offer a standardized vision for ideal data use. Yet, researchers could offer insights on specific data-use aims, practices, and outcomes that are more likely to enhance the quality of education and learning for students.

To start this conversation around possibilities for DDDM, I offer a few suggestions. First, data use should target instruction, as opposed to grouping and labeling students. This would require different data, data-use aims, and DDDM activities than what was observed at Greenbrook. As one study participant suggested, teachers could examine skill-level data and identify particular student learning needs and teachers who the data indicate have a track record of successful teaching. Then teachers could share their successful instructional techniques, model them for each other, and/or swap students for particular lessons. Or, in another example,

as indicated in the literature and in this study, teachers could use data to test particular hypothesis related to teaching and learning (Gallimore et al., 2009; Lachat & Smith, 2005). In this study, Charlie used data to test his hypothesis that if general education students had access to the gifted room, they too would flourish academically. These are just two of numerous examples of how data use could support teachers' conversations and inquiry into the nature and quality of students' instruction.

Second, teachers, school leaders, and policy makers should all practice data-driven decision making. Currently, the literature and policies on DDDM often target teachers. Yet, teachers are only one of multiple actors that impact teaching and learning. School leaders and policy makers are critical contributors to the learning environments of public schools. They too should engage with data to make decisions. For example, district administrators could practice DDDM in order to ensure an equitable distribution of resources. This was observed in a study by Slavin et al. (2013). In Slavin et al. (2013), district leaders recognized through their own engagement with data that the district had major disparities in student achievement that corresponded to major disparities in school funding and resources. Recognizing this issue via data, district leaders decided to redistribute resources across the district with a bias towards the lowest performing schools (Slavin et al., 2013).

Similar to the example illustrated in Slavin et al. (2013), policy makers and school leaders could practice DDDM with the aim of creating equitable learning environments for all students and educators. To do so, they could examine data that informs students' opportunities to learn. National, state, and local policy makers and educational leaders could examine indicators of students' access to (a) high quality teachers (b) well-funded schools and (c) safe, welcoming learning environments. Essentially, this would require that educational leaders and

policy makers examine key *inputs* to student learning as opposed to the typical *output* data (i.e. standardized test scores). This switch from engaging with input data to output data may enable policy makers and educational leaders to identify and rectify longstanding inequities in students' opportunities to learn.

Overall, I suggest that data use requires an "ideological predilection for equity" (Koschoreck et al., 2004, p. 286) that is shared by all stakeholders in public education. Teachers alone cannot transform low-performing schools. Further, policy makers and educational leaders cannot mandate equitable outcomes and expect this to occur in a public school system that is rampant with disparities. Educational leaders, policy makers, and teachers need a shared and explicit aim to create a school system of high quality in high-performing schools. In short, policy makers, educational leaders, and teachers would need to *collectively* take responsibility for students' learning. With these guiding principles of equity and collective responsibility for student learning, all stakeholders would examine a wide variety of data sources that inform this collective commitment to realizing an equitable school system. Above all else, data use requires a thoughtful consideration of how adults in this society can make more "humane" decisions that promote learning for all children.

> More and better data can help us make more efficient educational decisions and
> judgments, but they will not, of themselves, help us make wiser or more humane ones
> (Hargreaves & Braun, 2013, p. 6).

References

Akpan, N. (September 29, 2014). A doctor turned mayor solves murder mystery in Columbia. *National Public Radio.* Retrieved from http://www.npr.org/blogs/goatsandsoda/2014/09/29/352505891/a-doctor-turned-mayor-solves-a-murder-mystery-in-colombia.

Anderson, G. L., & Scott, J. (2012). Toward an intersectional understanding of process causality and social context. *Qualitative Inquiry, 18*(8), 674-685.

Anderson, J. D. (2004). The historical context for understanding the test score gap. *National Journal of Urban Education and Practice*, *1*(1), 1-21.

Baker, B. D., & Corcoran, S. P. (2012). The stealth inequities of school funding: How state and local school finance systems perpetuate inequitable student spending. *Center for American Progress*. Retrieved from https://www.americanprogress.org/issues/education/report/2012/09/19/38189/the-stealth-inequities-of-school-funding/

Ball, S. (2012). *Foucault, Power, and Education*. New York, NY: Routledge.

