TEACHERS' USE OF ASSESSMENT DATA TO IMPROVE STUDENT ACHIEVEMENT

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This review aims to evaluate and recommend interventions for continuous improvement of a PK–12 public school district's data-driven decision-making (DDDM) program for linking instructional adjustments to individual student assessment data. In this context, DDDM is the cyclical process of collecting, analyzing, and interpreting various types of assessment data to implement and evaluate research-based instructional strategies believed to improve student outcomes. The review summarizes research on DDDM specific to teachers' use of assessment data to inform instruction and increase student achievement. Specifically, it focuses on DDDM components, expectations for implementation of DDDM, analysis of assessments, and instructional actions implemented by teachers in response to the outcomes. In addition, factors promoting teachers' engagement in DDDM and intervention strategies for increasing teachers' capacity for DDDM are synthesized. Results indicate that leadership and context, teachers' attitudes and beliefs, teachers' capacity, and collaboration are critical factors to consider when implementing and supporting DDDM. In addition, intervention strategies for improving teachers' engagement with DDDM focused on teacher capacity, attitudes, and beliefs. Interventions that include job-embedded professional learning, ongoing coaching support and feedback, and team collaboration are the most promising for improving student outcomes. A driver diagram outlining primary and secondary drivers to improve teachers' use of assessment data to improve student achievement is provided.

Keywords: teacher data use, assessment, data-driven decision-making, data-based decision-making, student achievement, intervention, professional learning

This literature review was conducted in preparation for an evaluation of a PK–12 public school district's data-driven decision-making (DDDM) program designed to promote continuous improvement of student academic performance. Specifically, the evaluation focuses on teachers' use of assessment data to make instructional adjustments that increase student learning. Furthermore, this article aligns with the scan phase of the improvement science 90-day cycle by providing information to better understand a problem of practice (Park & Takahashi, 2013). The following problem of practice evidenced the need to improve student learning: 71% of students taking the sixth-grade state assessment in reading did not achieve *meets grade level performance in reading* in 2019 (Texas Education Agency, 2021).

This review was not developed to debate the value of DDDM or assessments but to identify best practices for the efficient and effective use of assessment data to improve teaching and learning. Furthermore, the emphasis on continuous improvement is intentional so as not to be confused with data use for accountability. Datnow and Park (2018) explained that data use for accountability focuses on compliance, high-stakes testing, and specific groups of students while data use for continuous improvement centers on using multiple data sources to make instructional improvements for all students.

The ultimate goal of the evaluation was to improve the district's DDDM program. Fitzpatrick et al. (2011) identified program improvement evaluations as formative. They specify that formative evaluations should consider the strengths and weaknesses of the program as well as how the program can be improved. Therefore, this literature review examines standard DDDM components and supports for implementation that improve student outcomes as well as suitable improvement interventions. Studying interventions addressed the call by Ansyari et al. (2020) to fill the gap in research regarding different methods and approaches to DDDM and their effects. In summary, this review answers the following questions:

1. How are assessments defined and used for DDDM?
2. What factors promote teachers' use of assessment data for DDDM?
3. What intervention strategies are most promising for improving teachers' use of assessment data and student academic performance?

Method

This review included literature identified through a search for *teacher data use* using The University of Texas at Tyler's Robert R. Muntz Library SwoopSearch with publication dates in the range 2016–2021. Articles were considered if they were in English, peer-reviewed, from Quartile 1 journals, reflected information about in-service teachers, and were specific to assessment data. The search terms "data-based decision-making," "data-driven decision-making," "data-informed decision-making," "capacity," "professional learning," and "intervention" were used to locate additional articles based on initial readings. In addition to research studies, several relevant special edition journals were found, including the November 2016 *Teaching and Teacher Evaluation* special issue on teachers learning how to use data, the 2017 *Journal of Educational Administration* special issue on data use and equity, the June 2021 *Studies in Education Evaluation* special issue on data use in schools, and the 2021 *Journal of Learning Disabilities'* two-part series on data-based decision-making. Three meta-analyses and five existing literature reviews were also located.

The snowballing technique was employed to expand the scope of the review, which involved exploring the reference lists of identified articles for frequently cited works and searching journals that regularly published relevant articles.

