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PRESIDENTIAL ADDRESS

A Perfect Time for Data Use: Using Data-Driven Decision Making to Inform Practice

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Data-driven decision making has become an essential component of educational practice across all levels, from chief state school officers to classroom teachers, and has received unprecedented attention in terms of policy and financial support. It was included as one of the four pillars in the American Recovery and Reinvestment Act (2009), indicating that federal education officials seek to ensure that data and evidence are used to inform policy and practice. This article describes the emergence of data-driven decision making as a topic of interest, some of the challenges to and opportunities for data use, and how the principles of educational psychology can and must be used to inform how educators are using data and the examination of its impact on educational practice.

Data-driven decision making (DDDM) pertains to the systematic collection, analysis, examination, and interpretation of data to inform practice and policy in educational settings. It is a generic process that can be applied in classrooms to improve instruction as well as in administrative and policy settings. It can be applied by teachers, principals, superintendents, other administrators, data entry clerks, chief state school officers, and federal education officials. DDDM crosses all levels of the educational system and uses a variety of data from which decisions can be made. These include instructional, administrative, financial, personnel, transportation, welfare, health, demographic, perceptual, behavioral, process, and other kinds of data.

As is described next, data and DDDM have become important in education within the past decade because of the increasing emphasis on rigor, as espoused by the U.S. Department of Education and the Institute of Education Sciences (IES), in practice and research. It is no longer acceptable to simply use anecdotes, gut feelings, or opinions as the basis for decisions. Just as Gage (1978) noted that there is both a science and an art to teaching, so too is there a place for both rigor and experience in the decision-making process. The emerging emphasis is placed strongly on the use of data and hard evidence from which to inform practice.

As an example of DDDM, consider the following.[1] A rural district was trying to understand why a particular subset of students was struggling academically. Teachers and other district and building administrators looked for explanations in student performance data, medical records, behavioral data, attendance, and other less quantitative information. No meaningful correlations emerged. Administrators began to examine what might seem to be unrelated data, including transportation data, where they finally found a direct connection. The students who were having the most difficulty were those who had the longest bus commute. Because of this finding, administrators modified the transportation arrangements to shorten the time students spent on the bus and to provide more productive time when students could concentrate on work. Other districts have identified similar issues. To address the problem, another school district actually installed wi-fi on their school buses to facilitate students'

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[1]I thank Diana Nunnaley from TERC's Using Data project for this example.

ability to do their homework during their commute (Dillon, 2010). Without the interrogation of the data and the ability to link student performance data with the transportation data, the district would not have been able to make progress on this problem.

CURRENT POLICY TRENDS

DDDM is not new, nor is the quest for using evidence in education to make decisions. Policymakers and educators have been debating the use of data, such as high-stakes tests results, for decades. I maintain that effective teachers and administrators have been using data for many years, but the process was neither systematized nor automated. Teachers scan their classes for signs of understanding or misconceptions. They ask questions. They observe their students. They examine student work products. All of this is DDDM. Typically, the teachers might process the information in their heads to determine next steps. But now there are technologies that can assist them in this process. There is no question that data now are proliferating, and new sources of data continue to emerge. The pressure on educators to use data is increasing, as is the public and policy rhetoric around DDDM.

When IES was created as the research branch of the U.S. Department of Education, its new leaders argued that it was time for the field to increase its rigor and become an evidence-based discipline (Whitehurst, 2003). The No Child Left Behind Act (2001) required the use of rigorous research methodologies and educational practice based on research findings. The What Works Clearinghouse (WWC) was created as a repository of studies to which educators could look to seek interventions or practices that were deemed[2] methodologically rigorous. A by-product of these efforts, critics argued, was an unbending pursuit of rigor without sufficient consideration for realism (ecological validity), relevance, and the practicalities of education (Schneider, 2009). Critics also argued that IES was devaluing methods that are in fact valuable in helping to understand the teaching and learning process. Many educational researchers, including me, agree that there must be an appropriate balance struck and that methods must align with questions. The American Educational Research Association (2003) passed a resolution to that effect. Even Easton (2009), upon his appointment as IES director, noted that rigor must be balanced by relevance. Without relevance, the rigor does no good.

The quest for rigor also impacted educational practice from state education agencies (SEAs) to school districts and ultimately to classrooms in the name of accountability and compliance. No Child Left Behind mandated increased attention to the provision of many kinds of data, much of which were measures of student learning that could be used to hold schools accountable. More emphasis was placed on whether a district achieved adequate yearly progress than how individual students were progressing to improve their skills and knowledge. Districts are required to collect data to show they are in compliance with the law; these data are transmitted to the SEA, which in turn sends the data to the U. S. Department of Education. Districts often see these data as having little to do with helping to improve teaching and learning directly, however (Mandinach, 2009b; Smith, 2009). Student performance data are typically state summative assessments that often have tangential links to instructional practice. Only a few states, such as Delaware and Arkansas, maintain more locally relevant data in their statewide longitudinal data systems (SLDS). Thus, an abyss has been created between data for compliance and data to inform teaching and learning. Margaret Spellings (2005), the Secretary of Education from 2005 to 2009, summarized the compliance position:

> Information is the key to holding schools accountable for improved performance every year among every student group. Data is [*sic*] our best management tool. I often say that what gets measured, gets done. Once we know the contours of the problem, and who is affected, we can put forward a solution.

More recently, policymakers have begun to emphasize the need for a fundamental philosophical shift from data for compliance to the principles of data for continuous improvement. This perspective shifts the focus away from schools and districts achieving adequate yearly progress to helping all students to learn. According to Arne Duncan (2009b), the current Secretary of Education, "I am a believer in the power of data to drive our decisions. Data gives us the roadmap to reform. It tells us where we are, where we need to go, and who is most at risk." Duncan continued,

> Our best teachers today are using real time data in ways that would have been unimaginable just five years ago. They need to know how well their students are performing. They want to know exactly what they need to do to teach and how to teach it.

This position implies a paradigm shift for teachers that would have direct implications for their practice. Data would no longer be used just to hold people and schools accountable. Instead, data would be used to stimulate and inform continuous improvement, providing a foundation for educators to examine multiple sources of data and align appropriate instructional strategies with the needs of individual students. John Easton (2009), the current director of IES, has explicitly stated that he sees the use of data as the means by which schools will improve. Thus, from the classroom to the school, to the district, to the SEA, and to the federal government, data are being viewed as the impetus for educational improvement.