Barrett, T. (2009). *Teacher conversation and community: What matters in smaller learning communities and inquiry-based high school reform* (Doctoral Dissertation). Retrieved from New York University, Dissertations and Theses Global. (3390451)

Bazeley, P. (2009). Analysing qualitative data: More than 'identifying themes'. *Malaysian Journal of Qualitative Research, 2*(2), 6-22.

Becker, H. (1996). The epistemology of qualitative research. In R. Jessor, A. Colby, & R. A. Shweder (Eds.), *Ethnography and Human Development*. Chicago, IL: University of Chicago Press.

Berliner, D. C. (2001). Learning about and learning from expert teachers. *International journal of educational research, 35*(5), 463-482.

Bernhardt, V. L. (2009). Data use: Data-driven decision making takes a big-picture view of the needs of teachers and students. *Journal of Staff Development, 30*(1), 24-27.

Biesta, G. (2007). Why "what works" won't work: Evidence-based practice and the democratic deficit in educational research. *Educational theory, 57*(1), 1-22.

Booher-Jennings, J. (2005). Below the bubble: "Educational triage" and the Texas accountability system. *American Educational Research Journal, 42*(2), 231-268. doi: 10.3102/00028312042002231

Boudett, K. P., City, E., & Murnane, R. (2005). *Data wise: A step-by-step guide to using assessment results to improve teaching and learning.* Cambridge, MA: Harvard Education Publishing Group.

Boykin, A. W. (2000). The talent development model of schooling: Placing students at promise for academic success. *Journal of Education for Students Placed at Risk (JESPAR), 5* (1-2), 3-25.

Burch, P., Hayes, T., Kowalski, T., & Lasley, T. (2009). The role of private firms in data-based decision making. In T. Kowalski and T. Lasley (Eds.), *Handbook of data-based decision making in education* (54-71). New York, NY: Routledge.

Bush, G. (2006). Learning about learning: From theories to trends. *Teacher Librarian, 34*(2), 14.

Carlson, D., Borman, G. D., & Robinson, M. (2011). A multistate district-level cluster randomized trial of the impact of data-driven reform on reading and mathematics achievement. *Educational Evaluation and Policy Analysis, 33*(3), 378-398.

Choppin, J. (2002). *Data use in practice: Examples from the school level*. Paper presented at the annual meeting of the American Educational Research Association, New Orleans, LA.

Coburn, C., & Turner, E. (2011). Research on data use: A framework and analysis. *Measurement, 9*(4), 173-206. doi: 10.1080/15366367.2011.626729

Coburn, C., & Turner, E. (2012). The practice of data use: An introduction. *American Journal of Education, 118*(2), 99-111.

Darling-Hammond, L. (1994). Performance-based assessment and educational equity. *Harvard Educational Review, 64*(1), 5-31.

Darling-Hammond, L. (2010). *The flat world and education: How America's commitment to equity will determine our future*. New York, NY: Teachers College Press.

DeAngelis, K. J., Presley, J., & White, B. (2005). *The distribution of teacher quality in Illinois* (Report No. 2005-1). Illinois Educational Research Council. Retrieved from http://www.siue.edu/ierc/publications/.

Demko, M., & Hedrick, W. (2010). Teachers become zombies: The ugly side of scripted reading curriculum. *Voices from the Middle, 17*(3), 62-64.

Diamond, J., & Spillane, J. (2004). Teachers' expectations and sense of responsibility for student learning: The importance of race, class, and organizational habitus. *Anthropology & Education Quarterly, 35*(1), 75-98. doi: 10.1525/aeq.2004.35.1.75

Dillon, R. (2010). Data as a social justice tool. *Principal Leadership, 11*(2), 32-35.

Doorey, N. (2012). Coming soon: A new generation of assessments. *Educational Leadership, 70*(4), 28-34.

Dowd, A. C. (2005). *Data don't drive: Building a practitioner-driven culture of inquiry to assess community college performance* (Report). Lumina Foundation. Retrieved from http://www.luminafoundation.org/publications/datadontdrive2005.pdf

Duncan, A. (2009). Robust data gives us the roadmap to reform. Speech given at the Fourth Annual IES Research Conference. Retrieved from http://www.ed.gov/news/speeches/robust-data-gives-us-roadmap-reform.

