ARTICLE IN PRESS

Studies in Educational Evaluation xxx (xxxx) xxxx

Contents lists available at ScienceDirect

Studies in Educational Evaluation

journal homepage: www.elsevier.com/locate/stueduc

Implementation of a collaborative data use model in a United States context

Jo Beth Jimerson[a,*], Vanessa Garry[b], Cindy L. Poortman[c], Kim Schildkamp[c]

[a] Texas Christian University, TCU Box 297900, Fort Worth, TX 76129, USA
[b] University of Missouri—St. Louis, 258 Marillac Hall, 1 University Blvd., St. Louis, MO 63121-4400, USA
[c] University of Twente, Faculty of Behavioural, Management and Social Sciences, Ravelijn 5446, P.O. Box 217, 7500 AE Enschede, the Netherlands

ARTICLE INFO

Keywords:
Data-driven decision making
Data-informed decision making
School improvement
Collaborative inquiry
Implementation

ABSTRACT

Collaborative data use requires educator capacity in moving data to action to address root causes of student underperformance. Implementation of the model used in the present study has proved promising in European countries for building educator capacity and addressing problems-of-practice, but this model has not been studied in the United States (US), where structural issues and accountability factors present different challenges. In the present study, we explored enabling and hindering factors of the implementation in an elementary school in the US to better understand how differences in policy and practice contexts influence collaborative data use. Organizational structures and some policies in the US hindered implementation. Drawing on our findings, we suggest shifting thinking around data use to accommodate for both short cycles of data use (for straightforward problems) and intentionally slow cycles for stickier problems; furthermore, nesting collaborative data use within high-priority initiatives may help mitigate barriers to future implementations.

1. Introduction

Educators are inundated with and expected to use data routinely, so they may assume that using data regularly equates to using data *well*. This is not always the case: When teachers are not adequately prepared to use data in their preservice experiences (Mandinach, Friedman, & Gummer, 2015), and subsequently accept positions in school districts that fail to provide adequate professional learning supports for data use (Jimerson & Wayman, 2015), they are doubly challenged to move data to action. Research on professional learning efforts around data use remains sparse: Only in the past few years has research become less focused on identifying systemic facilitators and challenges of data use (e.g., Kerr, Marsh, Ikemoto, Darilek, & Barney, 2006; Means, Padilla, DeBarger, & Bakia, 2009) and more attentive to the ways in which professional learning can be structured to support improved capacity for data use (e.g., Lai & Schildkamp, 2016; Lai, McNaughton, Timperley, & Hsiao, 2009; Mandinach et al., 2015; Poortman & Schildkamp, 2016).

Despite these broader issues of initial preparation for data use, the field has developed quite a bit of knowledge about what *does* hinder or enable collaborative data use in practice. For example, across contexts, research demonstrates that educators struggle to find adequate time to establish areas of focus, collect and analyze data, and determine action steps (Datnow & Hubbard, 2015; Huguet, Farrell, & Marsh, 2017; Jimerson & Wayman, 2015; Park & Datnow, 2009). We know from a growing body of research that access to data-capable support personnel influences how teachers and leaders engage in data use (e.g., Datnow & Hubbard, 2016; Huguet, Marsh, & Farrell, 2014; Marsh, McCombs, & Martorell, 2010). A lack of professional learning opportunities (post-hire) to help teachers become data literate works against effective data use efforts (Datnow & Hubbard, 2016; Mandinach et al., 2015).

Research across contexts (including multiple schools and districts/systems within and across states in the US, as well as in other countries) also points to the work of school leaders as a critical support for collaborative data use (e.g., Kerr et al., 2006; Louis et al., 2010; Schildkamp & Poortman, 2018; Wayman, Cho, Jimerson, & Spikes, 2012). Leaders are central to establishing trusting, improvement-oriented, and risk-embracing cultures within schools necessary for effective data use (e.g., Louis et al., 2010; Tschannen-Moran & Gareis, 2015). Where the prevailing leadership frame for data use is compliance and monitoring, or where leaders engage in "name and shame" practices, high-quality educational opportunities for students are precluded (Booher-Jennings, 2005; Marsh, Farrell, & Bertrand, 2016; Nichols & Harris, 2016). School leaders also play an important role in how data systems are used, serving as gatekeepers for logistics (who is allowed access to particular systems or reports) and expectations (who

* Corresponding author.
E-mail addresses: j.jimerson@tcu.edu (J.B. Jimerson), garryv@umsl.edu (V. Garry), c.l.poortman@utwente.nl (C.L. Poortman), k.schildkamp@utwente.nl (K. Schildkamp).

https://doi.org/10.1016/j.stueduc.2020.100866
Received 5 November 2019; Received in revised form 26 February 2020; Accepted 3 March 2020
0191-491X/

should be examining particular data at set intervals) (Schildkamp & Poortman, 2018; Wayman et al., 2012). How leaders talk about data, display data, make time in the schedule for data, and model their own growth related to data use enables or precludes constructive habits among teachers (e.g., Daly, 2012; Datnow & Hubbard, 2016; Datnow, Park, & Wohlstetter, 2007; Farley-Ripple & Buttram, 2015; Marsh et al., 2016; Schildkamp & Poortman, 2018). Across contexts, research suggests that how school leaders structure, frame, model, and engage in data use influences the shape, scope, and effectiveness of the practice.

One open question, then, is why, when so much is known about what constrains effective data use, and what enables effective data use, do so many practitioners still struggle to move data to action? One possible answer is that school teams have not been introduced to effective models for data use, or that the models they implement do not align with this well-developed body of research. Of course, another possibility is that existing models—even when well-evidenced themselves—are not adeptly implemented for one reason or another. We endeavored to explore these issues by implementing a model that aligns with data use research and has shown promise vis-à-vis empirical studies in Dutch (Schildkamp, Poortman, & Handelzalts, 2016) and Swedish (Blossing, Nehez, & Schildkamp, 2018) contexts in a United States (US) elementary school. Our study was guided by the broad question: What factors hinder or enable the implementation of an evidence-supported model for collaborative data use?

In what follows, we outline our framework for the study and briefly touch on differences in context that we considered to be important for whether and how school-based teams might be able to implement an evidence-based model for collaborative data use. We then describe our methods for this study and our findings, before discussing policy and practice implications stemming from our findings as they intersect with the broader literature around organizational coherence in mission/vision, the tenets of improvement science, and policy co-construction.

2. Conceptual framework

We began construction of our conceptual framework by considering two elements central to the implementation of collaborative data use models: (1) What ought an evidence-based model look like? And (2) What does research suggest about how a model must be implemented in order to reap desired benefits? We then considered how broad differences in implementation contexts (European to US) might be expected to influence our implementation efforts.

2.1. Adult learning theory and effective professional learning structures

In response to our first question, we drew on adult learning theory as well as work around effective professional learning in identifying characteristics that ought to well-position any collaborative data use model in leveraging benefit to school-based teams. Adult learning theory (e.g., Boud & Feletti, 1997; Helle, Tynjälä, & Olkinuora, 2006; Merriam, 2002; Wenger, 2011) suggests that adults learn best in communities/collaborative groups where they collectively address problems-of-practice and are actively engaged in sensemaking around the problem and potential solutions to the problem over time. Effective vehicles for adult learning must be collaborative and collective, should be situated in contexts of trusting adult relationships (where risk is not only possible, but welcomed), ought to encourage sensemaking by blending new learning and prior experience with new opportunities for learning, and make space for a degree of self-direction and choice in learning (Merriam, 2002).