[2]The WWC created standards by which studies are reviewed and identified as rigorous. See http://ies.ed.gov/ncee/wwc/references/idocviewer/doc.aspx?docid = 19&tocid = 1.

A PERFECT TIME FOR DATA USE

This article is intended to provide a context for the growing emphasis on DDDM in educational practice. It considers data-driven practice, writ large, but with a particular emphasis on instructional decision making. The article describes a conceptual or theoretical framework for educational DDDM. It also explores some of the many challenges to the implementation of data use, including policy, practice, methodological, and theoretical issues.

As previously noted, policymakers in the U.S. Department of Education have mandated that educators use data to inform their practice. Both researchers and practitioners are trying to respond to this mandate. Educators must begin to use data-driven practices but first must become data literate in order to use data effectively. Researchers can begin to conduct rigorous studies of data use as districts, schools, and classroom enculturate DDDM as a common practice. Researchers have begun to understand the components that are needed to form a data culture and to theorize about the skills and knowledge needed for the use of data. This article explores these issues and raises for discussion some of the pressing challenges that face educators, policymakers, and researchers. It is not intended to provide an extensive review of the literature (see Hamilton et al., 2009; Kowalski & Lasley, 2009; Mandinach & Honey, 2008; Moss, 2007). The article also explores the role that educational psychology can play in moving the field forward, both in terms of practice and research.

Contextual Information

Not only has there been recent attention from policymakers about the importance of DDDM, but there also has been a growing body of literature addressing the topic. For example, four edited volumes have been devoted to the use of data in educational settings (Herman & Haertel, 2005; Kowalski & Lasley, 2009; Mandinach & Honey, 2008; Moss, 2007), as well as two special issues of journals (Wayman, 2005b, 2006), and a national study funded by the U.S. Department of Education (Means, Chen, DeBarger, & Padilla, 2011; Means, Padilla, & Gallagher, 2010).

In addition, IES included a guide for DDDM among its practice guides (Hamilton, et al., 2009) and the Doing What Works website (see http://dww.ed.gov/topic/?T_ID=30), speaking to the topic's growing importance.[3] Practice guides provide an in-depth examination of a particular topical area, such as turning around low-performing schools, dropout prevention, and Response to Intervention in mathematics. Panelists (research and practice experts) review existing literature and apply the WWC standards for rigorous research to the reviewed studies (IES, 2011). For the practice guides, randomized controlled trials are the gold standard. Strong studies are considered those with high internal and external validity. Moderate evidence is defined as studies that have high internal validity and moderate external validity. The low level of evidence is based on "expert opinion derived from strong findings or theories in related areas and/or expert opinion buttressed by direct evidence that does not rise to the moderate or strong level" (Hamilton et al., 2009, p. 3). The guides then identify recommendations for practitioners based on the evidence. Each recommendation contains action steps and challenges to practice. The Doing What Works website takes information from practice guides and adds interviews with the panelists and with practitioners, resource materials, and examples of how the recommendations can be made actionable. The website serves as an excellent resource for practitioners.

Definitions to set the stage. DDDM tends to mean different things to different people. The data people use may differ. The interpretations may differ. Even the same data may mean different things to different people. Data, in and of themselves, are meaningless. They are simply numbers. Data gain meaning through context (Mandinach, Honey, Light, & Brunner, 2008; Williams & Hummelbrunner, 2011).

A confluence of events is occurring in which DDDM can become a reality on a large-scale basis in education. Data are proliferating and are not going to disappear. Educators are not only being confronted with more data but with different kinds of data from multiple sources. Many think only of achievement data (this is the focus of the IES Practice Guide; Hamilton et al., 2009). But there is a broad range of kinds of data that can be used. Educators therefore must find ways to use the full range of data effectively to inform their practice. Data may be used for instructional or administrative decision making. Different educators will use different data depending on their roles. Further, the same data will likely have different meanings and uses depending on the position of the user. For example, annual state assessment results will be used differently by a classroom teacher than by a district administrator, or even by state or federal officials.

DDDM is not just about the numbers or the data. It is about making actionable the data by transforming them into usable knowledge (Mandinach et al., 2008; Williams & Hummelbrunner, 2011). Some educators understand the data more in terms of simple statistical properties. Effective data use requires going beyond the numbers and their statistical properties to make meaning of them. Teachers who engage in DDDM must translate the data into actions that inform instruction. The ability to transform data to instructional action is called *pedagogical data literacy* (Mandinach, 2009a, 2009b, 2010b) or *instructional decision making* (Means et al., 2011). It entails combining the pedagogical content knowledge (Shulman, 1986) that teachers bring to an instructional event and their knowledge about how the data can be used to impact classroom practices and instruction to affect change in student learning and performance.

[3]IES administrators select topics that they seem particularly relevant to practice for these guides.

For example, consider a teacher who is given data that indicate that some of her students are struggling with the concept of understanding fractions as parts of unit wholes. The teacher examines the data, trying to identify the reasons why the students responded in certain ways on an assessment that indicate misconceptions or alternative conceptions. Based on her hypothesis about why the misconceptions have occurred, she puts into place an instructional strategy to remediate the problem and monitors subsequent student performance to determine if the instruction is correcting the learning deficits. Thus, what the teacher has done is (a) identify a student learning problem through the examination of relevant data, (b) verify the causes of the learning problem, (c) generate possible solutions strategies, and then (d) implement the instructional strategies and monitor their outcomes (Love, Stiles, Mundry, & DiRanna, 2008).

As previously noted, the use of data by educators is not new. Teachers and administrators have been using data for a long time. Teachers have been accumulating all sorts of data about their students, typically in less than systematic ways over time (Hamilton et al., 2009). That said, there is a growing recognition that the use of data to inform practice must be systematized and enculturated (Hamilton et al., 2009; Mandinach, 2009a, 2009b). Teachers need to integrate data and experience to inform their practice. Just as patients expect their physicians to use data from which to make medical diagnoses, so too should educators be expected to use concrete evidence from which to determine instructional or administrative actions (Shulman & Elstein, 1975).

IES practice guide recommendations. IES has recognized the growing importance of data use in education, particularly around student achievement data to improve instruction and therefore student performance. A panel of five researchers and one practitioner was convened and reviewed the existing literature. The outcome was a practice guide on data use that presents five recommendations (Hamilton et al., 2009). The guide focuses on recommendations aimed at the classroom, school, and district levels, synthesizing and translating existing research deemed rigorous in terms that are readily understandable to a lay audience.