Dunn, K., Airola, D., Lo, W., & Garrison, M. (2013). What teachers think about what they can do with data: Development and validation of the data driven decision-making efficacy and anxiety inventory. *Contemporary Educational Psychology, 38*(1), 87-98. doi: 10.1016/j.cedpsych.2012.11.002

Earl, L. (2009). Leadership for evidence-informed conversations. In L. Earl & H. Timperley (Eds.), *Professional learning conversations: Challenges in using evidence for improvement* (43-53). Dordrecht, Netherlands: Springer.

Earl, L., & Timperley, H. (2009). Understanding how evidence and learning conversations work. In L. Earl & H. Timperley (Eds.), *Professional learning conversations: Challenges in using evidence for improvement* (1-12). Dordrecht, Netherlands: Springer.

Fitzpatrick, M., & Margolin, J. (2004). Using data to guide school improvement. *Notes & reflections: For professional developers from professional developers, 7,* 1-14. Retrieved from http://files.eric.ed.gov/fulltext/ED518630.pdf.

Fletcher, G. (2010). Race to the top: no district left behind, the reforms elicited by the competition will likely affect your school system whether it was included among the winners or not. *Technological Horizons in Education, 37*(10).

Fuchs, D., & Fuchs, L. (2006). Introduction to response to intervention: What, why, and how valid is it? *Reading Research Quarterly, 41*(1), 93-99.

Fuchs, D., Mock, D., Morgan, P., & Young, C. (2003). Responsiveness-to-intervention: Definitions, evidence, and implications for the learning disabilities construct. *Learning Disabilities Research & Practice, 18*(3), 157-171.

Fuchs, L., Marston, D., & Shin, J. (2001). Using curriculum-based measurement to establish growth standards for students with learning disabilities. *School Psychology Review, 30*(4), 507-524.

Fuller, B., & Clarke, P. (1994). Raising school effects while ignoring culture? Local conditions and the influence of classroom tools, rules, and pedagogy. *Review of educational research, 64*(1), 119-157.

Gallimore, R., Ermeling, B. A., Saunders, W. M., & Goldenberg, C. (2009). Moving the learning of teaching closer to practice: Teacher education implications of school-based inquiry teams. *The Elementary School Journal, 109*(5), 537-553.

Goe, L., Bell, C., & Little, O. (2008). *Approaches to evaluating teacher effectiveness: A research synthesis* (Report). National Comprehensive Center for Teacher Quality. Retrieved from http://files.eric.ed.gov/fulltext/ED521228.pdf.

Gottfried, M., Ikemoto, G., Orr, N., & Lemke, C. (2011). *What four states are doing to support local data-driven decisionmaking: policies, practices, and programs* (Report). U.S. Department of Education, Institute of Education Sciences. Retrieved from http://ies.ed.gov/ncee/edlabs/projects/project.asp?ProjectID=286.

Gutierrez, R. (2000). Advancing African-American, urban youth in mathematics: Unpacking the success of one math department. *American Journal of Education*, 63-111.

Hamilton, L. (2011). The role of students in data use: Commentary on Coburn and Turner's research on data use: A framework and analysis. *Measurement, 9*(4), 207-210. doi: 10.1080/15366367.2011.632331

Hamilton, L., Halverson, R., Jackson, S. Mandinach, E., Supovitz, J., & Wayman, J. (2009). *Using student achievement data to support instructional decision making* (Practice Guide). U.S. Department of Education, Institute of Education Sciences, What Works Clearninghouse. Retrieved from http://ies.ed.gov/ncee/wwc/practiceguide.aspx?sid=12.

Hanushek, E., & Raymond, M. (2004). The effect of school accountability systems on the level and distribution of student achievement. *Journal of the European Economic Association, 2*(2-3), 406-415.

Hargreaves, A., & Braun, H. (2013). *Data-driven improvement and accountability* (Report). National Educaiton Policy Center. Retrieved from http://nepc.colorado.edu/publication/data-driven-improvement-accountability.

Henig, J. (2012). The politics of data use. *Teachers College Record, 114*(11), 1-17.

Herman, J., & Gribbons, B. (2001). *Lessons learned in using data to support school inquiry and continuous improvement: Final report to the Stuart Foundation* (CSE Tech. Rep. No. 535). Center for the Study of Evaluation, National Center for Research on Evaluation, Standards, and Student Testing, Graduate School of Education & Information Studies. Retrieved from https://www.cse.ucla.edu/products/reports/TR535.pdf.