Literature Review

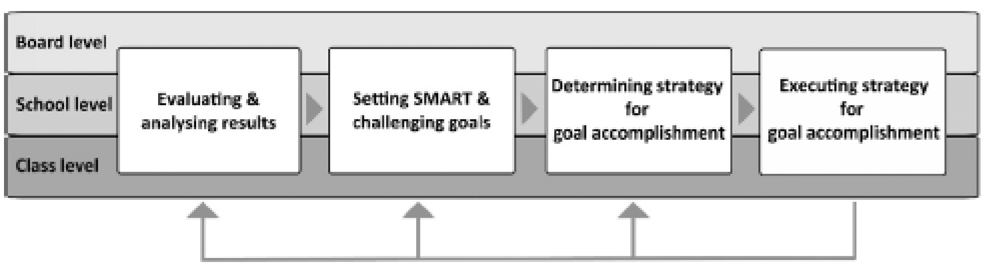
Data-Driven Decision-Making

In educational settings, DDDM, also referred to as data-based decision-making, data-informed decision-making, and data-based instruction (DBI), is frequently defined as a practice, process, or strategy used to improve teaching and learning through data use (Datnow & Park, 2018; Garner et al., 2017; Jimerson & Childs, 2017). The systematic, iterative process of DDDM requires collecting and analyzing data so that the resulting information can be applied to improve educational outcomes (Ebbeler et al., 2016; Hubers et al., 2017; Jimerson et al., 2021; Kippers, Poortman, et al., 2018; Mandinach & Gummer, 2016; Poortman & Schildkamp, 2016; Schildkamp, 2019; Schildkamp, Poortman, et al., 2019; Schildkamp, Smit, et al., 2019). Mandinach and Jimerson (2016) emphasized that DDDM should consist of multiple data points that various stakeholders can use to improve all aspects of educational organizations, not just student outcomes.

Two DDDM visualizations were seen frequently in the literature: (a) the general four-component model and (b) the more comprehensive eight-step model. The four-component model displayed in Figure 1 demonstrates that four DDDM process components (evaluating and analyzing results, setting SMART—specific, measureable, achievable, relevant, time-bound—and challenging goals, determining strategies for goal accomplishment, and executing strategy for goal accomplishment) can be implemented at three organizational levels of class, school, and board (Keuning et al., 2019; Staman et al., 2017; van der Scheer et al., 2017; van der Scheer & Visscher, 2016, 2018; van Geel et al., 2016, 2017; Visscher, 2021).

Figure 1

The Four-Component Model



Note. From "On the Value of Data-Based Decision Making in Education: The Evidence From Six Intervention Studies," by A. J. Visscher, 2021, *Studies in Educational Evaluation, 69*, p. 3. Copyright 2021 by the author. CC BY license (http://creativecommons.org/licenses/by/4.0).

The eight-step model, displayed in Figure 2, expands the four processes of Figure 1 into an eight-step cycle that can be used for data team interventions. The eight steps include problem definition, formulating a hypothesis, data collection, data quality check, data analysis, interpretation and conclusion, implementing improvement measures, and evaluation (Ebbeler et al., 2016; Ebbeler et al., 2017; Hubers et al., 2017; Kippers, Poortman, et al., 2018; Poortman & Schildkamp, 2016; Schildkamp, Poortman, et al., 2019; Schildkamp, Smit, et al., 2019).

For the remainder of this review, DDDM will refer to the iterative, systematic process teachers or educator teams (board members, district leaders, school leaders, instructional coaches, teachers) use to collect, verify, analyze, and interpret various forms of assessment data that result in the implementation of changes to instructional practice in the classroom that improve student achievement. This operational definition encompasses key points of both models and relevant literature.

Figure 2

The Eight-Step Model

Note. From "How School Leaders Can Build Effective Data Teams: Five Building Blocks for a New Wave of Data-Informed Decision Making," by K. Schildkamp, C. L. Poortman, J. Ebbeler, & J. M. Pieters, 2019, *Journal of Educational Change*, *20*(3), p. 286. Copyright 2019 by the authors. CC BY license (http://creativecommons.org/licenses/by/4.0).

Data Use Theory of Action

The data use theory of action aligns with the definition of DDDM and is contextual. In the theory of action, a purpose is identified (i.e., problem of practice) and related data are collected to better understand the problem (Ansyari et al., 2020; Ebbeler et al., 2016, 2017; Gelderblom et al., 2016; Marsh et al., 2016; Schildkamp & Poortman, 2015). Once all the necessary data have been collected, they are analyzed and turned into actionable information that, in the case of teachers' use of assessment data, increases the knowledge and skills of teachers such that they can adapt instruction to optimize student learning (Ansyari et al., 2020; Ebbeler et al., 2016, 2017; Gelderblom et al., 2016; Marsh et al., 2016; Schildkamp & Poortman, 2015). Finally, improvement of student learning results in increased student achievement (Ansyari et al., 2020; Ebbeler et al., 2016, 2017; Gelderblom et al., 2016; Marsh et al., 2016; Schildkamp & Poortman, 2015). Ansyari et al. added that evaluations of data use interventions should include professional learning as part of the data use theory of action cycle.