The first recommendation is that data should be "part of an ongoing cycle of instructional improvement." The cycle supports the notion that educators will collect a variety of data, interpret those data and develop hypotheses about how to improve student learning, and then make appropriate modifications to instruction to test the hypotheses and increase student learning. As previously noted, this document has limitations. It restricts the kinds of research synthesized and limits its scope to achievement data, whereas my argument is that data should be considered more broadly. Yet this recommendation reflects Education Secretary Duncan's (2009a, 2009b, 2009c) call for using data for continuous improvement, not just for compliance and accountability. It also reflects the recognition that the data inquiry process is iterative, as previously noted in this article (Abbott, 2008; Ikemoto & Marsh, 2007; Mandinach et al., 2008; Means et al., 2010).

Consider, for example, a district that is trying to identify early warning indicators for dropout prevention. The district might examine the relationship between 1st-year students' absences or course failure and the probability of dropping out. Data would be collected and analyzed. A hypothesis about the cause and effect would be developed. The district then might put into place an intervention to increase attendance or improve performance. Outcomes would be monitored through an ongoing evaluation process that would allow for modifications to the intervention. Thus, there is a cyclical process of collecting and examining data, and applying the results in a feedback loop.

The second recommendation is that students should be taught by their teachers to examine their own data (such as test scores and classroom assignments) and to set their own learning goals. Expectations for student learning should be made clear to students, and feedback should be provided in a clear and timely manner. One has to question how realistic this goal is for all students, especially those most challenged and those who may lack self-regulatory skills (Schunk & Zimmerman, 1994, 1998; Zimmerman & Schunk, 2001). Yet self-regulation theorists might also posit that the skills needed for such self-monitoring can be taught to many students.

Students can be taught to be their own data-driven decision makers through a four-step process. Teachers can help them to understand the assessment criteria against which they will be measured and the expectations for achievement that the teachers have set. Teachers must provide timely feedback that is specific, well formatted, and constructive. They must also provide tools that enable students to learn from the feedback, such as a template with learning strengths and weaknesses. Finally, teachers can help students use their own data analyses to inform student learning and to modify instruction. These steps are a summarization of findings from the IES Practice Guide (Hamilton et al., 2009).

The third recommendation is that there must be an explicit vision for how data should be used throughout a district (Datnow, Park, & Wohlstetter, 2007). Moreover, the superintendent must make clear the expectations for and purposes of data use. This recommendation also pertains to school-level data use, with which the principal is expected to provide leadership around data-driven practices (Choppin, 2002; Feldman & Tung, 2001; Herman & Gribbons, 2001; Ikemoto & Marsh, 2007; Knapp, Copland, & Swinnerton, 2007; Lachat & Smith, 2005; Long, Rivas, Light, & Mandinach, 2008). The vision should be clear and aligned across levels of a district. The absence of a vision can be a barrier to data use (Means et al., 2010).

Typically, a vision might be that all educators will use data to help address the learning needs of individual students. The principal might make explicit statements about how important data are; that teachers must use the data; and then model data use through communications with the teachers, the community, parents, and other stakeholders. Evidence of the vision might be found in the provision for resources to support data-driven practices, such as the creation of common planning time, data teams, or data coaches. Resources may also include incentives, the provision for professional development, and release time to examine data. At issue here is the extent to which educational leaders are empowered, prepared, trained, and sufficiently knowledgeable to articulate and implement a vision.

Take, for example, a school district that mandates use of data. The district requires all of its candidates for principal positions to take an authentic assessment in which they must examine a data set and create a school improvement plan based on those data. The district also makes personnel decisions on whether administrators promote data use. In one school in the district, the teachers know that their current principal does not care about data use, nor does he understand how to use data. This position is communicated both through actions and words. Teachers take their cues from the principal and see no reason to use data to inform their practice. Yet in another school, the principal ensures that all teachers are using data. She speaks, using data. She communicates to parents and stakeholders, using data. She works with teachers to use data. She has made explicit the expectation that all educators in the building will use data to help all students achieve to their potential. The vision of the district to use data is made clear when the first principal was removed because of his failure to provide a positive role model for his staff. The second principal was rewarded for helping to turn around a low-performing school through the use of data.

The fourth recommendation is that supports and resources must be provided to establish and sustain a data culture within schools (Datnow et al., 2007). A data culture is a

> learning environment within a school or district that includes attitudes, values, goals, norms of behavior and practices, accompanied by an explicit vision for data use by leadership for the importance and power that data can bring to the decision-making process. (Hamilton et al., 2009, p. 46)

The creation of a data culture is a direct result of the vision for data use. Researchers contend that a school should have a data coach or data facilitator who takes the lead in assisting educators' work with data (Armstrong & Anthes, 2001; Datnow et al., 2007; Wayman, Cho, & Johnston, 2007). This person is often the principal, an instructional leader, or an experienced teacher. The data coach can lead a data team, or a collaborative group of teachers around the examination of data (Datnow et al., 2007; Feldman & Tung, 2001; Halverson, Pritchett, & Watson, 2007; Knapp et al., 2007). In addition, it is important to structure and provide for collaborative planning time during which the data teams can examine data and develop instructional strategies (Ingram, Louis, & Schroeder, 2004). Other resources include the development of a data plan (Armstrong & Anthes, 2001; Mason, 2002) that can be incorporated into the school improvement plan, strong leadership that can support work around data (Long et al., 2008: Wayman et al., 2007), and the provision for professional development (Choppin, 2002; Feldman & Tung, 2001; Ikemoto & Marsh, 2007; Mandinach, 2009a; Mandinach & Honey, 2008; Mason, 2002). Districts also can provide technical experts, data dashboards,[4] instructionally sensitive assessments (Means et al., 2010), and time to focus on data (Ikemoto & Marsh, 2007; Ingram et al., 2004; Mandinach, 2010a). Although some educators believe that *data* is the new four-letter word in education, to others *time* is the actual enemy. There simply is not enough of it. However, with sufficient experience, data practices may become increasingly routinized.

Another challenge is the scarcity of resources. Funds to support release time, incentives, professional development, and other needed resources may be difficult to obtain. The commitment to providing much needed planning time, where teachers can investigate and discuss data collaboratively, may be a challenge due to contractual agreements with unions.

An example of successful implementation of the fourth recommendation can be found in a district that modified its academic schedule and created class-free Wednesday afternoons during which educators meet to examine data. Data teams were created within schools either at the grade level or course level. The "Wednesdays Out," as they are called, provided the opportunity for teachers to come together, examine student data, identify performance trends and individual needs, and discuss how to modify their instruction to address students' learning needs.