Hughes, J., Gleason, K., & Zhang, D. (2005). Relationship influences on teachers' perceptions of academic competence in academically at-risk minority and majority first grade students. *Journal of School Psychology, 43*(4), 303-320.

Ikemoto, G., & Marsh, J. (2007). Cutting through the "data-driven" mantra: Different

 conceptions of data-driven decision making. In P. Moss (Ed.), *Yearbook of the National*

 Society for the Study of Education (Vol. 106 (1), pp. 105-131). Retrieved from

 http://www.rand.org/pubs/reprints/RP1372.html.

Ingram, D., Louis, K., & Schroeder, R. (2004). Accountability policies and teacher decision

 making: Barriers to the use of data to improve practice. *Teachers College Record, 106*(6),

 1258-1287.

Iorio, J., & Adler, S. (2013). Take a number, stand in line, better yet, be a number get tracked:

 The assault of longitudinal data systems on teaching and learning. *Teachers College*

 Record. Retrieved from www.tcrecord.org (ID number: 17051).

Jacobs, J., Gregory, A., Hoppey, D., & Yendol-Hoppey, D. (2009). Data literacy: Understanding

 teachers' data use in a context of accountability and response to intervention. *Action in*

 Teacher Education, 31(3), 41-55.

Jennings, J. (2012). The effects of accountability system design on teachers' use of test score

 data. *Teachers College Record, 114*(11), 1-23.

Johnson, R., & La Salle, R. (2010). *Data strategies to uncover and eliminate hidden inequities:*

 The wallpaper effect. Thousand Oaks, CA.: Corwin Press.

Jorgenson, O. (2012). What we lose in winning the test score race. *Principal, 91*(5), 12-15.

Kagan, D. (1990). How schools alienate students at risk: A model for examining proximal

 classroom variables. *Educational Psychologist, 25*(2), 105-125.

Kallemeyn, L. (2014). School-level organizational routines for learning: Supporting data use.

 Journal of Educational Administration, 52(4), 529-548. doi:10.1108/JEA-02-2013-0025

Kerr, K., Marsh, J., Ikemoto, G., Darilek, H., & Barney, H. (2006). Strategies to promote data use for instructional improvement: Actions, outcomes, and lessons from three urban districts. *American Journal of Education, 112*(4), 496-520.

Klostermann, B., White, B., Litchtenberger, E., Holt, J., & IERC. (2014). *Use of the Illinois 5 essentials survey data* (Report No. 2014-12). Illinois Education Research Council. Retrieved from http://ierc.education/our-research/publications/.

Koschoreck, J., Skrla, L., & Scheurich, J. (2001). Accountability and educational equity in the transformation of an urban district. *Education and Urban Society, 33*(3), 155-174.

Kvernbekk, T. (2011). The concept of evidence in evidence-based practice. *Educational Theory, 61*(5), 515-532.

Labaree, D. (2014). Let's measure what no one teaches: PISA, NCLB, and the shrinking aims of education. *Teachers College Record, 116*(9), 1-14.

Lachat, M., & Smith, S. (2005). Practices that support data use in urban high schools. *Journal of Education for Students Placed at Risk, 10*(3), 333-349.

Ladson-Billings, G. (1995a). But that's just good teaching! The case for culturally relevant pedagogy. *Theory into practice, 34*(3), 159-165.

Ladson-Billings, G. (1995b). Toward a theory of culturally relevant pedagogy. *American Educational Research Journal, 32*, 465-491. doi: 10.2307/1163320

Little, J. (2012). Understanding data use practice amongst teachers: The contribution of micro-process studies *American Journal of Education, 118*(2), 143-166.

Little, J., & Curry, M. (2009). Structuring talk about teaching and learning: The use of evidence in protocol-based conversation. In L. Earl & H. Timperly (Eds.), *Professional learning*

conversations: Challenges in using evidence for improvement (pp. 29-42). New York, NY.: Springer.

Llamas, J. M. (2012). *The Perception Gap: Sociodemographic Factors Affecting Teacher Perceptions of Students in Urban Schools.* (Doctoral Dissertation). Retrieved from ProQuest Dissertation. (3491034)

Love, N. (2004). Taking data to new depths. *Journal of Staff Development, 25*(4), 22-26.