Unsurprisingly, research on effective professional learning echoes these principles. Guskey (2009) urged the field to “acknowledge that schools vary greatly, and that few if any professional development strategies, techniques, or activities work equally well in all” (p. 229). However, he also noted that a more productive approach would be to identify and subsequently employ as design elements “specific *core elements* of professional development that contribute to effectiveness,” even though those elements might need to be adapted to fit different school contexts (p. 229). Along these lines, a rich history of professional development suggests that professional development is more likely to effect changes in teacher practice when designs are collaborative (Desimone, Porter, Garet, Yoon, & Birman, 2002; Wei, Darling-Hammond, Andree, Richardson, & Orphanos, 2009); sensitive and responsive to specific job-contexts (Borko, 2004); active, engaging, and socially rich (Guskey & Yoon, 2009; Wei et al., 2009); job-embedded, as in a community of practice (Guskey & Yoon, 2009; Wenger, 2011); intense in both duration (total hours engaged) and span (engagement over time) (Garet, Porter, Desimone, Birman, & Yoon, 2001; Yoon, Duncan, Lee, Scarloss, & Shapley, 2007); and coherent—that is, fitting with prior learning and planned later work (Desimone et al., 2002; Wei et al., 2009)

This lens of adult learning theory, paired with empirical evidence on professional learning, well-described the collaborative data use model we targeted for implementation at the study site. The model was structured as an iterative eight-step process, in which a facilitator supports a campus-based team of educators as they move through phases of data use, building capacity as they engage in inquiry focused on a self-determined problem-of-practice. Each of the steps (i.e., problem definition, formulating hypotheses, collecting data, conducting a data quality check, data analysis/visualization, interpretation, implementation of improvement measures, and evaluation) is scaffolded through use of a workbook (which provides examples and defines terms along the way) and by the facilitator during team meetings (see Schildkamp et al., 2018 for a finer-grained description of structure and process).

As implemented in the European context, a data team meets approximately every 3 weeks for approximately 1.5 hours (Schildkamp & Poortman, 2018). Thus, the model itself was designed to be *collaborative*; to provide for a degree of *self-direction* as the team initiates the process by establishing an agreed-upon problem of practice to guide the work; to be *nested in the context of work* by working on a problem identified as relevant by the participants themselves; to be *actively engaging and socially-rich* as it not only invites, but depends on team members’ interactions to explore the proposed problem; and to be of sufficient *intensity* and *duration* that it could effect changes in practice. In short, the model seemed by all accounts to fit the design elements of an effective structure for team learning as well as for team-based data use (e.g., Jimerson & Wayman, 2015; Wayman & Jimerson, 2014). These factors are also important to note as they shape the way individuals and teams can come together to use data for improvement efforts, but they may prove implementable in some contexts and elusive in others.

2.2. Co-construction of implementation efforts

Despite our initial assessment of the fit of the collaborative data use model to the evidence base around adult learning and professional development, we also acknowledged differences in policy and practice contexts between where the model had been previously implemented and the US context (we detail this more briefly in our description of the study site in the next section). We therefore needed to consider how the model would need to be implemented in order to reap benefit. For this part of our conceptual framework we drew from Datnow’s (2006) work on co-construction of (policy) implementation, and from both Datnow (2006) and Honig (2006) on the importance of context in the consideration and assessment of policy implementation efforts. Datnow (2006) points out, “reform implementation involves an active and dynamic interaction between local education, the reform policy, and the social, organizational, and political life of the school” and notes that policies are transformed in “mutual adaptation […] between actors in schools and the wider social and political sphere” (p. 107). Similarly, Honig (2006) focuses on the complexity of educational systems and calls for policy analysis to focus "not simply on what's implementable and what works but rather investigate under what conditions, if any, various education policies get implemented and work" (p. 2). Though we were working to implement a data use model—not a policy per se—such work helped us recognize that the model would likely change somewhat during implementation, depending on contextual factors at the study site. At the same time, there comes a point at which an implementation can stray so far from design that it no longer accurately represents the intended model, and can no longer reasonably be expected to produce anticipated results. This was a wondering throughout the study: We thought the model well-positioned—due to its alignment with the evidence on data use in schools, with adult learning theory, and with the research on effective professional development—to help the school-based team make progress toward solving their identified problem of practice as they also improved capacity for data use, but we were unsure whether the model would be (could be) implemented with enough fidelity to produce that desired result. Implementation in a context of competing demands (on time, for resources, for attention) risked contributing to a sense of practice incoherence and, over time, devolution of the model as designed (e.g., Honig & Hatch, 2004).

3. Comparative contexts: Texas (US) and The Netherlands

The choice of a Texas school was useful to the focus of the project, as Texas public schools have been documented to broadly reflect the high-stakes accountability policies that have characterized much of US schooling over the past few decades (see Booher-Jennings, 2005; Palmer & Snodgrass Rangel, 2011; Vasquez Heilig & Darling-Hammond, 2008); as such, a Texas school provided an interesting contrast to the schools in low(er)-stakes accountability policies in which the collaborative data use model has been successfully implemented (i.e., Blossing et al., 2018; Schildkamp et al., 2016). In what follows, we provide a brief overview of the broader policy and practice context for the study (the US and Texas) before moving on to a description of our methods.

3.1. Study context: Texas (United States)

K-12 public schools in the US are accountable to a variety of entities, and data use tends to align with federal and state accountability efforts (Anderson, Leithwood, & Strauss, 2010; Booher-Jennings, 2005; Vasquez Heilig & Darling-Hammond, 2008). Much has already been written about the No Child Left Behind Act (NCLB) of 2001, which ushered in an intense era of required testing and reporting of data. Reauthorized as the Every School Succeeds Act (ESSA) in 2015, an emphasis on required standardized testing continues[1] (though ESSA also introduced an intensified emphasis on continuous improvement as well as threshold attainment). Under ESSA requirements, states (not the federal government) establish learning standards and designate/deploy assessments. Public schools in Texas align instruction with the Texas Essential Knowledge and Skills (TEKS), standards established by state statute, rather than the Common Core State Standards (CCSS)—standards adopted by 41 other states in an effort to bring consistency to learning standards across the US "About the standards" (2019). Beyond this difference, though, the policy context in Texas specific to test-based accountability is largely representative of accountability policies in the US more broadly: Organisation for Economic Cooperation and Development (OECD) reports indicate that the US tops international rankings in terms of percentage of students who attend schools for which achievement data are posted publicly and "uses standardised tests extensively" (2016, p. 132). One danger in closely coupling data use with accountability framing, as Datnow and Park (2018a) point out, is the temptation for teachers and leaders to adopt deficit beliefs about students—that is, rather than looking for ways to build on what students bring to their own learning, educators may label students as "low performers" and search for quick ways to "fix" students, rather than provide robust and equitable structures for addressing root causes of underperformance.

In preparing and supporting teachers to use data, approaches in the US vary: researchers have lamented the dearth of effective preservice teacher education for data use (e.g., Mandinach et al., 2015) while others have documented a need for more in-depth attention to supporting collaborative teacher data use post-hire (Datnow & Park, 2018b; Jimerson & Wayman, 2015). In general, time set aside for collaborative learning and planning among teachers in the US context lags that of many high-performing countries (Darling-Hammond, Wei, & Andree, 2010; Wei et al., 2009). The provision of relatively little time on a regular basis for professional collaboration in the US exacerbates a tendency to layer data use atop other tasks (including professional learning communities, grading/planning, and parent meetings, among other responsibilities).

The Texas context is reflective of these broader patterns. Only recently have efforts been made to embed elements of data literacy among requirements for teacher and school leader certification and continuing education requirements (Jimerson & Childs, 2017). Legal restrictions and district policies around such items as length of lunch and conference periods, minutes of instruction per school day, and the academic calendar have a combined effect of making the school day look remarkably consistent across districts (around 420 min of instruction, with teachers having a 30-minute lunch and a 45-minute conference period) while constraining time available for collaborative data use (see Texas Education Code §21 and §25 for more detailed information).