The final recommendation is to develop and implement a district-wide data system. As noted earlier, technology is a key component to establishing data use. Because of the proliferation of data, every district now needs to have a technology application to help it collect and analyze data and report results. Acquiring such data systems requires input from stakeholders about needs and how data should be used and the kinds of technology that can best support the data work (Wayman, 2005a, 2007). Not having technology to support DDDM is no longer an option because there is too much data to handle manually. Yet costs can be prohibitive, especially for the smallest districts.

Technological solutions to support DDDM can include large data warehouses (Long et al., 2008) or small solutions such as handheld computers that deliver diagnostic assessments (Hupert, Heinze, Gunn, & Stewart, 2008). A district could use something as simple as a spreadsheet or have more than 80 different applications and tools that support data use (Wayman et al., 2007).

[4]A data dashboard provides organization and the display of key data and information on educators' desktops in easily understandable and accessible formats.

Consider, for example, a large, urban district that was able to obtain funding to customize its own technological solutions to its data needs. The district developed two large data systems. One was a data warehouse in which resides the bulk of their data on student performance, demographics, attendance, and much more. The district also developed an assessment system that helps teachers create tests; administer and score them; and analyze, interpret, and report the results. Another district has built a separate data warehouse and student information system. Other districts have purchased commercial systems and suites of systems that merge the functions of the different types of data systems. The most important feature, though, is the alignment of the system with a district's objectives.

KEY COMPONENTS OF DATA-DRIVEN DECISION MAKING

There are at least two key components to the implementation of DDDM in educational settings. First, as noted in the Practice Guide, technological tools are being developed to support the data inquiry process. The second component is human capacity: For educators to use data effectively, they must acquire skills and knowledge or data literacy.

Technology Tools

Technological advances are one of the key components to the enculturation of DDDM to date, both at the local and state levels (Hamilton et al., 2009; Mandinach & Jackson, 2010; Smith, 2009; Wayman & Stringfield, 2006). The amount of data with which educators are confronted continues to grow and increase in complexity. This growth is beyond the capacity of humans to handle, thereby necessitating technological solutions to support data-driven practices.

There has been a proliferation of technological tools to support local DDDM (Wayman, 2005a, 2007). These tools include data warehouses, student information systems, instructional management systems, assessment systems, and handheld devices that help teachers to diagnose students' learning strengths and weaknesses. The purpose of these technologies is to help educators collect, analyze, and report data in meaningful ways. Data warehouses and student information systems are large repositories of data. Instructional management systems help educators structure their instruction based on data. Assessment systems create tests, score them, and then analyze and report the outcomes. Diagnostic systems provide almost real-time data that provide a tight feedback loop between assessment and prescriptive instruction.

Wayman and colleagues (2007) found that in one moderate-sized district, there were more than 80 technology tools that educators were using to support data practices. Yet the smallest districts were at a disadvantage in terms of their ability to afford and implement these tools, even though nearly 100% of the districts reported having some technology to support DDDM (Means et al., 2010).

At the state level, unprecedented attention and monies have been given to the development of the SLDSs. The SLDSs are large data warehouses or repositories of a broad range of state and local education data, mostly data used for purposes of accountability. These systems are now being developed to include data from early childhood through higher education and connected to workforce and other agencies' data stores (National Center for Education Statistics [NCES], 2010). The U.S. Department of Education recognized the importance of collecting good data and required SEAs to develop an SLDS as one of the four required pillars of the American Recovery and Reinvestment Act (2009). IES has funded four rounds of awards so that states could build and implement these systems. From 2005 through the 2010 funding, 41 states and the District of Columbia have received money from 74 grants, with 24 states having received multiple awards, totaling more than $514 million (NCES, 2010). A fifth round of funding is occurring in 2012 with three priorities: (a) K–12 data systems, (b) early childhood data, and (c) postsecondary and/or workforce data (NCES, 2011).

Human Capacity and Data Literacy

The other key component to the implementation of DDDM is one that that has received less attention and limited funding—the building of human capacity around data or data literacy (Duncan, 2010a; Mandinach, 2009b). The research literature consistently discusses the need to improve human capacity around data use (Choppin, 2002; Feldman & Tung, 2001; Hamilton et al., 2009; Herman & Gribbons, 2001; Ikemoto & Marsh, 2007: Mandinach, 2009a; Mandinach & Honey, 2008; Mason, 2002; Miller, 2009; Wayman & Stringfield, 2006). For the benefits of the technology solutions to be actualized, educators at both the state and local levels must know how to use data to inform practice. For teachers, this means understanding how to take data from a variety of sources, such as summative, formative,[5] and classroom assessments and activities, and transform those data into actionable instructional steps (Mandinach et al., 2008; Means et al., 2011). Following Shulman's (1986) concept of "pedagogical content knowledge" for teaching, I have called this pedagogical data literacy (Mandinach, 2009a). Pedagogical data literacy is more than simply looking at the numbers or statistics collected through analysis. It refers to a teacher's ability to transform the numbers and statistics into instructional strategies that meet the needs of specific students (Love et al., 2008). For administrators, knowing how to use data means examining the data to make decisions about

[5]Summative assessments provide an indication of what students have or have not learned as a culminating test, whereas formative assessments are intended to provide feedback during the course of instruction so that it may be altered in ways to improve student learning.

programs, staffing, resource allocation, personnel, or policies. To date, however, there is still no agreement among researchers, professional development providers, and practitioners about what it means to be data literate (Mandinach & Gummer, 2011b).

At issue is a dearth of formal and informal mechanisms by which educators can gain the skills and knowledge needed to become data literate. There are a small number of organizations that provide structured professional development around DDDM (see, e.g., Data Wise at Harvard; Boudett, City, & Murnane, 2005; the Using Data Project at TERC; Love et al., 2008) and related topics such as leadership (White, 2005) and formative assessment (Heritage, 2007, 2010; Heritage & Niemi, 2006; Stiggins, 2002, 2005). Many districts use a knowledgeable internal staff person to conduct training for teachers and administrators and then a turnkey model[6] to train other staff. Principals usually get trained first and then teachers. A third, and untapped option, is to look to schools of education to help train current and future educators in data skills and knowledge (Mandinach, 2009b; Mandinach & Gummer, 2010, 2011a). In fact, Secretary Duncan (2012) challenged schools of education to step up and begin to teach and integrate DDDM into their curricula to improve data literacy among educators. To date, few courses specific to DDDM exist, and most of them are at the graduate level and designed for administrators (Mandinach & Gummer, 2010; Mann & Simon, 2010). This dearth of coursework presents an opportunity for schools of education and educational psychology.