Mack, S. (April 8, 2014). Putting student data to the test to identify struggling kids. *National Public Radio*. Retrieved from http://www.npr.org/blogs/ed/2014/04/08/300587823/putting-student-data-to-the-test-to-identify-struggling-kids.

Mandinach, E. (2012). A perfect time for data use: Using data-driven decision making to inform practice. *Educational Psychologist, 47*(2), 71-85. doi: 10.1080/00461520.2012.667064

Mandinach, E., & Gummer, E. (2013). A systemic view of implementing data literacy in educator preparation. *Educational Researcher, 42*(1), 30-37.

Marchand-Martella, N. E., Ruby, S. F., & Martella, R. C. (2007). Intensifying reading instruction for students within a three-tier model: Standard-protocol and problem solving approaches within a Response-to-Intervention (RTI) system. *Teaching Exceptional Children Plus, 3*(5), Article 2.

Marsh, J. (2012). Interventions promoting educators' use of data: Research insights and gaps. *Teachers College Record, 114*(11), 1-48.

Marsh, J., Pane, J., & Hamilton, L. (2006). *Making sense of data-driven decision making in education: Evidence from recent RAND research* (Occasional Paper, No. OP-170-Edu).

Rand Cooperation. Retrieved from

http://www.rand.org/pubs/occasional_papers/OP170.html.

Martinez, S., & Rury, J. (2012). From 'culturally deprived' to 'at risk': The politics of popular

expressions and educational inequality in the United States, 1960-1985. *Teachers College

Record, 114*(6), 1-31.

Mason, S. (2002). *Turning data into knowledge: Lessons from six Milwaukee public schools*.

Paper presented at the American Educational Research Association, New Orleans, LA.

Mathis, W. (2003). *No child left behind: What are the costs? Will we realize any benefits?*

Retrieved from http://files.eric.ed.gov/fulltext/ED477646.pdf.

McKown, C., & Weinstein, R. (2008). Teacher expectations, classroom context, and the

achievement gap. *Journal of school psychology, 46*(3), 235-261.

McMurray, S. (2013). An evaluation of the use of Lexia reading software with children in year 3,

northern Ireland. *Journal of Research in Special Educational Needs, 13*(1), 15-25.

Means, B., Padilla, C., & Gallagher, L. (2010). *Use of education data at the local level: From

accountability to instructional improvement* (Report). Office of Planning, Evaluation and

Policy, U.S. Department of Education. Retrieved from

http://www2.ed.gov/rschstat/eval/tech/use-of-education-data/index.html?exp=0.

Means, B., Chen, E., DeBarger, A., Padilla, C. (2011). *Teachers' ability to use data to inform

instruction: Challenges and supports* (Report). Office of Planning, Evaluation and Policy

Development, U.S. Department of Education. Retrieved from

www.ed.gov/about/offices/list/opepd/ppss/reports.html.

Milner, H. (2013). Scripted and narrowed curriculum reform in urban schools. *Urban Education,

49*(7), 743-749.

Mislevy, R., Haertel, G., Cheng, B., Ructtinger, L., DeBarger, A., Murray, E., . . . Vendlinski, T.

    (2013). A "conditional" sense of fairness in assessment. *Educational Research and*

    Evaluation, 19(2-3), 121-140.

Moody, L., & Dede, C. (2008). Models of data-based decision making: A case study of the

    Milwaukee Public Schools. In E. Mandinach & M. Honey (Eds), *Data-driven school*

    improvement: Linking data and learning (233-254). New York, NY: Teachers College

    Press.

National Governors Association (NGA). (2014). *Common core state standards initiatives*.

    Retrieved from http://www.nga.org/cms/home/special/col2-content/common-core-state-

    standards-init.html.

National Research Council. (2000). *How people learn: Brain, mind, experience, and school*.

    Retrieved from http://www.nap.edu/catalog/9853.html

Newman, K., & Chin, M. (2003). High stakes: Time, poverty, testing, and the children of the

    working poor. *Qualitative Sociology, 26*(1), 3-34.

Oakes, J., & Guiton, G. (1995). Matchmaking: The dynamics of high school tracking decisions.

    American Educational Research Journal, 32(1), 3-33.

Park, V., Daly, A., & Guerra, A. (2013). Strategic framing: How leaders craft the meaning of

    data use for equity and learning. *Educational Policy, 27*(4), 645-675.