Federal and State Policy on the Use of Assessment Data

Federal Policy

For more than two decades, there has been a growing international expectation for educators to use data for school improvement (Datnow & Hubbard, 2016; Garner et al., 2017; Jimerson & Childs, 2017; Park & Datnow, 2017; Schildkamp, 2019). In the United States, this expectation was spurred on by the No Child Left Behind (NCLB) Act of 2001, a reauthorization for the federal Elementary and Secondary Education Act of 1965, that focused on high-stakes testing and accountability. NCLB also sought to improve learning opportunities for historically underperforming student groups by using DDDM to address inequities identified by differences in the educational outcomes of various student populations (Garner et al., 2017). The increase in expectation for systemic data use to improve student achievement was reinforced by the Race to the Top initiative of 2009, the Every Student Succeeds Act of 2015, and the Elementary and Secondary School Emergency Relief Fund (Garner et al., 2017; Gummer, 2021).

Texas State Policy

The origins of DDDM in Texas can be traced back to 1979 when legislators enacted a law resulting in the first of several statewide assessment programs measuring student performance on state-mandated curriculum (Texas Education Agency, 2011a). State accountability was mandated by legislation in 1993, almost a decade before NCLB's adequate yearly progress federal accountability plan was implemented (Texas Education Agency, 2011b, 2013). Beginning in 2004 with the development of the Texas English Language Proficiency Assessment System, the state assessment program expanded to align with NCLB requirements (Texas Education Agency, 2011a). Table 1 illustrates the timeline of state assessment and accountability development in Texas. As defined with each new iteration, Texas accountability results have been accompanied by support and interventions driven by DDDM for local education agencies (i.e., school districts) and schools performing below expectations as a way to improve school quality (Jimerson, 2016; Jimerson & Childs, 2017).

Table 1

Texas Assessment and Accountability System Timeline

Year	System
1979	Texas Assessment of Basic Skills
1986	Texas Educational Assessment of Minimum Skills
1990	Texas Assessment of Academic Skills
1994	Texas Assessment of Academic Skills-based State Accountability
2003	Texas Assessment of Knowledge and Skills
2004	Texas Assessment of Knowledge and Skills-based State Accountability Texas English Language Proficiency Assessment System
2012	State of Texas Assessments of Academic Readiness
2013	State of Texas Assessments of Academic Readiness-based State Accountability
2018	State Accountability: Ratings of A, B, C, D, F

Expectations for the Use of Student Assessment Data

DDDM is now a standard process for identifying and guiding school improvement efforts (Garner et al., 2017). Numerous resources exist to provide districts and schools with explicit procedures and protocols for using DDDM to develop, reach, and evaluate improvement goals. For example, Bernhardt's (2018) continuous school improvement framework guides districts through an in-depth DDDM process using four different types of educational data: demographics, perceptions, student learning, and school processes. Bryk et al. (2017) introduced six principles for applying improvement science to education with the first four relying on data use and analysis for decision-making. In addition, DuFour et al. (2016) provided protocols for how instructional teams can use data in "reoccurring cycles of collective inquiry and action research to achieve better results for the children they serve" (p. 10) while Knight (2018) provided instructional leaders with methods for using data to partner "with teachers to help them improve teaching and learning so students become more successful." (p. 2). Additionally, Bambrick-Santoyo's (2019) *Driven by Data 2.0* and Boudett et al.'s (2018) *Data Wise* specifically addressed using assessment data to improve instruction. Expectations for using data to make instructional decisions can also be found in professional standards for educators such as the Texas Superintendent Standards, Principal Standards, and Teacher Standards (Table 2).

Table 2

Texas Educator Standard Excerpts Referencing DDDM

Role	Standard	Description
Superintendent	g.2	"... implement processes for gathering, analyzing, and using data for informed decision making …"
	i.6	"... institute a comprehensive school district program of student assessment, interpretation of data, and reporting of state and national data results …"
Principal	1.A.ii	"In schools led by effective instructional leaders, data are used to determine instructional decisions and monitor progress. Leaders implement common interim assessment cycles to track classroom trends and determine appropriate interventions. Staff have the capacity to use data to drive effective instructional practices and interventions."
	1.b.iii	"Data-driven instruction and interventions. The leader monitors multiple forms of student data to inform instructional and intervention decisions and to close the achievement gap."
	2.A.i.V	"… facilitate professional learning communities to review data and support development …"
	3.A.IV	"When a strategy fails, these leaders analyze data, assess implementation, and talk with stakeholders to understand what went wrong and how to adapt strategies moving forward …"
Teacher	1	"Instructional Planning and Delivery. Teachers demonstrate their understanding of instructional planning and delivery by providing standards-based, data-driven, differentiated instruction that engages students, makes appropriate use of technology, and makes learning relevant for today's learners."
	5	"Data-Driven Practice. Teachers use formal and informal methods to assess student growth aligned to instructional goals and course objectives and regularly review and analyze multiple sources of data to measure student progress and adjust instructional strategies and content delivery as needed."
	5.B	"Teachers set individual and group learning goals for students by using preliminary data and communicate these goals with students and families to ensure mutual understanding of expectations."