Courses on DDDM are important for prospective and current teachers at both the undergraduate and graduate levels because of the skills and knowledge around data they will ultimately need to implement in their classrooms. If teachers can learn to use examples of authentic data, data use will no longer be a conceptual abstraction (Mandinach & Gummer, 2011a). Creating courses for continuing education credit can help to provide outreach to the current cohort of teachers. Finally, credentialing organizations can include data practices into licensing and credentialing procedures (e.g., Blue Ribbon Panel, 2010). If data literacy is required for credentialing, schools of education may have to respond, although the integration of such courses is highly complex and systemic (Mandinach & Gummer, 2011a). To date, few states include DDDM for teachers, principals, and superintendents in their credentialing criteria, although slow progress is being made (Data Quality Campaign, 2010, 2011, 2012).

A CONCEPTUAL THEORY OF DATA-DRIVEN DECISION MAKING

Several theoretical frameworks for DDDM have emerged as the literature continues to grow (Abbott, 2008; Easton, 2009; Hamilton et al., 2009; Ikemoto & Marsh, 2007; Mandinach et al., 2008; Means et al., 2010). They all have similar components involving a cyclical process of using data. The processes tend to be defined at a macrolevel, and each has different but similar components. The framework by Mandinach and colleagues (2008) has the advantage of drilling down to and outlining the cognitive skills that are hypothesized to be involved in DDDM. It is a theoretical model based on research on practitioners and a cognitive analysis of the results of that research.

As Figure 1 shows, the framework is grounded on a continuum in which data are transformed into information and ultimately to knowledge. Data are seen to exist in a raw state without meaning; they are just numbers. Information is data given meaning within a particular context. Knowledge is a collection of information deemed useful to guide action. For example, data would be students' scores on a formative assessment, the hard numbers. Information would be a summarization of the data into a report on how the students in a classroom performed on the assessment. Knowledge would be the transformation of this information into a set of priorities for actionable steps that the teacher might take to improve performance and address students' learning weaknesses.

This conceptualization is consistent with existing literature from different disciplines (Argyris & Schoen, 1978; Williams & Hummelbrunner, 2011). Through conducting the research on which this framework is based, it became clear that educators were using a variety of different cognitive skills, depending on where along the data-to-knowledge continuum they were working (Mandinach et al., 2008).

Six skills were identified and associated with the points along the continuum. At the data level, users *collect* and *organize* data. Collecting data is typically the first step in a data-driven inquiry process. For example, teachers will *collect* work samples, classroom assignments, student portfolios, and other student performance data. These data may be supplemented with demographic data, health data, or behavioral data. These data then must be *organized* in some way in order to make sense of them. That is, the teachers will triangulate among multiple sources of data and arrange them in a manner from which they can make sense. The data alone, however, are only numbers. There is a need to contextualize the numbers in order to make sense of them.

At the information level, users *analyze* and *summarize* information. They use context in which to ground the data and transform them into information. The teachers will *analyze* the data, examining performance trends, drilling down to item levels, and looking at aggregated and disaggregated data to try and make sense of performance patterns. They then can develop *summaries* of how individual students or groups of students are performing. These summaries will help them to focus on performance patterns that may require instructional intervention. Through analysis and summarization, the raw numbers have been transformed into statements

[6] A model in which some individuals are trained and they, in turn, train other staff.

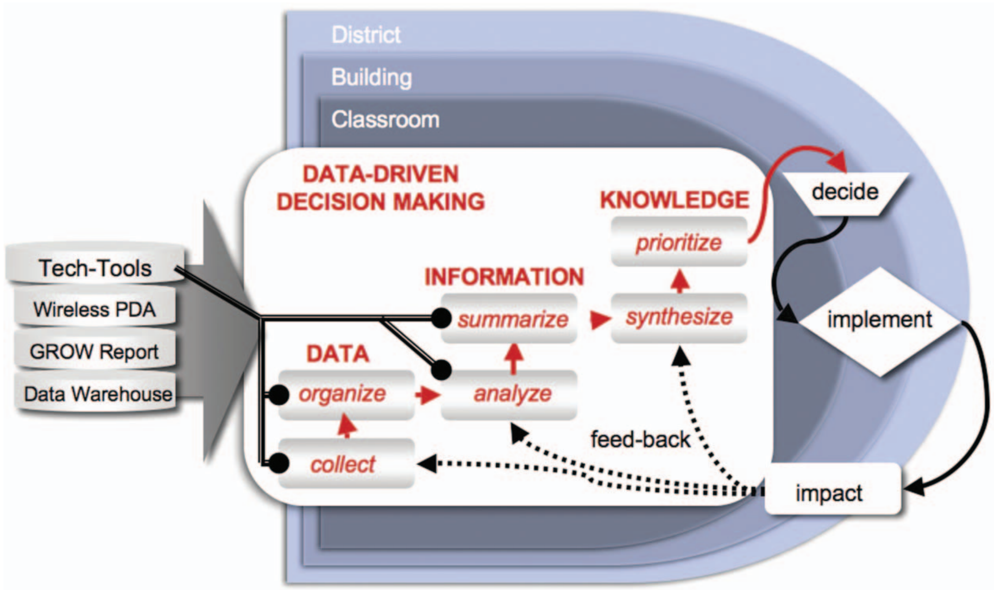

FIGURE 1 Conceptual framework for data-driven decision making. Reprinted with permission from *A Conceptual Framework for Data-Driven Decision Making* by E. B. Mandinach, M. Honey, D. Light, and C. Brunner. Copyright 2008 by Teachers College Press (color figure available online).

about what topics students have mastered and where there may be difficulties.

Information then becomes transformed into knowledge. At the knowledge level, users *synthesize* and *prioritize* knowledge. The information then is *synthesized* in a way that helps the teachers to form a knowledge base about student performance from which instructional decisions can be made. Finally, the teachers must *prioritize* among the information and knowledge to determine what courses of action to take. Prioritizing the synthesis allows the user to gain an understanding of the possible steps that can be taken and determine which steps to take that can be transformed into actionable steps based on knowledge of the situation.