Popham, W. J. (1999). Why standardized tests don't measure educational quality. *Educational*

    leadership, 56, 8-16.

Raths, J., Kotch, S. A., & Carrino-Gorowara, C. (2009). Research on teachers using data to make

    decisions. In T. Kowalski & T. Lasley (Eds.), *Handbook of data-based decision making*

    in education (pp. 207-221). New York, NY.: Routledge.

RTI Action Network. (2014). *Universal screening*. The National Center for Learning

      Disabilities. Retrieved from http://www.rti4success.org/essential-components-

      rti/universal-screening

Rubie-Davies, C., Hattie, J., & Hamilton, R. (2006). Expecting the best for students: Teacher

      expectations and academic outcomes. *British Journal of Educational Psychology, 76*(3),

      429-444.

Seawright, J., & Gerring, J. (2008). Case selection techniques in case study research : A menu of

      qualitative and quantitative options. *Political Research Quarterly, 61*(2), 294-308.

Shirley, D., & Hargreaves, A. (2006). Data-driven to distraction. *Education Week, 26*(6), 32-33.

Simmons, W. (2012). Data as a lever for improving instruction and student achievement.

      Teachers College Record, 114(11), 1-9.

Slavin, R., Cheung, A., Holmes, G., Madden, N., & Chamberlain, A. (2013). Effects of a data-

      driven district reform model on state assessment outcomes. *American Educational*

      Research Journal, 50(2), 371-396. doi: 10.3102/0002831212466909

Slavit, D., Nelson, T. H., & Deuel, A. (2013). Teacher groups' conceptions and uses of student-

      learning data. *Journal of Teacher Education, 64*(1), 8-21.

Sleeter, C. (2008). Equity, democracy, and neoliberal assaults on teacher education. *Teaching*

      and Teacher Education, 24(8), 1947-1957.

Spillane, J. (2012). Data in practice: Conceptualizing the data-based decision-making

      phenomena. *American Journal of Education, 118*(2), 113-141.

Stake, R. (1994). Case studies. In N. Denzin & Y. Lincoln (Eds.), *Handbook of Qualitative*

      Research (236-247.). Thousand Oaks, CA: Sage Publications.

Stake, R. E. (1995). *The art of case study research*. Thousand Oaks, CA: Sage Publications.

State Board of Education (SBE). (2008). *Response to intervention state plan*. Further information

about this citation was not included to protect participants confidentiality.

State Board of Education (SBE). (2014). *State report card 2013-14*. Further information about

this citation was not included to protect participants confidentiality.

St. Croix Central School District. (2015). *Response to intervention expectations*. Retrieved from

http://www.scc.k12.wi.us/district/ds_rti.cfm.

Sunderman, G., & Kim, J. (2007). The expansion of federal power and the politics of

implementing the No Child Left Behind Act. *The Teachers College Record, 109*(5),

1057-1085.

Timperley, H., & Earl, L. (2009). Using conversations to make sense of evidence: Possibilities

and pitfalls. In L. Earl & H. Timperly (Eds.) *Professional learning conversations:

Challenges in using evidence for improvement* (121-126). Dordrecht, Netherlands:

Springer.

Tozer, S., Senese, G., & Violas, P. (1995). *School and society: historical and contemporary

perspectives*. New York, NY: McGraw-Hill Education.

U.S. Department of Education. (2009a). *Implementing RTI using title I, title II, and CEIS funds:

Key issues for decision-makers*. Retrieved from

http://www2.ed.gov/programs/titleiparta/rti.html.

U.S. Deparment of Education. (2009b). *Race to the top: Executive summary*. Retrieved from

http://www2.ed.gov/programs/racetothetop/executive-summary.pdf.

U.S. Department of Education, Institute of Education Sciences, What Works Clearinghouse.

(June 2009). *Lexia Reading* (Report). Retrieved from http://whatworks.ed.gov

U.S. Department of Education, Institute of Education Sciences, What Works Clearinghouse.

(August 2009). *Success for All* (Report). Retrieved from http://whatworks.ed.gov

U.S. Department of Education, Institute of Education Sciences, What Works Clearinghouse.