Role	Standard	Description
	5.C	“Teachers regularly collect, review, and analyze data to monitor student progress.”
	5.C.i	“Teachers analyze and review data in a timely, thorough, accurate, and appropriate manner, both individually and with colleagues, to monitor student learning.”
	5.D	“Teachers utilize the data they collect and analyze to inform their instructional strategies and adjust short- and long-term plans accordingly.”
	5.D.i	“Teachers design instruction, change strategies, and differentiate their teaching practices to improve student learning based on assessment outcomes.”
	5.D.ii	“Teachers regularly compare their curriculum scope and sequence with student data to ensure they are on track and make adjustments as needed.”

Note. Source: Texas Administrative Code (2023).

Assess Student Learning For DDDM

High-stakes testing, accountability, and professional standards point to assessing student learning as a critical DDDM measure in the school improvement process. Student learning can be assessed formally (i.e., state standardized assessments) and informally (i.e., observation, active monitoring; Barnes et al., 2019; Jimerson et al., 2021; Kippers, Wolternick, et al., 2018; Spillane et al., 2018). Furthermore, assessments can be categorized loosely as formative, summative, and interim based on the purpose of the assessment. Within these categories, multiple forms and types of assessments can be used to improve learning for all students.

Formative Assessments

Teachers use formative assessments at the classroom level to measure student learning during instruction. Formative assessments such as reviews of student work, attention to student talk and dialogue, quick daily questions (warmups) before instruction, progress monitoring, end-of-class exit tickets, and teacher observations of student thinking are conducted frequently and provide immediate feedback to teachers to inform midcourse adjustments in their day-to-day practices as needed to increase student understanding of the material (Andersen, 2020; Datnow et al., 2021; Förster et al., 2018; Heitink et al., 2016; Kippers, Wolternick, et al., 2018). These assessments may be formal or informal and are referred to as assessments for learning because of their ability to inform instruction (Bernhardt, 2018; Gummer, 2021; Farley-Ripple et al., 2019; Heitink et al., 2016). “Formative assessment tools that provide teachers with timely information to inform daily instruction are paramount in the process of data-informed instruction” (Sun et al., 2016, p. 29).

Summative Assessments

Summative assessments are typically administered at the end of a unit of learning or school year to measure learning outcomes (Heitink et al., 2016). Summative assessments provide less instructional direction than other assessments and are used to determine whether students have mastered a specific set of skills (Andersen, 2020; Mandinach & Jimerson, 2016; Sun et al., 2016). Summative assessments are referred to as assessments of learning because they are administered after learning has taken place (Bernhardt, 2018; Datnow & Park, 2018). State-administered end-of-year assessments used to determine accountability ratings are an example of summative assessments that evaluate the effectiveness of programs, schools, and local educational agencies (Abrams et al., 2021).

Interim Assessments

Interim assessments are administered two or three times during a school year, provide educators with information about student achievement and progress over time, and may predict state assessment performance (Braaten et al., 2017; Datnow & Hubbard, 2016; Farley-Ripple et al., 2019; Wayman et al., 2017). Like formative assessments, interim assessments are considered assessments for learning because they can guide instructional planning (Datnow & Hubbard, 2016). However, interim assessments are still formal assessments and thus do not provide teachers with information they can use for immediate adjustments during instruction (Datnow & Hubbard, 2016).

Teacher Analysis of Student Assessment Data

The literature identifies several approaches teachers take to analyze student assessment data. One common approach is to rank or sort students by their scores on an assessment to identify strong and weak performance among students (Barnes et al., 2019; Farrell & Marsh, 2016a, 2016b; Gannon-Slater et al., 2017). Ranking students' scores also allows teachers to identify groups of students in specific performance level bands (i.e., *Does Not Meet Grade Level Performance*, *Meets Grade Level Performance*, and *Masters Grade Level Performance*; Barnes et al., 2019; Farrell & Marsh, 2016a, 2016b). In addition, teachers use student assessment data to pinpoint gaps in learning by identifying students' strengths and weaknesses based on their responses to individual questions or groups of questions within specific learning categories or skills (Farrell & Marsh, 2016a, 2016b; Gannon-Slater et al., 2017; Kippers, Wolternick, et al., 2018; Park & Datnow, 2017). Teachers also use assessments to determine how students think, what they understand, and what they may need more assistance with (Datnow et al., 2021). Furthermore, teachers compare assessment results between students, classes, and schools to identify broad patterns and trends in assessment results (Farrell & Marsh, 2016a, 2016b). They may also use other forms of student data such as attendance and behavior to make sense of student performance on assessments (Mandinach & Schildkamp, 2021b; Sun et al., 2016). Finally, teachers compare the results of assessments over time to determine if students are progressing toward understanding specific learning expectations (Barnes et al., 2019; Blumenthal et al., 2021; Farrell & Marsh, 2016a, 2016b; Förster et al., 2018; Kippers, Poortman, et al., 2018).