This knowledge is then used to make a decision that is implemented, and the impact examined. They will examine how the students have performed. The teachers will determine how to differentiate instruction according to students' needs. Because DDDM is an iterative process, not a linear one, the outcome will then determine if the user has to return to an earlier part of the process, for example, to collect more data or reanalyze some information. The teachers may decide they need more performance measures from which to make a decision. They may need to reanalyze the data by disaggregating to determine how certain groups of students are performing and then modify their instructional decisions.

Using the fraction example again, the six skills might follow the following process:

- A teacher collects data on her students' understanding of fractions. This is done through the collection of work samples, such as assigned problems or performance on local test items or the state summative test.
- The various sources of data are organized. In this case, the teacher amasses data from the problems and test items.
- The teacher then analyzes students' performance on the different sources of data, examining areas of strength and weaknesses and identifying points of understanding and misconceptions.
- The teacher will extract the information from the analyses and summarize them in a form that makes sense for interpretation. She may note that some students exhibited specific misconceptions or that particular groups of students were struggling with underlying concepts.
- The teacher will then synthesize her interpretations of individual, group, and classroom performance, thus creating a knowledge base of possible actions.
- Finally, the teacher will transform her synthesized knowledge of her students, and determine how to prioritize action steps to address the students' learning needs.

The teacher will make an instructional decision, implement the decision, and examine its impact. Based on the results, she may need to collect more data, reorganize the data, or perform additional analyses. She may realize that students never mastered skills or concepts that are foundational to understanding fractions. The order of the steps may not always be linear. The process is iterative.

Within the framework, Figure 1 also shows that data are seen as hierarchical in structure. There are classroom-level, school-level, and district-level data as well as state and federal data. Typically data flow from the classroom upwards. With reporting requirements, data then flow from the district to the state to the federal level in what has become known as the "data highway" (Smith, 2009). Even the same data may have different meaning and interpretations at different points along this highway (Mandinach & Smith, 2011). Sensemaking depends on the purpose for which the data are being collected and examined, as well as the role of the user.

Regardless of the type of data, the purpose, and the role of the user, DDDM is seen as a cyclical or iterative process of identifying a problem (administrative, programmatic, instructional), determining what solutions might be brought to bear on the problem, monitoring the implementation of the solution, and targeting "research" to see if progress is being made (Easton, 2009).

As an example, consider a district that is losing students to local charter schools. The district wants to identify the factors that contribute to students leaving the district so that they might try to improve the conditions to increase the probability that the students will be more likely to continue in the district's schools. The district determines through a study that parents pull their children out before they enter middle school because of the perception that the middle schools are too large, are too impersonal, and it cannot provide the kinds of educational programming that the parents are seeking. Further, the schools that proportionately lose the most students are the largest middle schools and those with geographic proximity to a charter school (Long et al., 2008). The district then might consider decreasing the size of the middle schools, changing the programming, and making other modifications to the schools to make them more attractive to the parents, and then evaluating the impact of the changes to determine if parents continue to remove their children in favor of the charters.

This model, like other conceptual models, is meant to be generic for DDDM. It is a process that can be used by teachers for instructional decisions, as well as principals and superintendents for administrative decisions. The model should be applicable for most forms of data. When the model was developed, it was based on data collected from both teachers and administrators and with a variety of data elements (Long et al., 2008; Mandinach et al., 2008). An empirical question is the extent to which all of the conceptual models can be validated, using a broad range of data.

ISSUES AROUND AND CHALLENGES TO DATA USE

High-level education officials are looking to DDDM as a potential solution to some of education's most pressing problems (Duncan, 2009a, 2009c, 2010a, 2010b; Easton, 2009) such as improving the graduation rate, decreasing the dropout rate, and better preparing students for higher education. DDDM is not, however, considered a panacea.[7] It is labor intensive and costly; but, given the recent mandates, it is no longer optional for educators.

As with any worthwhile endeavor, using data comes with both challenges and opportunities (Mandinach, 2009a, 2009b), CHOPS, as I call them. Although there may be a plethora of challenges, the opportunities seen in data use trump these. The vast majority of educators at the district level report that the reason they are using data is to help meet the needs of their students (Long et al., 2008; Mandinach, 2010b). Data can provide invaluable information about the learning strengths and weaknesses of students, as well as clues about how to structure instructional strategies to meet those needs. Some educators, however, believe that data are to be used to deal with accountability issues. For administrators, particularly at the district and state levels, data are seen to address programmatic questions of whether an intervention, curriculum, or program "is working" (Mandinach, 2010b). This is a summative question, but data, if well conceptualized and in place, can also address the formative question of how a program can be improved (Mandinach, 2010a, 2010b). But, according to educators, it is the rationale for using data to meet the needs of students that is of tantamount importance so that the data can inform how instructional practices might be altered to help all students learn.

However, there are many issues around and challenges to DDDM. It is neither a trivial research topic nor easily implemented in practice. Several of these issues are explored next.

Research-Related Issues

It is important to note some caveats about work in this field on which to ground this article. Because the IES Practice Guide (Hamilton et al., 2009) was limited in its scope to data as defined as achievement data, many potentially informative studies were omitted for consideration and review. In the process of preparing the Practice Guide, the panelists identified nearly 3,000 articles about educational data use, defined as use of achievement data. However, only 24 were deemed "rigorous" as defined by the WWC. The body of accumulated studies was deemed as having a "low" level of evidence. A preferred and more accurate term is "emerging." This is to say that the remaining studies fail to inform the field or are worthless in terms of their results. Many studies in this field are formative or implementation projects that examine the processes by which data-driven practices are evolving in districts, schools, and classrooms. It is difficult to conduct "rigorous" (*sic*, experimental designs) research when practitioners are only beginning to implement data-driven practices. The research must mirror the practice. Further, many of the studies cited in this article, as well as other documents on DDDM, do not necessarily appear in traditional, peer-reviewed journals. They are studies conducted on behalf of districts, case studies, implementation studies, and evaluations. Thus, the "literature" reflects the maturing nature of the field. Eventually, more rigorous studies will begin to emerge.

[7]This is the opinion of the author.

In addition, there are limited ways to fund work on DDDM, thereby constraining the pipeline of research. A proposal to the National Science Foundation or IES would require that the proposed work be subsumed within a particular content domain, not examining DDDM more generally. For example, a proposal to the National Science Foundation might focus on the technologies that support decision making in science, or a proposal to IES might examine how data inform student performance in science or mathematics with the actual focus on the content area, not general principles of data use. In the past, one of the few venues for funding was through evaluations sponsored by districts or vendors, thereby constraining the type of research that may be publishable and meet the WWC standards for rigor. Only recently has the Spencer Foundation (see http://www.spencer.org/content.cfm/data-use-and-educational-improvement) announced a strategic initiative on "data use and educational improvement." This initiative is likely to stimulate work in the area and provide a venue for funding for interested researchers.

