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CHAPTER 5

Cutting Through the “Data-Driven” Mantra: Different Conceptions of Data-Driven Decision Making

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High-stakes accountability policies such as the federal No Child Left Behind (NCLB) legislation require districts and schools to use data to measure progress toward standards and hold them accountable for improving student achievement. One assumption underlying these policies is that data use will enhance decisions about how to allocate resources and improve teaching and learning. Yet these calls for data-driven decision making (DDDM) often imply that data use is a relatively straightforward process. As such, they fail to acknowledge the different ways in which practitioners use and make sense of data to inform decisions and actions.

This chapter draws on two studies conducted by the RAND Corporation to answer the broad question: *What are the different ways in which educators use data to make decisions about teaching and learning?* To answer this question, we examine patterns in previously collected data to develop a framework that suggests the nature of DDDM varies with regard to the types of data educators use as well as how they go about analyzing and acting on those data. We then use examples of DDDM from the data to illustrate four models of DDDM that range from simple to complex and to suggest that simple models were more common than complex models. We outline factors that enabled or inhibited various types of DDDM and conclude with the implications of this framework for the national push for DDDM in education.

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What Do We Mean by DDDM?

Background

The need to conceptualize different forms of DDDM emerged from our experiences conducting two RAND studies. The first study focused on district-led efforts to improve teaching and learning—including efforts to use data—in three districts that partnered with an external organization, the Institute for Learning (hereafter, the IFL study).¹ The second study investigated education finance systems—one aspect of which examined how data and knowledge influenced resource decisions (hereafter, the finance study).² As reported elsewhere, the studies found that respondents at all levels (classroom, school, and district) believed that various forms of data were important and useful (Kerr, Marsh, Ikemoto, Darilek, & Barney, 2006; Marsh et al., 2005). For example, in the three IFL districts surveyed, a majority of teachers found data sources—including state and district assessment results—to be useful in guiding instructional decisions, and nearly all principals found these sources of information moderately or very useful for making decisions about instructional matters at their schools. Interview respondents in the finance study were similarly positive about the general practice of DDDM.

Educators across both studies also professed to analyzing data fairly frequently. For example, nearly all of the IFL principal survey respondents reported that they examine student achievement data on a weekly basis. Interviewees across both studies similarly reported using data on a regular basis. Several recited common mantras such as “We are completely data-driven” and “We base all our decisions on data.”

Yet, further probing revealed that educators meant very different things when they claimed to be using data or practicing DDDM. For example, some respondents described a straightforward process of using printouts of state test scores to determine areas of weakness and then targeting additional resources (e.g., staff, funding) to that area of need. Other respondents described a much more complex and ongoing process in which numerous stakeholders triangulated multiple forms of data and collected additional data to uncover underlying causes of patterns observed in the data. They also consulted experts to help them interpret data and decide how to respond.

Despite the fact that they were describing very different processes, these educators used similar terms to describe their DDDM practices. There was not a common understanding among educators of exactly what DDDM entails, or a sufficiently nuanced vocabulary for them to

describe various processes and activities in which they were engaged. The aim of this chapter is to develop a framework that might enable researchers and practitioners to better understand what data are being used and in what ways. More specifically, we seek to answer the following questions:

1. What do educators mean by DDDM? How do their conceptions vary?
2. What factors enable or constrain DDDM processes? Do these factors vary depending on the conception of DDDM being pursued by educators?
3. What are the implications for policy and practice?

Given that the policy environment is demanding that schools and districts become more “data-driven,” this chapter seeks to provide policymakers and administrators with the information they need to further promote and assist schools in implementing one or more types of DDDM.

Methods

To understand how educators conceptualized DDDM, the data from the IFL and finance studies was mined for practice-based examples that could help us elaborate dimensions along which DDDM varies in practice. Across the two studies, we had gathered data from educators in ten districts in four states, including interviews with more than 130 district leaders (central office administrators and board members), 100 school principals, and 80 other school leaders (assistant principals and coaches). We had also collected interview data from 115 teacher focus groups and survey data from 2,917 teachers and 146 principals in the three districts that partnered with the IFL. While none of the data collection efforts focused primarily on data use, they yielded a wealth of instances in which data were being used to make decisions. One limitation, however, is that the studies did not systematically examine whether instruction or student performance actually improved as a result of these decisions.

Analysis of these instances of DDDM took place in two stages. First, all project documents, interview notes, and transcripts were scanned to identify the broad types of data and analyses that educators reported using, the dimensions on which these types of data and analyses varied, and the factors that appeared to enable or hinder educators using data. Second, to further refine our emerging typology of DDDM, we identified a sample of 36 DDDM examples from seven

districts across the two studies for which we had sufficient details related to the dimensions outlined in the emerging framework (see “Conceptualizing Variation in DDDM” for further explanation). Because the framework we present in this chapter was not used for the original data collection, we did not sufficiently probe the various types of data and analyses in all interviews to generate the details necessary to categorize all of the examples of DDDM in our full data set. Given the limited number of examples that were included in the second stage of our analysis, we caution against generalizing our findings and encourage future research to apply this framework to guide data collection and analysis for a larger sample.