3.2. Prior implementation context: The Netherlands

Much of this differs from the policy contexts in the Netherlands—where the data teams model was developed and tested. In the Netherlands, schools have considerable autonomy. The Dutch Government is responsible for financial structures, general education policy and admission requirements, and structure and objectives of the education system (EP-Nuffic, 2015), but almost all decisions are made at the school level (OECD, 2008, 2010). There is no central curriculum, although there is one national assessment at the end of primary education and one national assessment at the end of secondary education (OECD, 2008). Learning objectives are specified at the different stages and different tracks of the education system, but schools are autonomous in deciding on the teaching and learning methods and curriculum design, including the subjects to be taught and the course content of these subjects, as long as they ensure the incorporation of these learning objectives (Béguin & Ehren, 2011; OECD, 2008).

In the Netherlands, most teacher training programs pay attention to data literacy in their curriculum, although the amount of time dedicated and the way it is addressed varies (Bolhuis, Schildkamp, Luyten, & Voogt, 2017). Every teacher in the Netherlands has 83 hours of professional development time yearly; for about half of those hours, teachers have autonomy over how they spend their professional learning time, and are allocated a budget of 500 euro (primary education) to 600 euros (secondary education) to invest in their professional development (PO Raad, 2018; VO Raad, 2018). Educators in the Netherlands could use participation in the data use model described in this study to fulfill 45 hours of their professional development requirement.

In sum, in both contexts schools are expected to use data to inform improvement efforts. In the US, such efforts are under greater formalized (and perhaps shaping) pressure from test-based accountability models, though in the Dutch context local expectations may weigh

[1] Students in all states must be tested in mathematics and reading annually in 3rd through 8th grades, and once in high school, and in science at least once in the elementary, middle, and high school grades.

heavily on decision-makers. Professional learning is also recognized as important in both contexts, but the Dutch system seems to be somewhat more intentional about allocating resources of time and funding to teachers, whereas in the Texas (US) system, professional learning that requires a set-aside of funding and/or collaborative time is likely to have to compete with other job duties, even within the same window of time (e.g., planning/conference periods).

4. Methods

Curious about whether and how any of the aforementioned differences in policy contexts might influence implementation of the data teams model, we facilitated a data team in an elementary school in north Texas over the course of the 2017–18 school year. In this section, we begin by providing an overview of the study campus before discussing our own positionalities; we then outline our data collection and analysis procedures.

4.1. Study site: Chase Cluff Elementary School

Schools in north Texas were recruited for participation via email invitation to professional networks; initial communication provided an overview of the data team structure and study parameters. After discussing the shape and scope of the project with interested parties, the principal of Chase Bluff Elementary School[2] (CBES) agreed to participate, and suggested implementation with a team of six third-grade teachers, as the team was already accustomed to meeting in a weekly professional learning community (PLC) with an administrator and an instructional specialist. Following a meeting with teachers to describe the study, the team of eight[3] agreed to engage in the data team during the 2017-18 school year.

CBES is located in a fast-growing suburb of a major metropolitan area. In the 2017-18 school year, just over 700 students in Pre-Kindergarten (4-year-old) through fourth grade attended the school. The staff of 40+ teachers, two administrators, and several support personnel served an ethnically diverse student population (approximately 40 % of students identified as African-American, 25 % as Hispanic, 20 % as White, and 10 % as Asian or Pacific Islander). Fewer than 10 % of enrolled students were emergent bilinguals. Slightly over half of CBES students qualified for free- or reduced-price meals (reflecting family incomes below or near the federal poverty threshold).

The teaching staff of CBES in 2017-18 was predominantly white (70 %) and female (over 90 %); both measures were slightly higher than statewide average. 70 % of CBES teachers had over five years of teaching experience (on par with statewide average). Academically, the campus received a “Met Standard” status in the year prior to the study as per the Texas accountability system. In the 2016–17 school year, 78 % of the tested third-grade students scored at “Approaches Grade Level or Above” in Reading (the threshold considered sufficient for accountability purposes), and 70 % attained that threshold in Mathematics.

Each teacher on the team was partnered with another teacher in the same grade level; one teacher in each dyad taught social studies and English language arts/reading instruction, while the other was responsible for mathematics and science instruction. Each dyad shared approximately 44 students, with each maintaining a “homeroom” of nearly 22 students. Each teacher was allotted a single conference period during the regular school day, of 45 min, though this included “walk time” (time needed to drop off/pick up students at “specials classes” such as art, music, and physical education).

The data use model was scheduled into ten conference periods across the nine-month school year, replacing the team’s PLC for those weeks. No other additional professional development time was allocated for collaborative work associated with this project, though professional development days dedicated to other district or campus priorities were scheduled for several days in August, two days in May, and four days total from September through April.

4.2. Positionality

Prior to describing data collection and analysis, it is important to clarify the roles and positionality of the authors. The data team at CBES was facilitated by the first author, who engaged as an observer-participant (Merriam & Tisdell, 2016). The first author collected all data at the study site, navigating the roles of researcher and facilitator. As the first and second authors have experience as former school principals and in leading data use initiatives, stepping into the facilitator role for this particular work was new, but not unfamiliar. Audio recording of data team meetings enabled the first author to remain in-the-moment as facilitator and to focus on more intense reflections and review of data at a later time. Peer checks and debriefs with the full research team provided means by which to bracket roles, as appropriate, during data analysis and interpretation. As noted, the second author filled the role of critical friend and provided regular feedback and questions to help steer facilitation and implementation efforts by providing a regular peer check on the process, and engaged as a full collaborator in data analysis and interpretation.

The third and fourth authors—who developed and have facilitated the collaborative data use model numerous times—provided a full day of formal training in facilitating the process to both US-based facilitators; they also provided materials (used by facilitators and team members throughout the study) to guide the work. To mitigate potential bias, the third and fourth authors did not participate in data collection or analysis; these were the purview of the first and second authors. Virtual meetings among all authors throughout the implementation year created space in which all authors engaged in peer checking and reflection on implementation efforts.

4.3. Data collection and analysis

Ten data team meetings of approximately 40 min each across the 2017–18 school year were audiotaped and subsequently transcribed; agendas ($n = 10$) and minutes for meetings ($n = 10$) were collected throughout. The researcher-facilitator also recorded a memo-to-self to capture issues, concerns, and initial impressions following each meeting. Altogether, over 450 pages of documentation were collected and subsequently analyzed over the course of the project.

To get a sense of initial data use capacity, each data team member completed a brief assessment at the start of the project to capture data use-related knowledge and skills. Assessment items engaged participants in brief open-ended tasks related to problem definition, data collection, formulating hypotheses, and interpretation and conclusions. Items originally constructed for use in the Netherlands were translated and adjusted to relate more specifically to the study context (for example, questions about test scores specific to “pre-university education” or “general secondary education” were adjusted to reflect Texas-specific assessments (i.e., STAAR) and grade levels. Finally, each member of the data team engaged in two interviews (at midyear and at the end of the project) to explore participants’ perceptions of the collaborative data use model. For example, at the midterm point, participants were asked what components of the process were causing frustration or needed adjustment heading into the second half of the school year; at the end of the project, participants were asked to describe the team’s process for problem selection, what (if anything) they learned about the problem via the process, and about any successes or challenges they experienced during the model’s implementation.

[2] All names are pseudonyms.

[3] The core team included eight members; Assistant Principal Green participated sporadically, and also participated in mid- and end-year interviews and the post-assessment.

Assessments were scored to gain a general sense of baseline data use capacity. Qualitative data (e.g., artifacts, memos, transcripts of meetings and interviews) were coded in alignment with the suggestions of Miles, Huberman, and Saldaña (2014). Using Dedoose web-based coding software to facilitate analysis, the first two authors collaboratively coded a subset of documents, beginning with a list of priori codes derived from our review of literature and our framework (e.g., *facilitators*; *preparation for data use*; *leadership—vision, norms, and goals; data process steps*; *advice/considerations for future data team* implementations, and *challenges/hindering factors*). We allowed for the emergence of other codes as appropriate. After finalizing the coding scheme, the remaining documents were coded independently, but cross-checked by the first and second authors. Any conflicts in code application were resolved through dialogue. Excerpts were subsequently analyzed by code, and codes assembled and disassembled to identify themes responsive to the guiding questions and framework (Miles, Huberman, & Saldaña, 2014).