Further, it is clear from the reviewed studies that an important theoretical assumption still has not been examined and proven. It is the basic assumption that educators should be using data to inform practice. The field assumes that training teachers to use data positively impacts student performance, which is why policymakers are, in part, pushing educators to use data. That is, using data or evidence to inform practice, just like in other fields such as medicine, makes absolute sense. IES funded a study in 2010 that is intended to test if training teachers to use data will impact their classroom practices and ultimately improve student performance (Mandinach, Lash, & Nunnaley, 2009). Even a study such as this is challenging. There is a need for a large number of schools to attain sufficient power to test the impact of the professional development. Few districts are sufficiently large and willing to participate in such a study. The field will have to wait a few more years to learn of the outcomes. Even if the results of such a study are negative, it would only suggest that one particular approach was ineffective for the specific district in which it was tested.

A Lack of Human Capacity and an Operationalization for Data Literacy

The lack of human capacity around DDDM is a challenge that impacts practice more than research. The problem is that teachers and administrators rarely receive systematic training in data-driven practice in their preparation to become educators (Mandinach & Gummer, 2010, 2011a). There is a dearth of formal courses specifically on DDDM. Access to good professional development is limited (Means et al., 2010). What is needed is a systemic and comprehensive education program for preservice and in-service teachers and administrators, with assistance from schools of education, professional credentialing organizations, and SEAs (Mandinach & Gummer, 2011a).

This issue is addressed next, especially in light of new recommendations put forth by a Blue Ribbon Panel (2010) of the National Council for Accreditation of Teacher Education that promotes DDDM as an important component of the clinical preparation of educators. According to the Blue Ribbon Panel, teacher candidates "need to have opportunities to reflect upon and think about what they do, how they make decisions, and how they 'theorize' their work, and how they integrate their content knowledge and pedagogical knowledge into what they do" (p. 9). The panel further stated that teacher preparation must provide "the opportunity to make decisions and to develop skills to analyze student needs and adjust practices using student performance data while receiving continuous monitoring and feedback from mentor" (p. 10). These are the principles of DDDM and continuous improvement that align teacher preparation with practice. They are emphases of the policymakers to which schools of education and educational psychologists can respond in order to develop current and future educators who are knowledgeable about data use.

A related issue is that there is no clear agreement about what data literacy is or how the construct is to be operationalized (Mandinach & Gummer, 2011b). The construct means different things to different people. Some people assume it is the same thing as assessment literacy. For example, I asked a dean of a school of education if his institution offers any courses on data. The response was telling. He replied, "Oh yes, we teach formative assessment and value-added modeling." Expecting schools of education to respond to the need to improve data literacy requires a better understanding of the data literacy construct. To that end, a conference is being convened with experts on DDDM and formative assessment from the research and professional development fields to discuss and explore a common definition for data literacy (Mandinach & Gummer, 2012). The objective of the conference is to examine models of professional development and theoretical frameworks for DDDM to identify common elements, differences, and missing components (such as transforming data into instructional action by applying pedagogical content knowledge to data analysis). The findings will help to inform schools of education about steps they can take to consider how to integrate DDDM into their course offerings.

Other Challenges

A practical challenge concerns the realities of a typical classroom, with one teacher and roughly 30 students. How does data use actually happen in a dynamic environment like that? I would postulate that good teachers are collecting data all the time on all their students whether by observation, questions, or work products. It may not be systematic or digitized, but it happens with every interaction with a student. Educators are confronted with increasing amounts of data and different sources of data all the time. Emerging technologies can help (Wayman, 2005a, 2007). The creation of data teams also can help. Means and colleagues (2011) found that collaboration around data can provide a forum for useful professional discourse and can compensate for individual teachers' lack of data skills. Teachers can learn from one another about how to help particular students by sharing successful instructional strategies. The reality is, however, that DDDM is hard. It takes time to learn to become comfortable with its implementation and the teaming process. Time is precious, and many teachers feel that asking them to engage in data-driven practices will require more time in an overcrowded schedule.

Even finding the time and funding for professional development may be difficult. Dedicating common planning time to data may require changes in the school schedule that run counter to collective bargaining agreements. Time is the issue, but creative administrators have found solutions to these issues. For example, in one district noted previously, Wednesday afternoons are devoted to professional development and data team meetings (Long et al., 2008). Teachers collaboratively examine data and discuss instructional strategies in grade-level or course-level meetings. These Wednesdays are part of the district calendar because the administration recognizes their importance.

Yet another challenge is the potential for overreliance on data. Data are not a panacea and may not even be the "gold standard." They cannot answer all educational questions. The pendulum has swung far to one side concerning a reliance on "hard" evidence, informed by credible and rigorous research (Whitehurst, 2003), not just data. Rigor is seen as trumping relevance, responsiveness, and often reality (Schneider, 2009). Education has often been accused of being a "soft" and unscientific field, thus the reliance on hard evidence and the emphasis on rigor. Has the field overreacted? Perhaps. And are educators being forced into overreliance on data? Perhaps. One educator I interviewed commented, "Without data, you are only an opinion." There needs to be a balance between the use of data and experience. If you see your doctor, you want that individual to be armed with evidence about your condition and from which to make a decision, not just relying on a gut feeling. However, you also want the doctor to apply years of experience to inform the decision. The same holds true for educators.

Related to the reliance on data is the fact that educators must be using the "right" data. The data must be aligned to and valid for the particular use and purpose. Making instructional decisions on TIMSS, PISA, SAT, ACT, or even state summative tests may be ill-advised (Wiliam, 2010). Using misaligned data may be worse than using any data; that is, data must be valid for the purposes for which they are being used and interpreted. Reliance only on high-stakes assessments may indeed cause a narrowing of the curriculum and may lead to more teaching to the test (Louis, Febey, & Schroeder, 2005; Valli & Buese, 2007). The consortia for the new assessments, previously described, may circumvent this problem (U. S. Department of Education, 2010).

A new policy is being discussed that would require the linking of student performance data with teachers for the purpose of teacher evaluation. To say that this is a contentious issue is an understatement at best. The premise is to evaluate and hold teachers accountable for their students' performance based on data. Recall Berliner's (2006, 2009) message not to blame the teachers because there are many factors beyond their control. Teachers cannot control what happens beyond the boundaries of the school. They cannot control health, parental support, nutrition, welfare, and other relevant factors that influence student performance. Being evaluated based on how their students perform is tenuous at best. Of course teachers impact student performance, but they are only one factor. Educators are right to be concerned about such a sole reliance on student performance data.