A Framework for Conceptualizing DDDM in Education

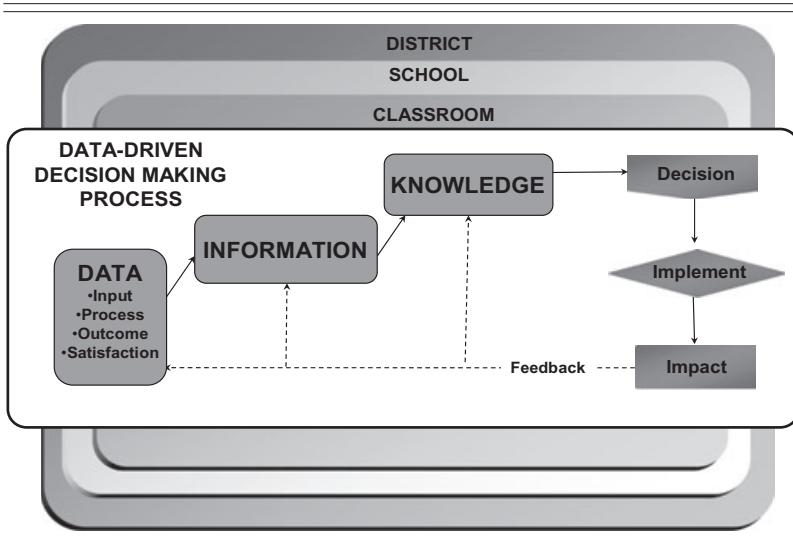
To provide a general definition of the DDDM process, we begin with a framework adapted from the literature. Although useful for providing terminology and an overview, the framework nonetheless fails to describe the ways in which this process can vary in practice. To address these limitations, we turn to our previously collected data to highlight the dimensions along which DDDM varies and present an elaborated framework that distinguishes different models of the DDDM process.

Defining the DDDM Process

DDDM in education typically refers to teachers, principals, and administrators systematically collecting and analyzing data to guide a range of decisions to help improve the success of students and schools.³ The framework presented in Figure 1 (adapted from Mandinach, Honey, & Light, 2006) illustrates how this process requires interpretation, analysis, and judgment. It suggests that multiple forms of data are first turned into information via analysis and then combined with stakeholder understanding and expertise to create actionable knowledge. The first step consists of collecting and organizing raw data. Educators might utilize multiple types of data, including: *input* data, such as school expenditures or the demographics of the student population; *process* data, such as data on financial operations or the quality of instruction; *outcome* data, such as dropout rates or student test scores; and *satisfaction* data, such as opinions from teachers, students, parents, or the community.

The framework suggests that during the second step of the process, these raw data are combined with an understanding of the situation (i.e.,

FIGURE 1
 FRAMEWORK FOR DESCRIBING DDDM PROCESS IN EDUCATION



insights regarding explanations of the observed data) through a process of analysis and summarization to yield information. Next, data users might convert information into actionable knowledge by using their judgment to prioritize information and weigh the relative merit of possible solutions. This knowledge can be used to support different types of decisions that might include: setting and assessing progress toward goals, addressing individual or group needs, evaluating effectiveness of practices, assessing whether client needs are being met, reallocating resources, or improving processes to improve outcomes. Depending on how this DDDM process plays out, similar raw data may point to very different solutions depending on the situation and judgment of data users. Once the decision to act has been made and implemented, new data can be collected to assess the effectiveness of those actions, leading to a continuous cycle of collection, organization, and synthesis of data in support of decision making.

The framework also recognizes that DDDM can be understood within a larger context. First, the types of data that are collected, analyses that are performed, and decisions that are made might vary across various levels of the educational system: the classroom, school,

and district (although not depicted, state and federal levels might also be relevant). Second, conditions at all of these levels might influence the nature of the DDDM process. For example, at a particular level of the system, the accuracy and accessibility of data and the technical support or training might affect educators' ability to turn data into valid information and actionable knowledge.

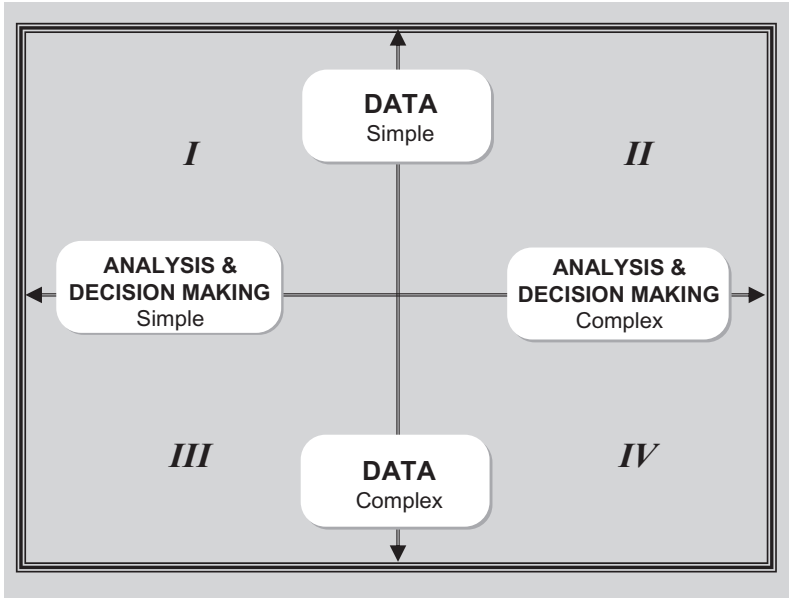
Despite the comprehensiveness of this framework, it fails to capture the nuances and variation that occur when educators go about making decisions in real-world settings with competing demands on their time and attention. DDDM in practice is not necessarily as linear or continuous as the diagram depicts. For example, educators might skip a step or two in this process by relying on intuition; decide to pause the process to collect additional data; draw on one data source or multiple data sources; or engage in the process alone or as part of a group. In the next section, we will draw on our previously collected data to flesh out some common dimensions along which DDDM processes vary in practice to create an elaborated framework for conceptualizing DDDM.

Conceptualizing Variation in DDDM

Based upon examples of data use in our studies, we argue that DDDM can vary along two continua: the type of data used and the nature of data analysis and decision making (Figure 2). This framework does not imply that one form of DDDM is universally better than another. In fact, as discussed later, all forms can be appropriate and useful, depending on the purpose and the resources that are available. While a particular type of DDDM might be more or less appropriate in a given situation, we argue that these evaluations should be made on a case-by-case basis.