5. Findings

Analyses suggested factors influencing the fit of the data team implementation at CBES fell into two broad categories: General/team-oriented factors, and leadership factors. Two enabling and four hindering factors fell into the general/team-oriented category—meaning that they were less person-dependent and more institutionalized (or at least dispersed throughout the system/team). Beyond such factors, the leader(s) of the campus personally seemed to engage in some actions during the process that pushed the data team process forward and, in a few cases, held it back. Three enabling and three hindering factors fell into this leadership-oriented category.

5.1. General/team-oriented factors

Of general/team-oriented factors, existing commitment to data use and a risk-embracing data culture functioned as enablers of the collaborative data use model; lack of time, restricted process continuity, limited capacity for data use, and a general bias to action linked to a heightened accountability orientation functioned as hindrances to data team fit.

5.1.1. Enabler #1: Existing commitment to using data

Commitment to the process was evidenced by existing expectations for collaborative data use during some PLC work in years prior to the implementation of the data use model. Additionally, the third-grade team and school leaders were present and actively engaged during facilitated data team meetings, even though they had competing initial ideas about the focal problem. Team members expressed positivity about the process from the outset: When asked (in the first session) to articulate hopes and expectations for the process, one member expressed excitement at the prospect of “having a system and putting it into place” and another hoped to find “new findings in the data, and realize something I didn’t know before.” Team members early on established “attendance,” “respect,” “input from all,” and “agreement that everyone’s opinions are valuable” among norms to guide their work.

At least part of the vibrant commitment to data use may have been linked to campus and district changes over the prior few years: Several team members described a recent, heightened commitment to collaborative data use, attributing the emphasis to Principal Rhodes and to the expectations of a new superintendent. Principal Rhodes and Instructional Specialist Johnson (independently in their respective interviews), as well as several teachers, described a “reflection on data” exercise, completed each grading cycle, that required teachers to analyze student data by standard; teachers also spoke to this expectation. That so many mentioned the exercise separately suggested the practice was becoming institutionalized.

5.1.2. Enabler #2: Risk-embracing culture of data use

The data team was accustomed to collaborative discussions around data (albeit largely assessment and benchmark data), and to (generally) adhering to constructive norms, including allowing individuals to voice dissenting opinions in productive ways. This seems to have been in part because most team members had worked together for at least a few years, and engaged each other in a fairly casual, friendly manner. Leaders (both school leaders and grade-level leaders) frequently laughed with each other in meetings as they discussed students and issues related to the project. As an outgrowth of this congenial atmosphere, team members readily jumped in to add to, correct, or disagree with each other during meetings. For example, during one session the team engaged in a lively conversation about the iterative nature of establishing hypotheses and collecting data to test those hypotheses:

> Teacher 1: So that’s what we agree. We’re going to pick the problem and then we’re going to pick a few things that lead to that problem—that cause that problem.
> Teacher 2: So, we’re practicing teachers like practicing physicians? We’re just guessing what the diagnosis is…
> Teacher 1: That’s what a hypothesis is!
> Teacher 3: Exactly. It’s a hypothesis.

In a context with poor relationships, even disagreements such as this could have devolved or effected shutdown from members. That they did not devolve suggested to us a positive culture that would withstand ambiguity and support healthy and productive conflict around data.

A contributor to this risk-embracing culture was the steady presence of the campus principal, who attended all of the meetings and frequently attempted to gently refocus the team when conversations steered away from the focal problem. He noted in an interview that he thought teachers were comfortable admitting to gaps in capacity, sharing, “They’re not reluctant to admit that, ‘Oh, I didn't really know how to do this, but I want to.’ […] Generally speaking … in this particular professional development experience, it’s been very enriching. It’s like nothing they’ve ever experienced before.” In addition to honoring teachers’ voices, he was empathetic to the team for the lack of time, and maintained realistic expectations. He stated:

> What is really hard about all of this is, you know, time. […] It’s [hard] to learn how to do something and then to actually do it given the time restraints. I don't know if there was enough time for them to actually put into place the interventions to see whether or not they actually had an impact.

5.1.3. Hindrance #1: Time

Several members of the CBES team talked about the need for more (and more regular) time to do the complex work of using data. Teacher Peggy Carter noted, “I think sometimes what gets in the way is we all feel busy. Like we just don't have the time to really put our 100 % effort into it.” This concern was echoed by teacher Clint Barton: “Time constraints just make things the way they are, but if you had more time, if you had more than just once a month, maybe twice a month, that might make things…because when you go like we did where we just get to a log jam nobody can get anywhere.” The challenge was recognized by Assistant Principal Green, who said, “Honestly, personally, I wish I would have been able to spend more time with it. I did more pop-ins, or I could stay one time and then the next time I couldn't stay. So, for me, I wish I would have been able to spend more time with it.” Though all three examples allude to lack of time, distinctions among the three reveal how critical time was to the data use model, but in different ways. The first comment referred to the amount of time needed for participants to fully engage and be present in the process, the second noted a desire for more regular time set aside for collaboration, and the third alluded to the process being in constant competition with other (also important) job tasks.

5.1.4. Hindrance #2: Restricted process continuity

Another hindrance was limited process continuity. The collaborative data use model required participants to move through process steps and tasks related to those steps; time in meetings was (ideally) to be used for debriefing and discussions/analysis of data. To ensure meeting time could be used for dialogue, team members were expected to scan the process manual prior to the formal meeting focused around the next step. Sometimes they were also expected to have carried out agreements determined in the prior meeting (like collecting and bringing student-level data to the team meeting for discussion). However, as data team meeting recordings evidenced, a substantial portion of each meeting was consumed by reviewing what was done in the prior meeting, and agreements on data collection were often fulfilled only by a few of the teachers, and even then in ways that diverged from processes that were agreed upon in previous meetings. More team time was consumed reviewing information in the manual, as most teachers seemed not to scanned the workbook in preparation for dialogue. This largely nonproductive cycle severely truncated the time available for active collaboration around the data, and the process began to stall. In interviews, several team members admitted that the work fell off their respective radars between meetings. Despite meeting in weekly professional learning communities (PLCs) and for other purposes, there was no evidence that team members or school leaders engaged in actions to keep the process going between formal meetings (for example, with reminders about agreed-upon data collection efforts).

5.1.5. Hindrance #3: Limited data use capacity

Limited capacity for data use was another hindrance. Though some of the participants were skilled in using data, others were not. Initial assessment scores ranged from 3.75 to 14.25 (of a maximum of 25 points). Three scores were particularly low, perhaps because those persons were unable to complete the assessment within the 30-minute time allotment. Interview data suggested capacity for inquiry was further limited in ways not directly measured with the assessments. For example, one teacher described everything beyond routine quantitative data (attendance, test scores) as "opinion" rather than "subjective" or "qualitative," which seemed to preclude her from buying into the process. Others talked about analyzing data with Excel, but, in team meetings, struggled to use Excel to reorder data or calculate means or differences in scores using Excel's formula functions. Team members not only varied in capacity for data use, but also seemed more adept at some kinds of data use (e.g., dissecting item analysis reports) than in navigating a structured, data-rich inquiry process.

5.1.6. Hindrance #4: Bias to action/accountability orientation

The last hindrance was a bias to action—a sense of urgency to implement solutions even before verifying the presence or magnitude of assumed problems through data analysis. This bias to action seemed related to the centering of accountability system metrics. In fact, as the process pushed into the spring (when schools in Texas take state-mandated exams), teachers and leaders more frequently referenced STAAR, and the team more frequently referenced reading and mathematics benchmark assessments in dialogues (even though STAAR progress was only one of three aspects of the initial problem statement). Some interviews and team dialogues were characterized by varying levels of anxiety around whether kids would be "ready" come testing time. The closer the inquiry process came to testing time, the more the entire process became tightly coupled with STAAR readiness/outcomes.