Teachers' Instructional Decisions Based on Analysis of Student Assessment Data

Research indicates that teachers make various instructional decisions in response to student assessment findings. Teachers review, reteach, resequence, or retest the curricula in alignment with student learning needs (Barnes et al., 2019; Ebbeler et al., 2016; Farley-Ripple et al., 2019; Farrell & Marsh, 2016a, 2016b; Gelderblom et al., 2016; Kippers, Wolternick, et al., 2018). They reorganize students into instructional groups (whole, small, one-on-one, heterogeneous, homogenous) based on assessment performance to better target specific academic needs (Barnes et al., 2019; Farley-Ripple et al., 2019; Farrell & Marsh, 2016a, 2016b; Förster et al., 2018; Gelderblom et al., 2016; McMaster et al., 2020; Park & Datnow, 2017). Teachers also provide students with individualized support such as tutoring and online tools to assist them with learning the curriculum (Barnes et al., 2019; Farrell & Marsh, 2016a, 2016b; Park & Datnow, 2017). In addition, teachers change their instructional approach using new strategies to improve student learning (Blumenthal et al., 2021; Datnow et al., 2021; Farrell & Marsh, 2016a, 2016b; Gannon-Slater et al., 2017). These methods can collectively be defined as instructional differentiation (Park & Datnow, 2017; van der Scheer et al., 2017). Farrell and Marsh (2016a, 2016b) added that teachers may focus instructional decisions on activities that promote test preparation. Marsh et al. (2016) noted that teachers may ask students to reflect on their performance and set personal goals for learning. While teachers have been found to take these actions in response to student performance, the literature indicates that teachers struggle to make instructional decisions based on student outcomes (Andersen, 2020; Datnow et al., 2021; Ebbeler et al., 2016; Gannon-Slater et al., 2017; Sun et al., 2016).

Factors Influencing Teacher Use of Assessment Data to Improve Student Learning

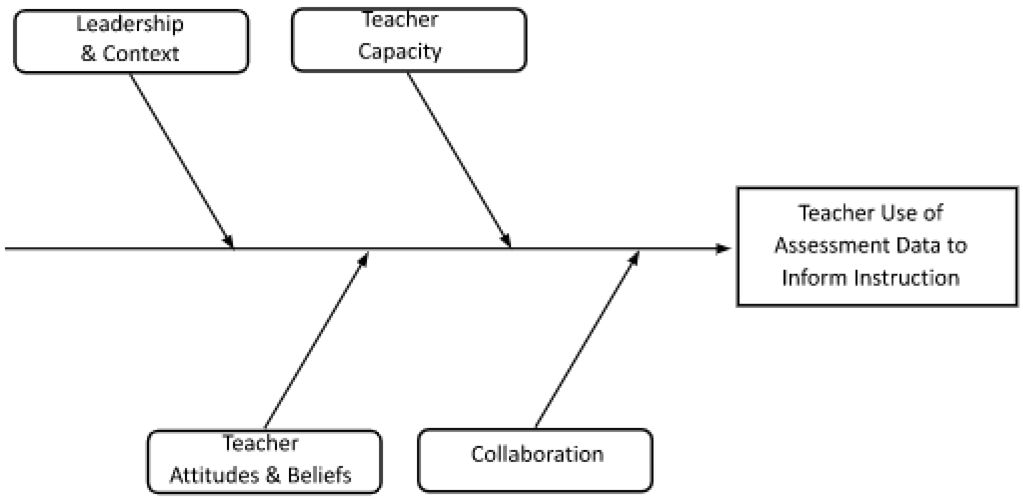
To better understand and examine teacher use of assessment data to inform instructional decision-making, it is essential to consider influencing factors (Schildkamp et al., 2017). Influencing factors identified in the literature can be grouped into four themes: leadership and context, teacher capacity, teacher attitudes and beliefs, and collaboration (Figure 3). These factors can either support or hinder classroom-level implementation of DDDM (Jimerson et al., 2021; Schildkamp et al., 2017; Schildkamp, Poortman, et al., 2019).