Simple versus complex data. In a DDDM process, educators can utilize a wealth of different kinds of data that range from simple to complex. Simple forms of data tend to be less complicated and comprehensive and often only illuminate one particular aspect of the subject at hand or come from only one perspective or point in time. Complex data, by contrast, are often composed of two or more interwoven parts and tend to be more multidimensional. Both quantitative and qualitative data can vary from simple to complex along the following dimensions: time frame (data from one point in time versus trend data); types (one versus multiple types, such as input, process, outcome and/or satisfaction data); source of data (one versus multiple sources,

FIGURE 2
 FRAMEWORK FOR SIMPLE VERSUS COMPLEX DDDM



such as data from multiple individuals or role groups); source of collection (secondary versus primary data); and level of detail (aggregate versus disaggregate data).

Simple versus complex analysis and decision making. Regardless of the type of data used, educators interpret that data and decide how to take action in various ways. These types of analyses and decision making also vary from simple to complex along the following dimensions: basis of interpretation (use of assumptions versus empirical evidence); reliance on knowledge (basic versus expert, such as consulting with advisors); type of analysis (straightforward techniques, such as descriptive analyses, versus sophisticated analyses, such as value-added modeling); extent of participation (individual versus collective); and frequency (one-time versus iterative).

Four quadrants of DDDM. As depicted in Figure 2, a given DDDM process can fall within one of four quadrants depending on the level of

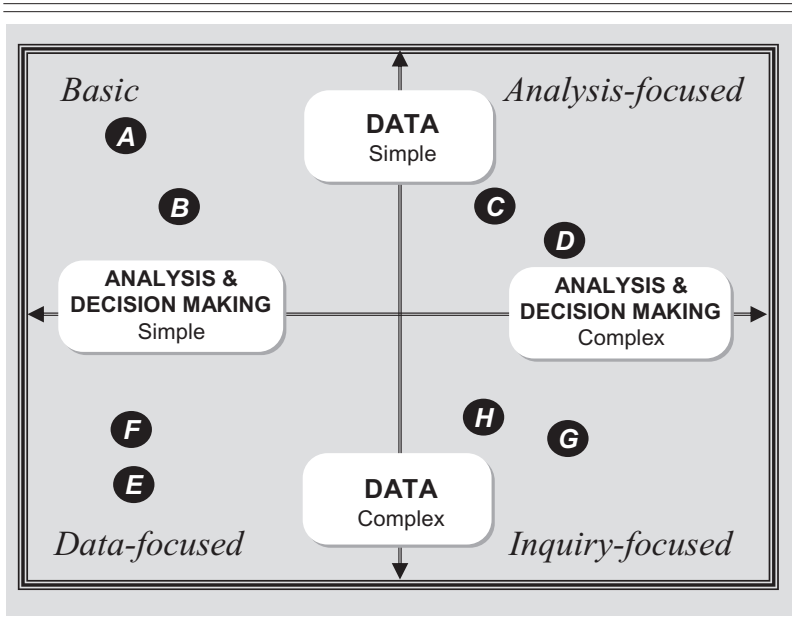
complexity along the two continua. We label these four models of DDDM *basic* (quadrant I), *analysis-focused* (quadrant II), *data-focused* (quadrant III), and *inquiry-focused* (quadrant IV). Basic DDDM entails using simple data and simple analysis procedures whereas inquiry-focused DDDM involves using complex data and complex analyses.

The term “inquiry-focused” was chosen because this term has been used by some researchers (e.g., Copland, 2003; Halverson, Grigg, Prichett, & Thomas, 2005) to describe DDDM processes more complex in nature. Inquiry-focused DDDM, as described in the literature, purposefully utilizes the process as a means of continuous improvement and organizational learning (Feldman & Tung, 2001). It is an explicit process with delineated steps, whereby educators formulate a question—to which they do not have an immediately obvious answer—and then consult data and other forms of evidence to answer the question.⁴ Researchers differentiate this type of DDDM from instrumental approaches such as using test scores to determine which students are eligible for additional services (Murnane, Sharkey, & Boudett, 2005)—an example of using data to make a decision rather than to build understanding and improve the quality of educational services. We illustrate some of these differences in the following section and discuss arguments regarding their relative merit at the end of this chapter.

DDDM in Practice

Given that the original data collection focused generically on whether or not educators were using data—as opposed to the nuances of *how* they were using the data—most accounts in the data lack sufficient detail to be categorized into the four quadrants. For example, we often did not know whether the data had been disaggregated or whether the process included consultation with an expert because we had not probed these specific dimensions. It is also possible that respondents simplified their descriptions for purposes of brevity during the interview process. Therefore, to conduct the analysis of frequencies that follows, we relied on a sample of 36 examples for which we had adequate information to place them into one of the quadrants of the framework (Figure 3).⁵ We were able to categorize these particular examples because we had probed the various dimensions of DDDM (e.g., we had asked clarifying questions regarding the types of data that were used, who was involved in the process) and, where relevant, were able to triangulate these reports across various respondents (e.g., we heard similar accounts of the DDDM process from principals and district

FIGURE 3
EXAMPLES OF DDDM MODELS



leaders). As we discuss, preliminary patterns suggest that, to some extent, educators were employing all four types of DDDM, but that their efforts tended to reflect simpler models.

Basic Models

Fifteen of the 36 examples of DDDM analyzed resembled basic models of DDDM. The vast majority of these examples involved using state test results, as illustrated by examples A and B.