Likely because of this tight coupling with accountability metrics, typical practices of "data use" as described by CBES team members seemed to involve analyzing assessment data (usually benchmark or state tests), identifying standards on which students scored poorly, and determining strategies to use to reteach skills (despite such data being appropriate only for a portion of the initially proposed problem statement). In essence, they identified problems based in assessment data and attempted to implement quick fixes. In contrast to this "quick fix," approach, the collaborative data use model is an elongated inquiry process that pushes teams to establish clear problem statements, research questions and/or hypotheses, and to engage in data collection and analysis to verify problems prior to moving to action. At several points early in the process, participants tried to jump to solution formation, rather than using data to verify suspected problems and contributing factors to those problems. Interview data evidenced that some participants were frustrated at the pace of inquiry, particularly in the first half of the year, as they wanted to get to solutions faster. Yet bias to action itself hindered early progress, as the team had to be redirected several times when dialogues would turn away from problem verification and toward brainstorming of potential solutions.

5.2. Leadership factors

Beyond the general/team-oriented factors that influenced the fit of the collaborative data use model at CBES (albeit also influenced by leadership), we identified some actions taken by leaders prior to and during the data use model that paved the way for the process. Although most of the principal's actions at CBES seemed positive and constructive (and hence squarely in the "enablers" category), we did note a few missed opportunities and ways in which leadership actions seemed to hinder the viability of the data team as a robust and sustainable vehicle for school improvement.

5.2.1. Leadership enabler #1: Creating a climate for data use

Leaders at CBES directly contributed to the risk-embracing data culture during the implementation by emphasizing that different interpretations of data could be shared without fear of reprisal. Principal Rhodes was consistently present and engaged in a collegial manner. Teacher Peggy Carter noted:

> He wasn't doing other stuff while we were talking. He was part of the group, but he kind of sat outside the group and helped facilitate it if needed. … he listened a lot, which was good because it's kind of what we needed—for him to listen and let us hash out things.

Three of the six teachers on the team talked about Principal Rhodes being open to ideas and concerns. In meetings, he elaborated on ideas initially offered by teachers, or indicated agreement as they talked. Only one member of the team suggested that the presence of the principal was cause for self-censoring of opinions or ideas.

In reflecting on his role in the team, Principal Rhodes told us that he worried the study process could cause undue stress or anxiety for teachers, so he was intentional about his interactions. He wanted implementation of the model to be a positive, improvement-oriented experience for the teachers, so that the shape and scope of inquiry-for-improvement could expand to other teams in coming years. His collegial stance during data team meetings fit with his articulated desire to mitigate anxiety and help the team focus on incremental improvements.

Another way leaders personally contributed to a constructive data use climate was by gently pushing back on proffered ideas and asking questions to extend or challenge ways of thinking about data, students, or problem framing. For example, when teachers discussed the ways in which student motivation might be linked to students' perceptions of relevance, Principal Rhodes prodded them to consider classroom practices:

> Are you including *why*? Are you including that rationale? When you give instructions, when you give a consequence, whether positive or negative, when you teach a new skill, whether it's a social, emotional, or academic skill [are you] including some sort of rationale for why it's important?

When teacher talk sometimes devolved into externalizing sources for student underperformance (e.g., blaming family engagement or society-at-large), Principal Rhodes encouraged the team to be intentional about identifying student strengths. He reminded, "If some can do it and some can kind of do it and some can't do it, that's learned behavior. Whoever can do it, it's not just because they're that way; they've learned that, right? So how do we figure out how they learn that and then put an intervention in place?" In this way, he redirected conversation towards factors within the team's control. He also chimed in to provide suggestions related to foundational issues of data use, such as triangulating and accessing existing data or the importance of establishing baseline data.

5.2.2. Leadership hindrance #1: Lack of depth in inquiry

A missed opportunity on the part of school leadership with regard to strengthening data-informed team dialogues may be related to Principal Rhodes' intentional positioning of himself as a co-learner with team members. He shared that he wanted the data use model to be considered "their work" and that he did not want to stifle conversation. Still, data team meetings captured instances where teachers made sense of lack of student growth by situating failure within students (or their families), sometimes using terms like "lazy" and "just don't care." School leaders rarely pushed back directly, though they also did not voice agreement.

A challenge related to the sustainability of a constructive data culture was a general lack of space for the kinds of professional dialogues the team experienced within the structured meetings of the data use model. Instructional Specialist Johnson shared, "I think their collaboration and sharing amongst a grade level is helping them talk through issues. They're departmentalized and they don't always get together like that." Principal Rhodes and three of the teachers explicitly mentioned valuing the discussions around issues related to teaching and/or to data trends across the whole grade level (as opposed to just within a departmentalized dyad). Still, these discussions within the structured sessions seemed more akin to initial dialogues that were rarely informed by evidence or by purposeful reflection on any theories-of-action. Creating space for conversations (perhaps in the ongoing weekly PLC time), and encouraging teachers to link assumptions and interpretations of data to underlying theories-of-action, could have enriched and sharpened the work of the grade-level team.

5.2.3. Leadership enabler #2: Connecting data team work to vision, norms, and goals

Principal Rhodes typically worked to keep data use oriented toward a goal. "Think about our mission," he prodded in one meeting, when the team was struggling to craft a clear problem statement. "[Students] are making progress academically, socially, and behaviorally or academically, socially, and emotionally—however you want to word it. But those are things that we can measure." Yet despite his own wishes, he engaged in "pull" rather than "push" leadership—wanting them to find a meaningful problem and connect data to action without him mandating the process. He reflected, "I wanted the team to land on a problem that could help them, ultimately, in terms of student achievement, whether that be academic, social, or emotional—something related to our mission." He also talked about establishing his role as co-learner, rather than sole driver, of data use within teacher teams: "This isn't mine," he insisted. "This is not my data team. This is not my PLC. This is [the teachers']. So I like that idea of me not being the leader or facilitator. It's more organic when they own it."

5.2.4. Leadership hindrance #2: Devolving data use norms

Principal Rhodes' "pull" leadership may have inadvertently fed the devolution of the process at times: The frequency with which dialogues were sidetracked into tangential conversations, instances of members interrupting and talking over each other, and the fact that teachers sometimes came to meetings having not collected data they had agreed to bring, suggested that norms to guide data use were not firmly established. Here, implementation of the data team could have benefitted from explicit statements from school leaders of the importance of the data team work and how it connected to other campus priorities. All members of the leadership team at CBES articulated (in interviews) that teachers were expected to use data. However, two of six teachers could not locate data needed to engage in analysis (despite having been provided data collection forms and offers of assistance by the instructional specialist) near the end of the project. Other teachers diverged from agreed-upon data collection schemes, making comparisons difficult. These instances of divergence from the model and from what was agreed upon within data team meetings suggest that some expectations around data use remained unclear.

5.2.5. Leadership enabler #3: Readiness to provide individual support

To make implementation of the collaborative data use model feasible, Principal Rhodes navigated district-wide and legislative constraints (e.g., length of teacher workday, days of instruction, the presence of other initiatives) to reserve ten 45-minute sessions for data team dialogues. This act of inviting researchers into the school when it was not required was in and of itself an act of priority-setting that demonstrated a level of commitment to collaborative data use. He also recognized the "initiative fatigue" possible for teachers, and worked to dedicate already-scheduled PLC time to the data team process. Near the end of the project year, he shared:

> I was really a little bit worried about this year […] I was worried that [participating in the data team study] would cause anxiety and stress and that I would hear from them from time to time about it, like, "Hey, we really need to plan that day. Do we have to [meet in the data team]?" But not one time has anyone said that to me.

Principal Rhodes also described his personal efforts to provide direct supports to teachers: He talked about sitting with teachers to show them how to access data in the district's systems, and how to organize data for analysis in Excel, both in grade-level team meetings and on an as-needed basis. Beyond Principal Rhodes, Instructional Specialist Johnson also evidenced this aspect of leading for data use: She created and disseminated Excel templates to support data collection, once the team determined goals and data collection needed to inform their problem statement, and more than once offered to visit with teachers one-on-one to help them enter data or to find resources specific to needs they articulated in data team meetings. She described helping teachers find data in the district data systems as well as running reports for teachers, so they could spend their time on analysis and planning.