I have touched on a number of issues around data use. No doubt there are and will be limitations and misuses. Data must be aligned to the purposes around which decisions are being made. Appropriate data can lead to informed decisions and valid interpretations. The pendulum must not swing too far in either direction, from overreliance on data to ignoring hard evidence. An appropriate balance must be struck.

THE GOALS FOR DATA-DRIVEN DECISION MAKING AND THE INTERFACE WITH EDUCATIONAL PSYCHOLOGY

Relevance of Data-Driven Decision Making to Educational Psychology

DDDM is a generic tool that can be applied across content areas and levels of the educational organization. This tool also encompasses many topics that are incorporated into educational psychology. To use DDDM, educators must accumulate a composite of skills and knowledge, typically through a variety of courses (Mandinach et al., 2008). These courses include assessment, statistics, instructional psychology, pedagogy, differential psychology, and classroom management, among others. DDDM is more than the numbers of a statistics course or the assessments of a measurement course. It also encompasses more than instruction and pedagogy. None of these courses alone, as traditionally taught, deals specifically with how educators can transform data into actionable knowledge, whether in a classroom, school, or central office.

Assessment courses help educators understand the general principles of measurement and how to construct classroom tests. Statistics courses for educators help them learn to analyze numbers at an elementary level but are usually quite abstract and fail to deal with the practical issues around data analysis and the implementation of instructional strategies. A course in instructional psychology traditionally deals with theories of instruction, whereas pedagogical principles courses focus on the actual practices of teaching. Differential psychology courses deal with the theory of how different individuals function cognitively and affectively, the foundation of differentiated instruction. Classroom management helps educators to translate some of the principles of differential psychology into practice through the concepts of whole class, small group, and individualized instruction. DDDM may be embedded in these courses but is not the primary emphasis in any of them. Each course has as goals particular skills and knowledge. DDDM and data literacy skills fall at the intersection of all of these courses and, thus, because of its emergence is seen as an important topic to which educational psychology can contribute.

Shifting notions about assessment. Educational psychology also can play a major role in data-driven practices because of the evolving and subtle transformation about what is deemed useable as assessments. Until recently, policymakers and educational administrators relied solely on summative state assessments, or assessments *of* learning (Nichols & Berliner, 2007; Petrides, 2006). These assessments provided data on what and how much students learned. The data were often considered difficult to use to adapt instruction because they were not sufficiently sensitive to varying instructional goals (Stecher & Hamilton, 2006). In contrast, assessments *for* learning have begun to take hold because of their ability to provide data that can help to improve teaching and student learning. Assessments *of* learning provide data on what and how much students have learned, whereas assessments *for* learning provide data to help improve teaching and student learning.

For example, the Arkansas Department of Education is integrating formative assessments into their assessment system, and Jefferson County Public Schools (KY) has expended substantial resources to provide training on formative assessments for their educators. This trend will help to decrease what was deemed a disconnect between state assessments and instructional relevance (Stecher & Hamilton, 2006). In addition, the U. S. Department of Education (2010) has created two consortia of states to revise state summative tests to reflect more authentic, problem-based content and procedural knowledge. This trend is a major departure from the typical summative assessments that test only declarative knowledge. Educational psychologists are perfectly positioned to examine the feedback loop that occurs amongst individual differences, assessments, data, and instructional action and respond to the new forms of assessment for the 21st century.

Goals

The objective in DDDM is to move educators, schools, districts, and states from being "data rich but information poor" to using data and transforming them into actionable knowledge. Educational psychologists can help achieve this goal. As previously noted, the components that will facilitate the use of data by educators at local levels include (a) adequate and targeted professional development, (b) technological tools and infrastructure aligned to educational goals, (c) making sure that the right data exist, (d) determining what the right data elements are to address educational questions and planning for their collection before a stakeholder requests an impact or return-on-investment study, (e) having an explicit vision for data use that addresses (f) an explicit need, and (g) providing the needed support and resources to make data-driven practices possible.

Educational researchers have examined and implemented work that has addressed all of these components. Our discipline has examined the components that comprise effective professional development and have applied those components in authentic settings (Desimone, 2009; Desimone, Porter, Garet, Yoon, & Birman, 2002; Hochberg & Desimone, 2010; Mandinach et al., 2009). We have examined the need for the technological infrastructure to support DDDM (Means et al., 2010; Wayman, 2005a, 2007). There are efforts ongoing to ensure that the right data elements are being collected and aligned to programmatic, administrative, and instruction that can inform practice at all levels (Smith, 2009). There is evaluation and research work ongoing to explore issues around implementing and enculturating data-driven practices within districts (Datnow et al., 2007; Long et al., 2008; Wayman et al., 2007). It is hoped that research in the field will have practical educational implications. That is one of the objectives of the IES Practice Guide (Hamilton et al., 2009). This document contains five explicit recommendations with action steps that educators can take to implement DDDM in their classrooms, schools, and districts. It also explores the many roadblocks to implementation.

Educational psychologists can play an invaluable role by conducting research that examines both the processes and impact of DDDM and by working closely with educational agencies charged with the development of policy and practice aiming at these goals. It is the implementation of the research findings that can contribute to educational practice.

Educational psychologists can also help improve human capacity around DDDM through the development of courses for current and future educators. As a discipline, educational psychology focuses on the many components that comprise data use. Educational psychologists understand the principles of measurement, statistics, individual differences, instruction, pedagogy, and methods that are fundamental to the use of data. They are experienced in examining the varied influences of educational technology and professional development on teaching practice. They are trained in the use of data and even in DDDM. Thus, there is a symbiotic interface between the topic and the discipline.

It is a perfect time for the topic of DDDM because of the unprecedented attention being given to the technologies and the growing emphasis on using data to inform practice. One hope is that funding agencies and the U.S. Department of Education will now turn their attention to the need for building human capacity around data literacy. Schools of education can play a key role in the transformation and the training component. They can create suites of courses or embed data-driven practice into existing courses (Mandinach & Gummer, 2011a). Educational psychologists are uniquely positioned at the intersection to inform this work through theory, methods, and implementation and by helping educators to use data effectively. The opportunities for educational impact are vast, but serious challenges must be overcome. This is about helping all students, which is both a challenge and an opportunity.

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