(July 2013). *Reading recovery* (Report). Retrieved from http://whatworks.ed.gov

van Harmelen, M., & Workman, D. (2012). *Analytics for learning and teaching* (Report). Centre

for Educational Technology & Interoperability. Analytics Series, 1(3), 1-44.

Vanneman, A., Hamilton, L., Anderson, J. B., & Rahman, T. (2009). *Achievement gaps: How

black and white students in public schools perform in mathematics and reading on the

National Assessment of Educational Progress* (Report, NCES 2009-455). U.S.

Department of Education, Institute of Education Sciences, National Center for Education

Statistics.

What Works Clearinghouse [WWC]. (2015). Find what works. Retrieved from

http://ies.ed.gov/ncee/wwc/findwhatworks.aspx.

Zirkel, P. (2012). *The legal dimensions of RTI: Part II. state laws and guideline*. RTI Action

Network. Retrieved from http://www.rtinetwork.org/learn/ld/the-legal-dimension-of-rti-

part-i-the-basic-building-blocks.

Appendix

	Observation of team data use	Teacher Interviews	Literature on DDDM
Table 2 *Comparison of data derived from different sources*			
Data sources	Single assessment that was utilized district-wide	Varied sources, including teachers' anecdotal observations	Multiple assessments, often de-values teachers' anecdotal observations (Boudett et al., 2005; Little, 2012)
Major influences on DDDM	a) Principal-led b) Agenda often seemed focused on complying with RtI policy for data use c) District selection of assessment tool	a) teachers' previous experience with DDDM b) teachers' personal beliefs about students and their philosophies of teaching c) teachers' level of power in the team d) teachers' level of buy-in to the team DDDM	The literature indicates a variety of influences, most of which were present at Greenbrook including DDDM being principal-led (Little, 2012), teachers' knowledge of data and personal beliefs (Coburn & Turner, 2011; Means et al., 2010), and the extent to which external accountability policies mediate DDDM (Hargreaves & Braun, 2013; Moody & Dede, 2008).
Data-use conditions	Assessment system that supported data interpretation and housed data; federal, state, and local	Teachers described similar data-use supports as the ones observed and listed in the previous column. However, teachers also pointed out that particular supports were missing,	Data-use conditions described in the literature were both present and absent at Greenbrook. For example, teachers

	policies that mediated data-use; school and district leadership that encouraged particular types of data-use	primarily professional development on data-use and the district-wide assessment system.	had access to data and time to analyze data but had little professional development to foster their capacity for data-use and little voice in the process. (See literature review in Chapter 1 for a more comprehensive list)
Data-use aim	Enhance the educational outcomes of the lowest performing students	Teachers differed on this topic but half of the participants wanted to enhance the learning environment for students by rectifying inequities in students' opportunity to learn.	Often described in vague terms in the literature as enhancing educational outcomes for students or stopping teachers from using their "gut" (Mandinach, 2012, p. 71; Simmons, 2012)
Data-use process	Step 1: Teachers receive color-coded data from school leadership Step 2: The team identifies students who are color-coded red, i.e., the lowest performing students Step 3: The team determines educational placement for lowest performing students.	Teachers described the data-use process similarly to what was observed in data-use meetings. Yet, they often expressed that they were not invested in this process and made suggestions for other steps. For example, multiple teachers wished to identify and discuss students who made progress over time.	Often visually displayed as a cycle where teachers examine students' performance data; interpret data; make instructional decisions or an action plan based on data; and then revisit this cycle with new data to evaluate their former decisions(Boudett et al., 2005; Means et al., 2010)

Characteristics of data-use process	Predictable and superficial	Teachers differed on how they characterized the data-use process. One teacher compared the data-use process to an "auction" or an "NFL draft" as students were 'auctioned off' into various educational tracks. All teachers wanted a more meaningful routine.	Predictable, goal-oriented, and meaningful for participants (Carlson et al., 2011; Means et al., 2010; Park et al., 2013)
Decisions made with data	Place students with similar test scores into similar educational routes	Varied across teacher primarily included (a) tweaking students' learning environment, (b) place students into pre-existing educational routes based on score, or, (c) not making decisions based on assessment data	The literature indicates educators *should* use data to make a number of instructional and logistical decisions (Carlson et al., 2011; Johnson & La Salle, 2010; Simmons, 2012) Researchers have observed a number of 'data-driven decisions' including inappropriate ones (Booher-Jennings, 2005; Marsh, 2012)