5.2.6. Leadership hindrance #3: Lack of urgency

Despite these efforts by leaders, observations and interview data suggested that the work was largely "out of sight, out of mind" between data team meetings. Teacher Gwen Poole admitted she rarely thought about the team's work until she received an agenda from the researcher for the next meeting: "…and then we're like, 'Oh my god–what were we supposed to do?' the day before. Forty-five minutes once a month… I don't believe anybody was involved enough, including myself." Such responses suggested that leaders missed opportunities to keep the work at the fore of teachers' minds between data team sessions by allocating more frequent time for sessions across the year (minimizing 'down time' between meetings), by including reminders of the team's data use work in weekly PLC meetings, or by checking in with team members to see how planned data collection was proceeding. In retrospect, leaders at CBES may have focused so intently on the managerial supports around data use (forms, accessing systems) that they neglected to engage in deeper, conceptual work alongside teachers.

6. Discussion

Though our findings helped us identify a range of factors that enabled or hindered the fit of the collaborative data use model to the CBES context, we also came away from the experience wondering if the contextual factors of the Texas (US) system are too-heavy a constraint on school teams' ability to implement collaborative data use models without substantial rethinking of issues related to capacity and scheduling. The model itself aligns with the research on data use, with adult learning theory, and with the research on effective professional development. In theory, the collaborative data use model *should* work well to support school-level improvement. Despite being implemented by energetic, enthusiastic, and positive educators, the CBES data team diverged from the shape and scope of the original design most starkly in terms of total time allotment over the course of the school year (i.e., *intensity* in addition to *duration*). In this, our findings dovetail with much of the extant literature on challenges to data use in schools (e.g., Jimerson & Wayman, 2015; Kerr et al., 2006; Mandinach et al., 2015). Re-confirming the challenges of time and capacity (which have been demonstrated in numerous studies, though not specifically related to this particular data use model) is not ultimately significant. However, we think the findings here may point to two productive ways to address these challenges of context such that the collaborative data use model as originally designed may be a better fit for schools in contexts like CBES; a better fit between model design and implementation fit may increase the likelihood of the model supporting school improvement efforts, as it has done in other contexts. These two adjustments involve working to shift mental models of data use to highlight both long-term as well as short-term processes and goals, and nesting collaborative data use efforts within high-priority, "carrier" initiatives.

6.1. Shifting mental models: Creating space for slow data use

In order to better utilize allocated time, increase professional learning in data use, and enable leaders to help build teachers capacity and elevate the data dialogues, we think efforts to shift mental models around data-driven decision making could create fertile ground for the collaborative data use model and increase readiness for implementation efforts. Research well-documents ways of thinking about data use that tightly couple data-driven decisions and improving students' tests outcomes (Booher-Jennings, 2005; Daly, 2009; Jimerson, 2014; Nichols & Harris, 2016), and the deficit thinking such coupling belies (Booher-Jennings, 2005; Datnow & Park, 2018a). This is unsurprising, as schools' efforts to measure learning in ways that are reportable and comparable are largely dependent on external tests. However, reinforcing (even unwittingly) models that privilege using data to address immediate next steps (or "find-and-fix" approaches) also reinforces a sense of urgency to jump to solutions—perhaps prematurely—that we observed within the team at CBES. We do not suggest that educators cease focus on working to measure learning vis-à-vis standards and well-crafted assessments, and to respond in timely ways to student learning gaps, but we do think school-based teams might benefit from efforts to bifurcate data practice into parallel but mutually beneficial paths for short-term and long-term data-rich problem solving.

Short-term problem identification and resolution do not require extended data use processes, while complex problems require longer periods of time to resolve. For example, if benchmark assessments indicate that a large percentage of students were confused by items related to place value in mathematics, a teaching team might appropriately reach a decision during the space of a single planning period to reteach material in a new way, or to arrange tutorial groups. Underneath that problem, however, a more complex, longer-term problem may lurk: Perhaps a large number of students who missed the items are new to the school, and/or missed out on critical curriculum in the prior year. Perhaps teachers are applying outdated curricula or instructional methods related to these items. Multiple reasons might account for a lack of demonstrated learning, and if teaching teams only apply short-term solutions, they may well have to "re-solve" the same problems, year after year.

Solving complex problems requires teams to apply in-depth data use skills in deliberate ways to identify challenging problems, posit hypotheses related to those problems, and collect/interpret data to inform adjustments to teaching practice. To build this capacity for data use—and to engage in the kinds of thoughtful question-posing and data collection and interpretation needed to address long-term challenges—requires time, space, and data literacy. Wicked problems require the allocation of more frequent and perhaps larger blocks of, collaborative time, in addition to attention to diverse data sources. Such efforts may require policy and structural change, depending on how daily, weekly, or even annual schedules currently allow for educator collaboration.

This second, highly intentional and thoughtful movement from problem to solution aligns well with movements toward the adoption of improvement science approaches (Lewis, 2015) and, more broadly, with the "Slow movement" (e.g., Berg & Seeber, 2016; Carp, 2012; Holt, 2002). Carp asserts: "Practices are slow when decision making and policy development takes into account human-scale knowledge and experience tends to be collaborative, take time to develop, and vary in how they are adapted to particular situations" (p. 114). Berg and Seeber apply elements of the Slow movement to the university, calling for pushback against the "language of crisis" that often presses educators to action before sensemaking is allowed to unfold over time and in thoughtful ways (2016, p. x). Calling for more intentionality in schools (as well as for more attention to broader educational aims and less attention to high-stakes testing outcomes), Holt (2002) notes that an intentional *slowness* in schools could allow for the reuniting of theory and practice, as it allows for the space and time needed for in-depth reflection, thought, and dialogue.

At CBES, we observed not only a bias to action and sense of urgency around STAAR requirements, but also a lack of space and time for the team to dive beyond the numbers into their own theories of action and how those connected to practice. The teachers at CBES already seemed adept at short cycle data use like item analyses; however, implementing the data use model through an improvement science or *slow data* lens could help school leaders and teachers resist pressures to jump to solutions before verifying the nature of a problem. An internalized model that accommodated the co ncept of *slow data use* and when it would be appropriate (i.e., when exploring complex or stubborn problems) might have helped the team push against a bias to action and instead allocate adequate space and time to explore deeper issues related to their problem-of-interest. Such an approach would also be a better fit for building teacher capacity for data use. Professional learning literature routinely suggests that effective models for professional learning are collaborative, rooted in practice, and coherent across time (Desimone, 2011; Wei et al., 2009) and studies on strengthening teachers' data use capacity echo these characteristics (Datnow & Hubbard, 2015, 2016; Farley-Ripple & Buttram, 2015; Wayman & Jimerson, 2014;).

6.2. Nesting the collaborative data use model within carrier initiatives

Despite team members' positivity and enthusiasm for implementing the data use initiative, CBES struggled with allocating adequate time to the data use initiative. We note that CBES is in a context with relatively weak union presence: Texas is a "right to work" state, and although Texas teachers often join unions or associations, unions that represent Texas teachers have no collective bargaining rights in Texas school districts. Thus, Texas teachers have a "guaranteed" conference period, but various meetings (and PLCs) are often scheduled into this same time slot. Planning for classroom instruction, assessment/grading, training, meetings, and communication with a range of stakeholders typically compete for limited time and attention in the oft-overscheduled teacher conference period.