Example A: Targeting teacher professional development on areas of weakness. One elementary school principal reported looking at state test scores that clearly indicated that his students were performing poorly in mathematics. In response, he decided to focus teacher professional development time on strategies for teaching math. In his words, “We take our data and we look at, OK, where are our gaps? And then we focus our professional development on where those gaps are by subject area.” More specifically, he invited a mathematics professional development

provider from his district to lead seminars on instructional strategies in mathematics during the schools' scheduled professional development days. In this example, DDDM relied on one type of data (outcome data), from one point in time, and from a source that was readily available. Further probing revealed that the principal acted alone and decisively in interpreting the data and determining a solution based on a hunch that teacher training would improve math instruction, which would in turn improve student performance.

Example B: Adapting schedules to address areas of need. A central office leader reported that her district encouraged secondary schools to enroll students in two class periods for subjects in which school-wide state test results revealed weaknesses or student subgroups experienced difficulty. As a result, she noted, "some [schools] just double block math because that's their need at their school, where others double block language arts because they've got a huge LEP population." As her example illustrates, schools were using both achievement data and demographic data to design their master schedules. However, further discussion and interviews revealed that this response to the data was based upon one district leader's intuition that the best way to improve achievement was to spend more time on task. Interestingly, some school-level respondents questioned this strategy. In the words of one principal, "We are just giving them more of what doesn't work." These responses and others suggested that the decision had not been the result of a collaborative process and was not based on knowledge of best practices.

Analysis-focused Models

The sample of 36 examples included nine instances of analysis-focused models of DDDM. Although these instances of DDDM also typically relied on state test data, they often involved groups (such as school leadership teams and grade-level teams) and an iterative examination of data (particularly when interim test scores were available). Even though considered complex on collective and iterative analysis dimensions, these examples were less likely to take advantage of expert knowledge, empirical evidence, and sophisticated analysis techniques to interpret and explain the data.

Example C: Differentiating services for low-performing students. One central office leader reported regularly visiting schools to discuss individual student results on the district interim assessments. During

visits, the administrator held meetings with the principal, assistant principal, and school coaches to identify through the data areas of weakness as well as potential services and supports to address individual student needs. In her words, “We sit there and we take one subject at a time and we talk about ‘okay, what can we do here? You know, we need to put these kids in intervention or we need to bring a coach into that teacher’s room and have that coach team teach with her,’ and we have dialogue to decide.” After these meetings, curriculum staff from the central office held follow-up meetings with teachers and principals. They helped develop a pacing calendar of curricular objectives and conducted further analyses of the interim test results and state release test results to identify which objectives needed additional attention. District and school staff also used the data to place students into “intervention groups” for tutoring during the day, after school, and on weekends. The central office administrator also reported following up with weekly school visits to ensure accountability for the decisions made. She explained,

I go out to the schools on a weekly basis to walk through the classrooms but also to talk to the principal. “Okay, show me your groups, show me your this, show me your plan for this and let’s talk about this” . . . [T]hen we just continue to monitor until it’s time for the next [district interim] assessment. Then we start the whole process over again.

Although educators in this example primarily drew on one type of data, the district leader’s description suggests that multiple individuals engaged in an iterative process of examining the test scores and utilized knowledge from school-based experts to interpret and act on the results.

Example D: Using disaggregated data and expertise to adopt literacy curriculum. The principal in this elementary school guided her teachers in a process of disaggregating state test results to find patterns that might explain low literacy scores. Over a series of meetings, teachers offered hypotheses and the principal ran further analyses of test scores to examine the merit of the hypotheses. For example, one teacher noticed that newly enrolled students had stronger skills than her other students and the principal was able to examine whether test score data supported her claim. Through this process, the school discovered that students transferring into the school in kindergarten through second grade were outperforming other students. Knowing that the other schools in the district were using a different curriculum than the one used in their

school, the teachers began exploring how each curriculum was addressing the skill areas that were posing problems for their students. As a result of this process, the staff discovered that their school's curriculum was not as thorough as the other in covering skills, such as letter recognition, that were emphasized by the state standards and assessments. Drawing on the expertise of their school's literacy coaches, the staff decided to develop supplementary materials for these skill areas, and to ultimately adopt the curriculum being used by other schools in the district for the following year. In this example, the school started with existing data, but engaged in further data collection and analysis before ultimately deciding how to respond to the data. Although they had hunches regarding the underlying causes of the data results, educators did not assume that these inclinations were correct. They combined evidence with expertise through a collective process to develop actionable knowledge and identify a solution.

Data-focused Models

The 36 examples included seven instances of data-focused DDDM, in which educators drew on complex forms of data, often as a group, but did so at only one point in time and often did not draw on expert knowledge or empirical evidence.

Example E: Deciding to allocate resources toward reading specialists. When the district awarded this elementary school extra financial resources mid-year, the principal turned to data for direction. He described how his staff drew on multiple types of data (including input, outcome, process, and satisfaction data), some of which his school collected, to focus school improvement efforts and allocate the new funds. The principal and his leadership team examined school-wide test scores and discipline data to determine, in his words, "Where can we make the most difference?" School leaders also convened 41 parent meetings to ask, "What do you need from your child's school? What is it that we can do to make this a better place for your child?" After analyzing the results, the leadership team identified reading as the school's "number one problem" and voted to hire two additional reading specialists. When asked why they chose this option rather than others, such as purchasing new curriculum or materials, the principal responded, "Basically we just felt like the small group instruction and the one-on-one instruction . . . is what would benefit our kids most this year." The principal's description suggests that while his school used complex data, the analysis process was much simpler. Although it was collaborative in

nature, it relied on educators' hunches about the underlying causes of the reading difficulties and how they should be addressed.