Leadership and Context

When leaders support the culture and climate of DDDM, teachers are more likely to use assessment data for instructional decision-making in organizations (Hubers et al., 2017; Jimerson & Childs, 2017; Jimerson et al., 2021; Schildkamp, Poortman, et al., 2019). Districts and campuses accomplish this by establishing policies and procedures that prioritize using assessment data for DDDM (Abrams et al., 2021; Hubers et al., 2017; Jimerson & Childs, 2017). Furthermore, when vision and norms for data use are established, it helps provide teachers with purpose, direction, and guidance for using assessment data (Hubers et al., 2017; Jimerson et al., 2021; Schildkamp, Poortman, et al., 2019).

Figure 3

Fishbone Diagram of Factors Influencing Teacher Use of Assessment Data to Improve Student Learning



Organizational leaders can convey their expectations for using assessment data to make instructional decisions and support teachers in those efforts in several ways. First, leaders support teachers by establishing a time to administer, analyze, and interpret data from assessments and plan instructional actions to implement because of their findings (Jimerson & Childs, 2017; Jimerson et al., 2021). Second, leaders support teachers by providing professional learning opportunities, including strategies and protocols to effectively and efficiently use assessment data to change instructional practices (Abrams et al., 2021; Hubers et al., 2017). Third, leaders participate in discussions with, be a model of, and coach teachers about using assessment data for decision-making (Abrams et al., 2021; Jimerson et al., 2021; Schildkamp, Poortman, et al., 2019). Finally, leaders establish a climate of trust and respect that encourages teachers to actively discuss assessment data and make recommendations for changes (Jimerson & Childs, 2017; Jimerson et al., 2021; Schildkamp, Poortman, et al., 2019). A lack in these leadership actions may hinder teachers' use of assessment data to improve student learning (Beck & Nunnaley, 2021).

Teacher Capacity

Teacher capacity as an influencing factor encompasses both data literacy and content pedagogy as teachers who are data literate and have a strong understanding of content pedagogy are more likely to use assessment data for instructional decision-making (Datnow et al., 2021; Oslund et al., 2021). Data literacy refers to the knowledge and skills needed to collect, analyze, interpret, and use data to adjust instruction and improve student achievement (Hoogland et al., 2016; Kippers, Poortman, et al., 2018; Mandinach & Gummer, 2016; Schildkamp, Smit, et al., 2019). Hoogland et al. included the development of assessment instruments as a component of data literacy while Schildkamp, Poortman, et al. (2019) and Datnow et al. emphasized a teacher's ability to identify students' instructional needs using the data. After data are interpreted, pedagogical content knowledge is necessary for appropriate subject-based adjustments to classroom instruction

(Datnow et al., 2021; Hoogland et al., 2016; Lai & McNaughton, 2016; Mandinach & Gummer, 2016; Schildkamp et al., 2017). Mandinach and Gummer provided the following comprehensive operational definition of data literacy that merges all of the explanations above:

> Data literacy for teaching is the ability to transform information into actionable instructional knowledge and practices by collecting, analyzing, and interpreting all types of data (assessment, school climate, behavioral, snapshot, longitudinal, moment-to-moment, etc.) to help determine instructional steps. It combines an understanding of data with standards, disciplinary knowledge and practices, curricular knowledge, pedagogical content knowledge, and an understanding of how children learn. (p. 367)

Teacher Attitudes and Beliefs

Literature indicates that personal attitudes and beliefs influence how teachers use data to inform teaching and learning. These beliefs center around the value teachers put on assessment data and the extent to which teachers feel they can use it to adjust instruction in ways that improve student learning (Andersen, 2020; van der Scheer & Visscher, 2016). Broadly speaking, teachers may not believe that specific assessment data are useful or provide new information about their students' learning needs (Andersen, 2020; Barnes et al., 2019; Ebbeler et al., 2017; Farrell & Marsh, 2016a). More specifically, teachers may question the relevance of assessment content to the curriculum or the validity, reliability, and purpose of assessments (Andersen, 2020; Barnes et al., 2019; Farrell & Marsh, 2016b). In addition, teachers with higher levels of self-efficacy or confidence regarding their DDDM capacity (see *Teacher Capacity* section) may be more likely to engage in DDDM (Hoogland et al., 2016; Jimerson et al., 2021; van der Scheer & Visscher, 2016; Oslund et al., 2021).