The tension between all that must be done in the face of multiple pressures and what can *reasonably* be accomplished in a limited time frame means that CBES exists in a fairly intense context of competing goods. In the same year that we worked to implement the collaborative data use model, CBES was also adjusting to being a designated campus for a magnet STEAM (Science, Technology, Engineering, Arts, and Mathematics) program and to entering year one of a multi-year planned phase in of AVID (Advancement via Individual Determination). In fact, the AVID focus no doubt played a role in the teachers' having "student motivation" (which they sometimes talked about in terms of "individual determination") in mind when establishing a problem-of-practice for the data team's work. Rather than see this context of competing goods as a barrier to collaborative data use efforts, we think an opportunity exists to nest the work of data teams within other high-priority initiatives. To this end, we would suggest that school leaders and researchers aiming to implement this or similar collaborative data use models consider identifying potential "carrier initiatives"—initiatives that are already considered priority and well-resourced by the district/campus.

If inquiry cycles vis-à-vis the collaborative data use model can be nested within such initiatives, teams of educators can still work to identify and address problems of practice, albeit ones related to the carrier initiative. In early cycles with the data use model, this can help provide a concrete focus, and perhaps mitigate the problem-identification-paralysis we initially observed with the CBES team. For example, groups of CBES teachers were already scheduled into summer AVID training on a rotating basis (so that within a given number of years, all teachers would be AVID-trained). If orientation to the data use model were paired with such training, then scheduled throughout the year to dive deeper into AVID-related issues, it is conceivable that both the AVID training and the data use model could benefit from designed synergy. AVID, however, was just one of several programs with carrier initiative potential: STEAM and a focus on writing workshop could also have proven to be mutually beneficial pairings. Coupling data use with other priorities has been shown to be beneficial—both in terms of building data use capacity and in progressing the initiative (see Lai et al., 2009 for one such example). Intentional entanglement of data use with pedagogical or programmatic initiatives provides teams of educators with a coherent schema through which they can make connections between existing expertise and data collection/analysis practices.

7. Conclusion

Our findings from this study are limited by the inherent nature of a single case study; what we learned is specific to the one study school, and as such is not generalizable to a broader swath of schools. Still, our exploration into the fit of the collaborative data use model at Chase Bluff Elementary may provide some insight into how this model could work in similarly situated schools in the US. We know from this study that even in a context with enthusiastic, forward-thinking leaders and a generally positive group of collaborative teachers, the model will face challenges related to time and scheduling, capacity, and competing priorities and demands. We also know that the mere presence of data use-related activity does not necessarily make for a smooth implementation of this particular collaborative data use model. In some cases, bias to action and prior habitual uses of data may pose challenges when teachers are pushed to slow down to engage in intentional inquiry practices.

Current research in data use routinely identifies barriers to collaborative data work but is lacking in terms of identifying potential solutions. Our exploration of the work in the CBES contexts suggests that transitioning toward a bifurcated model for data use (quick data cycles for less complex issues, and slow data for more complex ones) and nesting early data team experiences within well-resourced, high-priority carrier initiatives may be fertile ground for stronger implementation of the data use model in similarly situated US-based school contexts.

Funding

The research reported in this article was made possible by a grant from the Spencer Foundation (#201800054). The views expressed are those of the authors and do not necessarily reflect the views of the Spencer Foundation.

Declaration of Competing Interest

The third and fourth authors were part of the team that developed the collaborative data use model assessed in this study. To mitigate bias, they were not involved in the direct facilitation of the model, in data collection, or in data analysis or interpretation, but served as sources related to establishing differences in international context, as providers of training in model facilitation for the first and second authors, and as thinking partners throughout the study.

References

"About the standards" (2019). *Common core state standards initiative.* Retrieved fromhttp://www.corestandards.org/about-the-standards/.

Anderson, S., Leithwood, K., & Strauss, T. (2010). Leading data use in schools: Organizational conditions and practices at the school and district levels. *Leadership and Policy in Schools, 9*(3), 292–327.

Béguin, A., & Ehren, M. (2011). Aspects of accountability and assessment in the Netherlands. *Zeitschrift für Erziehungswissenschaft, 14*, 25–36.

Berg, M., & Seeber, B. K. (2016). *The slow professor: Challenging the culture of speed in the academy.* Toronto: University of Toronto Press.

Blossing, U., Nehez, J., & Schildkamp, K. (2018). From data to learning: A data team Professional Learning Network. *Networks for Learning* (pp. 97–113).

Booher-Jennings, J. (2005). Below the bubble: "Educational triage" and the Texas accountability system. *American Educational Research Journal, 42*(2), 231–368.

Borko, H. (2004). Professional development and teacher learning: Mapping the terrain. *Educational Researcher, 33*(8), 3–15.

Boud, D., & Feletti, G. (1997). Changing problem-based learning. Introduction to the second edition. In D. Boud, & G. E. Feletti (Eds.). *The challenge of problem-based learning* (pp. 1–14). London, England: Kogan Page Limited.

Bolhuis, E. D., Schildkamp, K., Luyten, H., & Voogt, J. M. (2017). Het gebruik van data door lerarenopleiders van de pabo [The use of data in teacher training institutes]. *Pedagogische studiën, 94*(1), 49–70.

Carp, J. (2012). The study of slow. In B. E. Goldstein (Ed.). *Collaborative resilience: Moving through crisis to opportunity* (pp. 99–126). Cambridge, MA: MIT Press.

Daly, A. (2009). Rigid response in an age of accountability: The potential of leadership and trust. *Educational Administration Quarterly, 45*(2), 168–216.

Daly, A. J. (2012). Data, dyads, and dynamics: Exploring data use and social networks in educational improvement. *Teachers College Record, 114*(11), 1–38.

Darling-Hammond, L., Wei, R. C., & Andree, A. (2010). *How high-achieving countries develop great teachers.* Stanford, CA: Stanford Center for Opportunity Policy in Education.

Datnow, A. (2006). Connections in the policy chain: The "co-construction" of implementation in comprehensive school reform. In M. I. Honig (Ed.). *New directions in education policy implementation: Confronting complexity* (pp. 105–124). Albany, NY: SUNY Press.

Datnow, A., & Hubbard, L. (2015). Teachers' use of assessment data to inform instruction: Lessons from the past and prospects for the future. *Teachers College Record, 117*(4), 1–26.

Datnow, A., & Hubbard, L. (2016). Teacher capacity for and beliefs about data-driven decision making: A literature review of international research. *Journal of Educational Change, 17*, 7–28.

Datnow, A., & Park, V. (2018a). Opening or closing doors for students? Equity and data use in schools. *Journal of Educational Change, 19*, 131–152. https://doi.org/10.1007/s10833-018-9323-6.

Datnow, A., & Park, V. (2018b). *Professional collaboration with purpose: Teacher learning towards equitable and excellent schools.* New York, NY: Routledge.

Datnow, A., Park, V., & Wohlstetter, P. (2007). *Achieving with data.* Los Angeles: University of Southern California, Center on Educational Governance.

Desimone, L. M. (2011). A primer on effective professional development. *Phi Delta Kappan, 92*(6), 68–71.

Desimone, L. M., Porter, A. C., Garet, M. S., Yoon, K. S., & Birman, B. F. (2002). Effects of professional development on teachers' instruction: Results from a three-year longitudinal study. *Educational Evaluation and Policy Analysis, 24*(2), 81–112.

EP-Nuffic (2015). *Education system in the Netherlands: The Dutch education system described.* Nuffic: The Hague Retrieved June 2019 from https://www.epnuffic.nl/en/publications/education-system-the-netherlands.pdf.

Farley-Ripple, E., & Buttram, J. (2015). The development of capacity for data use: The role of teacher networks in an elementary school. *Teachers College Record, 117*(4), 1–34.

Garet, M. S., Porter, A. C., Desimone, L., Birman, B. F., & Yoon, K. S. (2001). What makes professional development effective? Results from a national sample of teachers. *American Educational Research Journal, 38*(4), 915–945.

Guskey, T. R. (2009). Closing the knowledge gap on effective professional development. *Educational Horizons, 87*(4), 224–233.

Guskey, T. R., & Yoon, K. S. (2009). What works in professional development? *Phi Delta Kappan, 90*(7), 495–500.