Example F: Using surveys to inform resource allocation decisions. One district faced with a budget deficit relied heavily on survey data to determine budget cuts that would minimize the direct impact on students. Central office staff administered surveys to principals, teachers, parents, and community members using an online service to gauge their needs and priorities for district-wide investments. Prior to administering the surveys, a budget committee created a preliminary list of potential areas for trimming based on their preferences as well as from the individuals responsible for those areas on the "chopping block" (e.g., a principal from an alternative high school spoke to the committee about the cuts that she could and could not "live with"). Surveys then asked respondents to select from a final list of services, programs, and staff positions in order to achieve two potential reduction goals: a lower amount that would allow for teacher salary increases (\$1.8 million) and a higher amount that would defer a raise until future years (\$3.2 million). Many district staff members were surprised to discover that respondents overwhelmingly preferred to forgo teacher salary increases in order to protect staff positions such as school librarians and nurses. Based on these data and recommendations from the budget committee, the superintendent and board ultimately voted to cut \$1.8 million from the budget. District leaders noted that without this process of data collection, school staff may not have been as willing to accept the budget decision. As the teacher association president explained,

There was a lot of solicitation from not only . . . teachers, but also parents and community members too . . . And I think teachers found it difficult to make those choices, [but] you know, they were willing to put up with . . . some cuts in benefits if it meant that some of their colleagues would keep their jobs. And I don't think if they had [not] been asked to give their input that they would have felt that way.

In this example, although district staff relied on a sophisticated collection of satisfaction data from multiple stakeholders to make budget decisions, the analysis and action did not utilize empirical or expert knowledge to interpret and explain these data.

Inquiry-focused Models

Finally, we found five instances of inquiry-focused models of DDDM in the sample. These examples represented a significant

investment in time and resources to probe a particular problem of practice. They were often the focus of formal meetings (e.g., district principal meetings, school faculty meetings) or professional development time.

Example G: Improving capacity to support English language learners (ELL). Leaders in one district pursued an inquiry-focused DDDM process after noticing that the low scores of ELL were jeopardizing the district's ability to meet Adequate Yearly Progress under NCLB guidelines. With help from an external organization, the IFL, the district first began examining the underlying causes of poor ELL performance. Using an IFL-developed protocol (called the Learning Walk) to walk through a school's halls and classrooms to collect evidence on current teaching practices, school and district administrators began a series of observations in ELL and non-ELL classrooms across the district. By questioning students, examining their work, and observing instruction and classroom materials, "walkers" systematically collected information on, among other things, the nature and quality of student dialogue and the clarity of instructional expectations. Drawing on these qualitative data and IFL and district expertise regarding best practices for ELL instruction, district leaders concluded that ELL teachers were not instructing ELL students with the same level of rigor observed in the non-ELL classrooms. As the superintendent explained, "Many of my bilingual teachers could only do conversational Spanish. They haven't been trained deep enough." In response, the IFL and district language development experts explored research knowledge regarding rigorous instruction for ELL and crafted professional development opportunities for teachers and administrators. They invited prominent researchers to attend district-wide staff meetings, disseminated books and articles, and convened study groups with "master" ELL teachers who were expected to promote rigorous instruction across the district. Participating master teachers engaged in another process of qualitative data collection and inquiry in monthly meetings: watching videos of instruction, observing each other demonstrating lessons, and discussing ways to inspire ELL students to excel. According to the IFL coach, one participating teacher reported that this process taught her a lot about the importance of "pressing" students, noting

I didn't want to do that because I thought I was being mean to the children. So seeing children being pressed [in classroom observations] was a very important part of . . . what we had to teach about English learners, avoiding the "pobre-

cito” [poor you] syndrome and going in there and demanding that they really do rigorous thinking.

In this example, educators drew on multiple types and sources of data, engaged in a collective effort to examine evidence, and considered expertise as part of an ongoing process of improvement.

Example H: Deciding how to improve high schools. Another district from the finance study engaged in an inquiry process to address perceived problems with its high schools. One district leader summed up this process as “very inclusive [in] trying to get feedback from people about what their needs are and then matching that against what the data is telling us . . . and designing a program.” First, a team of principals, teachers, community members, and district leaders met for more than a year to examine a wide range of data, including student achievement and discipline data. They also convened focus groups with high school students who represented various levels of achievement—from “top performers” to students assigned to alternative campuses for disciplinary purposes—and interviewed school and district leaders to determine their needs and their perceptions of the problems. According to district leaders, this first phase of data collection helped identify “what we need to improve and why we need to improve it.” The second phase focused on “how.” District leaders contracted with a prominent professional development provider and expert on high school reform to help lead this “change process.” The consultant met regularly with staff during professional development days to share research on effective practices in high schools and discuss ways to improve the conditions at schools and the performance of students. The district ultimately adopted an action plan for improvement that included, for example, a set of strategies to address perceived problems with freshmen students—such as requiring ninth graders to start the new school year one day early so that they could become familiar with each other and their teachers, be paired with adult mentors, and experience greater flexibility in selecting courses. Similar to example G above, participants in this DDDM example collectively analyzed multiple sources and forms of data and drew on outside expertise as part of a broad improvement effort.

As these examples illustrate, educators were referring to very different processes when they described using data to drive decision making. Our analysis of 36 instances of DDDM suggests that educators in the case studies tended to pursue basic models. However, we caution against generalizing this finding because of the small number of examples we were able to include in this analysis.

Why do some educators use one model of DDDM rather than another? What enables or constrains particular models of DDDM? In the next section we address these questions, exploring the factors that influence DDDM in general and the various forms it can take.

Factors Affecting DDDM

Across two studies, we found a common set of factors that were important in explaining why educators engaged in DDDM and why some did so with greater levels of complexity than others. To establish these findings, we mined all of our data sources for evidence of factors that enabled or hindered educators in using data. Then we looked to see whether particular factors seemed to be more or less relevant for the various models of DDDM. In general, we found that the factors were relevant to all forms of DDDM, but were particularly salient to more complex models. Within the general discussion of each factor, we highlight how the factor related to more complex models of DDDM.