Collaboration

Collaboration is an essential part of DDDM and can develop a teacher's capacity for using data to make instructional decisions (Abrams et al., 2021; Ebbeler et al., 2017; Hoogland et al., 2016; Mandinach & Gummer, 2016; Schildkamp et al., 2017; Schildkamp, Smit, et al., 2019; Van Gasse et al., 2016). Collaboration in the context of assessment and instructional decision-making refers to the interaction of educators (board members, district leaders, campus leaders, teachers, instructional coaches) where student performance is discussed and educators reflect on instructional practices proven to improve student learning (Andersen, 2020; Ebbeler et al., 2016; Hoogland et al., 2016; Mandinach & Schildkamp, 2021a, 2021b). However, collaboration can be used more generally to solve any educational problem (e.g., Ebbeler et al., 2016; Hubers et al., 2017; Jimerson et al., 2021; Kippers, Poortman, et al., 2018; Poortman & Schildkamp, 2016; Schildkamp, Poortman, et al., 2019; van Geel et al., 2016).

Moreover, the literature indicates that collaboration can occur informally between individuals as delineated by Van Gasse et al. (2016, 2017a, 2017b) or more formally in teams or through coaching (Abrams et al., 2021; Datnow et al., 2021; Ebbeler et al., 2017; Gannon-Slater et al., 2017). Poortman and Schildkamp (2016) and Schildkamp, Poortman, et al. (2019) found positive trends when heterogeneous groups of staff members were purposefully brought together as a data team to solve a school wide problem. Abrams et al. identified similar trends with homogeneous teams arranged by grade-level (horizontal) or subject-level (vertical) peer groups.

Whether heterogeneous or homogenous, teams that collaborate to improve teaching and learning are commonly referred to as professional learning communities (Ebbeler et al., 2016; Farley-Ripple et al., 2019; Farrell & Marsh, 2016a; Gannon-Slater et al., 2017; Huguet et al., 2017; Lai & McNaughton, 2016). Supovitz and Sirinides (2018) noted that collaboration can also take place through peer observation and feedback.

In addition to identifying collaboration as an influencing factor for teacher data use, researchers have emphasized the importance of instructional leaders providing support for collaboration through scheduled time, space, professional learning, guidance, and material resources (Abrams et al., 2021; Gannon-Slater et al., 2017; Huguet et al., 2017; Jimerson et al., 2021; Schildkamp, Poortman, et al., 2019; Schildkamp, Smit, et al., 2019). Leaders must also consider the social aspects of collaboration and purposefully create opportunities for relationship-building that foster a culture of trust rather than judgment among collaborative teams (Gannon-Slater et al., 2017; Jimerson et al., 2021; Schildkamp, Poortman, et al., 2019; Van Gasse et al., 2016).

Interventions to Improve Teacher Use of Assessment Data to Improve Student Outcomes

Twenty-five intervention studies were identified for this review. The studies can be divided into those that address only the factors influencing teacher use of assessment data and those that reference student achievement outcomes. The studies can be further separated by whether or not the intervention was conducted with individual teachers or data teams (Table 3). Moreover, 13 of these studies were conducted in the Netherlands in response to the expectation that 90% of Dutch schools would implement systemic data use by 2018 (Ebbeler et al., 2016, 2017; Gelderblom et al., 2016; Staman et al., 2017; Visscher, 2021).

The data use interventions include multiple educator roles such as teachers, principals, and academic or instructional coaches and are usually led by a researcher or external consultant. Interventions encompass various procedural methods and tools such as guidance manuals and protocols, online courses, face-to-face professional development, coaching, assessment reporting, content pedagogy, and discussion and collaboration. In addition, implementation timelines extend from 3 days for individual teacher online courses to 2 years for teams (primarily embedded within the workday). It is important to note that most studies investigated the impact of a specific intervention developed at the University of Twente in the Netherlands (Table 4). This intervention, identified in some articles as Focus, leads data teams through the eight-step DDDM cycle while incorporating adult learning principles and considering factors that increase data use.

Table 3

Intervention Studies by Participant Type and Focus

Participants	Focus Only on Factors Influencing Teacher Use of Assessment Data	Focus Includes Student Achievement
Individuals	Reeves & Chiang (2018)[US] van den Bosch et al. (2019)[N] van der Scheer et al. (2017)[N] van der Scheer & Visscher (2016)[N]	Förster et al. (2018)[G] McMaster et al. (2020)[US] Peters et al. (2021)[G] Powell et al. (2021)[US] Supovitz & Sirinides (2018)[US] van der Scheer & Visscher (2018)[N]
Teams	Abrams et al. (2021)[US] Andersen (2020)[D] Datnow et al. (2021)[US] Ebbeler et al. (2016)[N] Ebbeler et al. (2017)[N] Hubers et al. (2017)[N] Kippers, Poortman, et al. (2018)[N] Jimerson et al. (2021)[US] Schildkamp, Smit, et al. (2019)[S] van Geel et al. (2017)[N]	Keuning et al. (2019)[N] Lai & McNaughton (2016)[NZ] Poortman & Schildkamp (2016)[N] Staman et al. (2017)[N] van Geel et al. (2016)[N]

Note. Conducted in [D]Denmark, [G]Germany, [N]Netherlands, [NZ]New Zealand, [S]Switzerland, and [US]United States.