Helle, L., Tynjälä, P., & Olkinuora, E. (2006). Project-based learning in post-secondary education—Theory, practice and rubber sling shots. *Higher Education, 51*(2),

287–314.
Holt, M. (2002). It's time to start the slow school movement. *Phi Delta Kappan, 84*(4), 264–271.
Honig, M. I. (2006). Complexity and policy implementation: Challenges and opportunities for the field. In M. I. Honig (Ed.). *New directions in education policy implementation: Confronting complexity* (pp. 1–24). Albany, NY: SUNY Press.
Honig, M. I., & Hatch, T. C. (2004). Crafting coherence how schools strategically manage multiple, external demands. *Educational Researcher, 33*(8), 16–30.
Huguet, A., Marsh, J. A., & Farrell, C. (2014). Building teachers' data use capacity: Insights from strong and struggling coaches. *Education Policy Analysis Archives, 22*(52), 1–26.
Huguet, A., Farrell, C. C., & Marsh, J. A. (2017). Light touch, heavy hand: Principals and data-use PLCs. *Journal of Educational Administration, 55*(4), 376–389.
Jimerson, J. B. (2014). Thinking about data: Exploring the developemt of mental models for "data use" among teachers and school leaders. *Journal of Studies in Educational Evaluation, 42*, 5–14.
Jimerson, J. B., & Childs, J. C. (2017). Signal and symbol: How state and local policies address data-informed practice. *Educational Policy, 31*(5), 584–614.
Jimerson, J. B., & Wayman, J. C. (2015). Professional learning for using data: Examining teacher needs and supports. *Teachers College Record, 117*(4), 1–26.
Kerr, K. A., Marsh, J. A., Ikemoto, G. S., 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.
Lai, M. K., McNaughton, S., Timperley, H., & Hsiao, S. (2009). Sustaining continued acceleration in reading comprehension achievement following an intervention. *Educational Assessment, Evaluation and Accountability (formerly: Journal of Personnel Evaluation in Education), 21*(1), 81–100.
Lai, M. K., & Schildkamp, K. (2016). In-service teacher professional learning: Use of assessment in data-based decision-making. In G. T. L. Brown, & L. R. Harris (Eds.). *Handbook of human and social conditions in assessment* (pp. 77–94). New York, NY: Routledge.
Lewis, C. (2015). What is improvement science? Do we need it in education? *Educational Researcher, 44*(1), 54–61.
Louis, K. S., Leithwood, K., Wahlstrom, K. L., Anderson, S. E., Michlin, M., & Mascall, B. (2010). *Learning from leadership: Investigating the links to improved student learning, vol. 42*, Center for Applied Research and Educational Improvement/University of Minnesota and Ontario Institute for Studies in Education/University of Toronto50.
Mandinach, E., Friedman, J. M., & Gummer, E. (2015). How can schools of education help to build educators' capacity to use data? A systemic view of the issue. *Teachers College Record, 117*(4), 1–50.
Marsh, J. A., McCombs, J. S., & Martorell, F. (2010). How instructional coaches support data-driven decision making: Policy implementation and effects in Florida middle schools. *Educational Policy, 24*(6), 872–907.
Marsh, J. A., Farrell, C. C., & Bertrand, M. (2016). Trickle-down accountability: How middle school teachers engage students in data use. *Educational Policy, 30*(2), 243–280.
Means, B., Padilla, C., DeBarger, A., & Bakia, M. (2009). *Implementing data-informed decision making in schools: Teacher access, supports and use*(Report prepared for the U. S. Department of Education, Office of Planning, Evaluation and Policy Development). Menlo Park, CA: SRI International.
Merriam, S. B. (2002). Andragogy and self-directed learning: Pillars of adult learning theory. *New Directions for Adult and Continuing Education, 2001*(89), 3–14.
Merriam, S. B., & Tisdell, E. J. (2016). *Qualitative research: A guide to design and implementation.* San Francisco, CA: Jossey-Bass.
Miles, M. B., Huberman, A. M., & Saldaña, J. (2014). *Qualitative data analysis: A methods sourcebook.* Los Angeles: SAGE.
Nichols, S. L., & Harris, L. R. (2016). *Accountability assessment's effects on teachers and schools. Handbook of human and social conditions in assessment.* 40–56.
OECD (2008). *Education at a glance 2008: OECD indicators.* Paris: Organisation for Economic Co-operation and Development (OECD).
OECD (2010). *Education at a glance 2010: OECD indicators.* Paris: Organisation for Economic Co-operation and Development (OECD).
OECD (2016). *PISA 2015 results (Volume II): Policies and practices for successful schools.* Paris: OECD Publishinghttps://doi.org/10.1787/9789264267510-en.
Palmer, D., & Snodgrass Rangel, V. (2011). High stakes accountability and policy implementation: Teacher decision making in bilingual classrooms in Texas. *Educational Policy, 25*(4), 614–647.
Park, V., & Datnow, A. (2009). Co-constructing distributed leadership: District and school connections in data-driven decision-making. *School Leadership and Management, 29*(5), 477–494.
PO Raad (2018). *CAO PO [collective labour agreement primary education 2018/20190].* Retrieved June 2019 from https://www.poraad.nl/themas/werkgeverszaken/cao-po/cao-po-2018-2019.
Poortman, C. L., & Schildkamp, K. (2016). Solving student achievement problems with a data use intervention for teachers. *Teaching and Teacher Education, 60*, 425–433.
Schildkamp, K., Handelzalts, A., Poortman, C. L., Leusink, H., Meerdink, M., Smit, M., ... Hubers, M. D. (2018). *The Data Team™ Procedure: A systematic approach to school improvement.* Cham, Switzerland: Springer International Publishing.
Schildkamp, K., & Poortman, C. L. (2018). Leadership to support and sustain data use in data teams. In E. G. Mense, & M. Crain-Dorough (Eds.). *Data leadership for K-12 schools in a time of accountability (98-118)*. Hershey, PA: IGI Global.
Schildkamp, K., Poortman, C. L., & Handelzalts, A. (2016). Data teams for school improvement. *School Effectiveness and School Improvement, 27*(2), 228–254.
Tschannen-Moran, M., & Gareis, C. R. (2015). Faculty trust in the principal: An essential ingredient in high-performing schools. *Journal of Educational Administration, 53*(1), 66–92.
Vasquez Heilig, J., & Darling-Hammond, L. (2008). Accountability Texas-style: The progress and learning of urban minority students in a high-stakes testing context. *Educational Evaluation and Policy Analysis, 30*(2), 75–110.
VO Raad (2018). *CAO VO 2018/2019 [collective labor agreement secondary education 2018/20190].* Retrieved June 2019 from https://www.aob.nl.wp-content/uploads/2018/10/Cao-voortgezet-onderwijs-2018-2019.pdf#page=5.
Wayman, J. C., Cho, V., Jimerson, J. B., & Spikes, D. D. (2012). District-wide effects on data use in the classroom. *Education Policy Analysis Archives, 20*(25), 1–31.
Wayman, J. C., & Jimerson, J. B. (2014). Teacher needs for data-related professional learning. *Journal of Studies in Educational Evaluation, 42*, 25–34.
Wei, R. C., Darling-Hammond, L., Andree, A., Richardson, N., & Orphanos, S. (2009). *Professional learning in the learning profession: A status report on teacher development in the United States and abroad*Dallas, TX: National Staff Development Council.
Wenger, E. (2011). *Communities of practice: A brief introduction.* Retrieved from http://hdl.handle.net/1794/11736.
Yoon, K. S., Duncan, T., Lee, S. W.-Y., Scarloss, B., & Shapley, K. (2007). *Reviewing the evidence on how teacher professional development affects student achievement (Issues & Answers Report, REL 2007–No. 033)*Washington, DC: US Department of Education Institute of Education Sciences, National Center for Education Evaluation, and Regional Assistance Regional Educational Laboratory Southwest.