Accessibility and Timeliness of Data

Across the two studies, access to and timeliness of receiving data greatly influenced individual use. In the IFL study, we found that educators were much more likely to use data in a district that enabled access through an online data system. Even though technological problems limited access on some campuses, most schools had the ability, on site, to see a variety of student data, disaggregate it, run item analyses, and display results in multiple formats. In contrast, school staff in another district had to issue data requests to a district administrator or an outside organization to run the analysis for them. Despite these overall differences, individuals in many districts across both studies commonly complained that state test data were not timely. Many individuals in one district from the finance study, for example, criticized the district's emphasis on using state test results in the school improvement process because they felt these data were out of date and less relevant than other, interim assessment data.

Accessibility of multiple forms of data was a particularly important enabler of educators pursuing complex DDDM processes. We found that educators who were more likely to examine, analyze, and triangulate multiple forms of evidence (e.g., by comparing state test results with local assessment results, survey responses, and student demo-

graphic data) tended to be in states or districts that collected and published data beyond typical achievement, attendance, and demographic summaries. For example, one school engaged in complex data use was able to access parent survey data because the district regularly collected and published these results.

Perceived Validity of Data

School staff in each site often questioned the accuracy and validity of measures. These doubts greatly affected individual buy-in, which past research has identified as an important factor affecting meaningful data use, for the various data sources (Feldman & Tung, 2001; Herman & Gribbons, 2001; Ingram, Louis, & Schroeder, 2004). In one district, some principals and many teachers questioned the validity and reliability of the interim assessments, believing that some tests' quality had changed after the initial administration, or that students were not motivated to perform well. Some educators in other districts voiced similar concerns about state test data, believing the results were not good measures of student skills. As a result, to varying degrees, teachers often reported relying on data other than state test scores to inform their practice.

Interestingly, the validity factor was less of a concern to educators engaging in complex DDDM—probably because they were more likely to use multiple data sources and were more likely to engage in their own data collection to address missing data or data perceived to be invalid. Previous research has found that multiple indicators can alleviate concerns about validity because they provide better balance and more frequent evidence, and reduce the stakes of any single assessment (Keeney, 1998; Koretz, 2003; Supovitz & Klein, 2003).

Staff Capacity and Support

Numerous studies have found that school personnel often lack adequate capacity to formulate questions, select indicators, interpret results, and develop solutions (Choppin, 2002; Dembosky, Pane, Barney, & Christina, 2005; Feldman & Tung, 2001; Mason, 2002). Our study districts are no exception. For example, while a range of data-use skills and expertise in all three IFL districts was observed, capacity gaps were most visible in one district where teachers reported feeling less prepared to use data. Only 23% of teachers responding to surveys in this district reported feeling moderately or very prepared to interpret and use reports of student test results, compared to 36% and 43% in the other two IFL districts. Compounding the reported lack of capacity were

accounts of principals' unwillingness to help teachers with these tasks and professional development that was less focused on data use—which, according to interviews with district leaders, was because appropriate data and data systems were not yet available.

In contrast, the other two IFL districts made stronger district-level investments in supporting school staff with data analysis. They employed several individuals in the district office with strong data analysis skills and tasked individuals to “filter” data and make them more usable for school staff (a strategy found to be successful in several studies, such as Bernhardt, 2003; Choppin, 2002; Herman & Gribbons, 2001). In one district, school-based coaches often took the first step of analyzing test results and presenting them in usable forms to school faculties. Both districts also targeted extra support for data use in the lowest performing schools, frequently presenting state and district assessment data in easy-to-read reports and visiting schools to assist in planning and benchmarking progress.

While all forms of data use required capacity to translate data into information and actionable knowledge, more complex models of DDDM required additional skills, such as being able to craft good questions, design data-collection instruments (such as surveys), disaggregate and analyze existing data to address new questions, and critique research and other forms of knowledge. Complex analysis was enabled by the extent to which expert knowledge existed within the organization or was easily accessible. For example, one school's examination of the underlying causes of poor math scores benefited from the assistance of a district-level math specialist who analyzed test items and explained the math skills tested by each item. She was also deeply knowledgeable about the school's curriculum program and therefore able to point out that the curriculum was not adequately addressing the skills tested by the state assessment. The principal believed that the school would never have reached such a fine-tuned diagnosis of the problem without the math specialist's in-depth knowledge of math content, the curriculum, and the state assessment.

Time

Lack of time to analyze, synthesize, and interpret data also limited DDDM in multiple study sites (a finding consistent with several research studies; see Feldman & Tung, 2001; Ingram et al., 2004). In contrast, when administrators made DDDM a priority during professional development sessions and/or faculty, department, and grade-level meetings, this time enabled the process.

Districts and schools that pursued complex DDDM processes had to allocate valuable time (e.g., common planning time) or create new structures (e.g., study groups) to enable individuals to collectively interpret data and decide what action to pursue. As previous research concludes, adequate time for collaborative inquiry can help educators understand the implications of data for school improvement (Lachat, 2001).

Partnerships with External Organizations

Given the additional time and capacity required by DDDM, schools and districts were more likely to engage in DDDM—both basic and complex data use and analysis—when external organizations, such as universities, consultants, and state departments of education, were available to help them by providing valuable technical assistance and needed resources (see also Feldman & Tung, 2001; Lachat, 2001). We found that information technology companies were able to assist districts primarily by creating data systems that improved accessibility and timeliness of data. One state invested in a data management system that made demographic, achievement, and resource data easily available to schools.

External organizations were particularly helpful in facilitating more complex forms of DDDM by assisting educators in the process of transforming raw data into information and actionable knowledge. In one district, all high schools had access to technical support from an external data management organization, which sent a representative to meet with school-based teams to review existing data; craft inquiry questions; design, collect, and analyze new data; and facilitate conversations aimed at transforming information into actionable knowledge—the types of activities illustrated by examples G and H.

Tools

Several users of complex DDDM processes strongly emphasized the importance of tools and processes, which often came from external organizations, in guiding the overall inquiry process. For example, one district in our finance study used a protocol developed by an external organization to guide participants through explicit DDDM “steps” (e.g., how to identify the problem or how to prioritize solutions based on analysis). As mentioned earlier, the IFL offered tools to facilitate systematic observations of instruction, including protocols for recording information, rubrics for comparing these data to notions of best practices, and worksheets and procedures to guide reflections and action

steps. The IFL and other organizations also provided protocols to help educators examine student work (e.g., essays) as a source of process data (about the quality of instruction) and a source of outcome data (about student knowledge and skills).

Even when examining simple data, educators valued data dashboards that summarized data and data software systems that allowed them to manipulate and display raw data. Educators also benefited greatly from processes and tools for gathering additional data. For example, the district in example F that regularly administered surveys benefited greatly from an online, inexpensive survey service.

Organizational Culture and Leadership

The culture and leadership within a school or district influenced patterns of data use across sites. Administrators with strong visions of DDDM who promoted norms of openness and collaboration greatly enabled data use in some places, whereas other districts with entrenched organizational beliefs that instruction is a private, individual endeavor constrained the inquiry process. Other studies have consistently found that school leaders who are able to effectively use data for decision making are knowledgeable about and committed to data use in their schools (Choppin, 2002; Copland, 2003; Feldman & Tung, 2001; Herman & Gribbons, 2001; Lachat & Smith, 2005; Mason, 2002) and that the existence of professional learning communities and a culture of collaboration facilitate DDDM (Chen, Heritage, & Lee, 2005; Holcomb, 2001; Keeney, 1998; Lachat & Smith; Symonds, 2003).

A trusting, data-driven culture was a particularly important enabler of complex DDDM in the districts across our two studies. Several respondents explained that complex processes involved digging beneath the surface to develop deeper understandings of the underlying causes of problems, and involved asking tough questions like, “Why did one teacher’s students come closer to meeting standards than another teacher’s students?” Respondents told us that teachers had to be willing to acknowledge both strengths and weaknesses and be willing to openly discuss these with colleagues. In addition, organizational cultures that viewed accountability as helpful rather than threatening enabled complex DDDM processes. In data-driven cultures, colleagues were willing to constructively challenge each other to provide evidence for claims made during an inquiry process—and these challenges were viewed as fruitful efforts to deepen the rigor of the DDDM process.

Federal, State, and Local Policy Context

The NCLB Act has created strong incentives for districts around the country to examine student achievement data and gauge student and school progress at meeting standards. Some districts have also experienced pressures from long-standing state accountability systems aimed at developing school and student measures of achievement. These districts operated for years in an environment with strong incentives to carefully analyze student learning and test scores at student and classroom levels, which may have contributed to the greater accessibility of comprehensive data and a stronger motivation and capacity to analyze data in this way. Federal and state policies, however, have tended to emphasize the value of standardized achievement test data and have not necessarily encouraged the use of multiple sources and types of data.

Other state and local district policies encouraged educators to focus narrowly on state test data, particularly requirements to conduct annual school improvement planning processes. Guidelines for these plans typically required schools to identify actions that would be taken to improve teaching and learning, and to justify the proposed actions with data. However, the format of these school improvement planning processes typically did not ask schools to make the processes by which data were interpreted and transformed into actionable knowledge explicit. Educators also reported that short time frames for school improvement planning often prevented them from being as thorough and collective as they preferred to be.

In summary, these various factors were generally important in enabling or constraining DDDM, particularly complex forms of DDDM, and as we discuss in the next section, policymakers may need to pay greater attention to them if they are interested in promoting DDDM.

Summary and Discussion

This chapter illustrates that DDDM is not a monolithic, straightforward activity. To the contrary, DDDM varies along a set of dimensions that range from simple to complex. That is, the data used in DDDM might vary in the way they were collected (drawing on one or more sources, relying on previously collected data or primary sources), the points in time they represent (one time versus longitudinal), their type (outcome, process, input, satisfaction), and the level of detail and comprehensiveness (aggregated versus disaggregated). Analysis and

decision making based on these data can also vary in the way they are conducted (collective versus individual), the extent to which they rely on evidence, expertise, and sophisticated analysis techniques to explain data patterns and identify next steps, and the frequency of the work over time (one time versus iterative). Depending on where a particular DDDM process falls along these two continua, it can be characterized as one of four types: basic, analysis-focused, data-focused, or inquiry-focused.

These distinctions are important to consider for several reasons. Even though some of the policymakers in our studies explicitly promoted inquiry-focused models of DDDM, their efforts were stymied by perceptions among educators that they were already “doing it.” Although we found instances of all four models being used in practice, educators in the sample tended to use simpler forms that focused on narrow types of data—primarily state test scores—and limited analysis procedures. Although these educators professed to being “totally data-driven,” it was not clear they understood that being data-driven could also mean something very different from what they were pursuing. Some research suggests that reliance on simple analyses can be problematic because this may lead to erroneous conclusions, particularly when educators lack statistical knowledge for interpreting quantitative data (Confrey & Makar, 2005; Streifer, 2002).

This is not to say that educators should be encouraged unilaterally to pursue complex DDDM—there is a time and place for all four models. For example, in providing technical assistance to schools engaged in DDDM, Herman and Gribbons (2001) found that simple data and analyses were sufficient for answering all of their questions. Celio and Harvey (2005) suggest that “less may be more” (p. 71) and warn that some educators are feeling overwhelmed by the volume and complexity of the data currently available.

Although we caution against evaluative judgments regarding simple versus complex models, it is worth noting that the literature on DDDM tends to emphasize the value of engaging in inquiry-focused DDDM. Research findings suggest that DDDM is more powerful and useful to educators when multiple forms of data are used (Choppin, 2002; Keeney, 1998; Mason, 2002; Supovitz & Klein, 2003) and when analysis processes involve a collaborative and iterative approach that uses empirical evidence and expert knowledge to interpret results (Choppin, 2002; Feldman & Tung, 2001; Ingram et al., 2004; Lachat, 2001). Feldman and Tung found that the inquiry process not only resulted in improved student achievement, but also led to a more professional culture where

teachers became more reflective and also modeled the kinds of behavior they wanted students to practice. This emerging literature *suggests* that the inquiry process can be a means for building capacity for school improvement (Copland, 2003) in addition to enabling better decision making.

While the data do not allow us to empirically evaluate which type of DDDM is most effective, the findings do point to a set of conditions that are important to enabling DDDM broadly, and suggest how they may be particularly relevant to inquiry-focused forms of DDDM. We discuss these implications in the following section.

Implications for Policy and Research

If policymakers want to encourage educators to pursue DDDM—particularly more complex forms—they should focus policy supports on the enabling conditions outlined in this chapter. More specifically, they should consider:

- *Acknowledging that DDDM is not a straightforward process.* Policymakers might take care that their policies do not assume that data are readily available and unambiguously point to clear courses of action. Furthermore, policymakers might allocate more time—or extend planning time frames, such as school improvement planning schedules—so that educators can deeply examine the data available to them and can collaborate in interpreting data and deciding actions;
- *Improving the availability, timeliness, and comprehensiveness of data.* State and local policymakers might consider investing in systems and technology that facilitate data gathering and easy, timely access to results. Given that many state and local educational agencies have already made this sort of investment with regard to quantitative student outcome data, they may want to consider broadening these efforts to include collection and management of quantitative and qualitative data regarding inputs, processes, and satisfaction levels;
- *Providing professional development aimed at building educators' capacity to examine data and conduct research and act on these findings.* Policymakers might provide focused training to help educators develop data analysis skills (e.g., how to interpret test results). However, it is equally important to build educators' capacity to pose important questions, collect additional data, and determine

appropriate action based on data analysis—which can be more challenging and require more creativity than the analysis; and

- *Helping educators access external partners, expertise, and tools.* Policymakers might consider partnering with organizations that can help with data collection and analysis, as well as organizations that can assist in building educators' capacity to examine and act on data. They might also consider facilitating educators' access to expertise—which can be internal (e.g., district-based curriculum experts) or external (e.g., university-based curriculum experts)—to assist educators in interpreting data and deciding appropriate action. Finally, policymakers might provide or assist educators in accessing tools and protocols that can guide various steps in the DDDM process or the overall process itself.

These recommendations notwithstanding, a new conceptualization of various models of DDDM raises several questions that should be addressed by future research:

- *Which models of DDDM are better and for which purposes?* The literature suggests that inquiry-focused models are preferable, but this claim has not been sufficiently tested empirically. Since our research did not systematically collect evidence regarding the outcomes of DDDM (i.e., did decisions ultimately change practice and improve student performance?), we do not have sufficient evidence to advise policymakers and educators on whether and how these models might influence teaching and learning.
- *What are the relative costs and benefits of pursuing one model rather than another?* Efforts to engage in complex models of data use tend to require more labor and time to collect and analyze data, and likely entail greater costs to provide needed support and infrastructure. Further research is needed to inform policymakers of the relative benefits and costs of particular DDDM approaches.

Answers to these questions, and others, can advance our understanding of DDDM and the extent to which it can leverage educational improvement.

NOTES

1. This research on district-led instructional improvement efforts was funded by the William and Flora Hewlett Foundation and took place between 2002 and 2005. For further details, see Marsh et al. (2005).

2. We conducted this research on school finance reform with researchers at the University of Washington in 2005. The study was supported by the School Finance Redesign Project at the University of Washington's Center on Reinventing Public Education, through funding by the Bill & Melinda Gates Foundation, Grant No. 29252. For details see <http://www.schoolfinanceredesign.org/>.

3. These notions are modeled on successful practices from industry and manufacturing—such as Total Quality Management, Organizational Learning, and Continuous Improvement—that emphasize that organizational improvement is enhanced by responsiveness to performance data over time (e.g., Deming, 1986; Juran, 1988; Senge, 1990). The concept of DDDM in education is not new and can be traced to debates about measurement-driven instruction in the 1980s (Popham, 1987; Popham, Cruse, Rankin, Sandifer, & Williams, 1985); state requirements to use outcome data in school improvement planning and site-based decision making processes dating back to the 1970s and 1980s (Massell, 2001); and school system efforts to engage in strategic planning in the 1980s and 1990s (Schmoker, 2004).

4. A number of different inquiry-focused models exist, each offering its own set of prescribed steps. For examples, see the Data-Driven Instructional System described by Halverson et al. (2005) and the Bay Area School Reform Collaborative's inquiry process described by Copland (2003).

5. Although we have no way to definitely determine whether these examples are representative of those in the larger data set, we note that they come from both studies and nearly all of the districts in the original sample. Moreover, all school-level examples come from different schools: no one school accounts for more than one example. Thus, we do not believe any one study, district, or school biases the examples. We have no reason to believe that these 36 examples are in any way different from the larger set of examples that arose in the larger data set.

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