Table 4

Summary of Findings for the Impact of the Netherlands' Eight-Step DDDM Intervention on Data Teams

Author (year)	Method	Outcome(s) measured	Finding(s)
Ebbeler et al. (2016)	Mixed-methods**	Data use	Increased awareness and data use
Poortman & Schildkamp (2016)	Mixed-methods	Team problem solving Student achievement	Five of nine teams solved problems related to student achievement Final senior exam grades increased* (d = 0.45) English exam grades increased* (d = 0.54)

Author (year)	Method	Outcome(s) measured	Finding(s)
			English exam grades increased* (*d* = 0.66)
van Geel et al. (2016)	Quantitative	Student mathematics achievement	Positive effects equal to a month of instruction Results varied by campus More benefit for schools with larger SES populations
Ebbeler et al. (2017)	Mixed-methods	Capacity, attitudes/beliefs	Increased data literacy and attitudes* (*d* = 0.06) Increased data literacy knowledge* (*d* = 0.32) Satisfaction with intervention
Hubers et al. (2017)	Mixed-methods**	Sustainability	Data team cycle was not completed No new data teams created Limited vision and policy
van Geel et al. (2017)	Quantitative**	Data literacy	Increased data literacy Initial gaps due to education level and role minimized
Staman et al. (2017)	Quantitative	Student mathematics achievement	One main effect in Grade 5* (effect size [ES] = 0.18). No main effect in Grade 2 (ES < 0.01), Grade 3 (ES = 0.17), or Grade 4 (ES = 0.16) Students with lower scores and those in schools with larger SES populations had statistically significant positive interaction effects
Kippers, Poortman, et al. (2018)	Mixed-methods	Data literacy	Increased data literacy* (*d* = 0.71) Participants struggled most with setting a goal
Keuning et al. (2019)	Quantitative	Student mathematics & spelling achievement	Achievement generally increased Schools with larger SES populations experienced higher effects in mathematics Students identified as low and high SES saw larger effects than middle SES students Larger intervention effects were found when the same subject was the focus of the intervention for multiple years

Author (year)	Method	Outcome(s) measured	Finding(s)
Schildkamp, Smit, et al. (2019)	Qualitative	Enabling/hindering factors Perception of collaboration effects	Identified relevant/quality data, data literacy and content knowledge, attitude, collaboration, leadership vision, goals, and encouragement for data use as enabling/hindering factors Effectiveness limited to awareness
Jimerson et al. (2021)	Mixed-methods**	Enabling/hindering factors	Identified vision, norms, goals, and data-use culture established by leadership through trust as enabling factors Identified lack of time, fidelity, capacity, urgency, lack of deep inquiry, and inadequate facilitation as hindering factors.

*$p \leq .05$; **no effect size identified.

Individual Participant Interventions Focusing Only on Factors Influencing Teacher Use of Assessment Data

Reeves and Chiang (2018) implemented two variations of their data in five by four (D5x4) intervention focusing on five levels of data (student, subgroup, classroom, grade, campus) and four types of questioning (location/identification, strengths and weaknesses, status and growth, instruction). Participants were provided with three online, asynchronous learning modules on the DDDM process to improve beliefs, reduce anxiety, and encourage data use for instructional change. The training included pedagogy, collaborative discussion boards, and scaffolded instruction. Pedagogical scaffolds were provided for some participants but not for others. The researchers used data from a pre and posttest survey and conducted repeated-measures analyses of covariance to determine outcomes. While results from the study specific to 25 in-service teachers found that DDDM implementation did not change significantly when considering pre and posttest outcomes, significant increases in participant self-efficacy (effect size range 0.54–0.63) and decreases in anxiety dimensions (effect size -0.62) were identified. However, no significance was found between in-service teachers who received pedagogical scaffolds and those who did not.

An intervention study (van den Bosch et al., 2019) was conducted using curriculum-based measurement progress-monitoring graphs. For this randomized control study of 164 elementary school teachers, three treatment groups were provided with different amounts and types of online learning for analyzing, interpreting, and linking data to instruction. Pre and posttest data were collected by observing and coding teachers' actions in a graph-description task and measured for sequential coherence, specificity, data-to-data comparisons (compared student data from one phase to student data in another phase), data-to-goal comparisons (compared student data to a goal), and data-to-instruction links (linked student data to instructional needs or changes). Results showed significant improvements in participants' capacity to interpret graphs if they were in any one of the three treatment groups as compared to the control group. Specifically, participants in analysis, interpreting, and linking data treatment groups showed more improvement on comparing data to goals ($\eta^2_p = 0.10$) and linking data to instruction ($\eta^2_p = 0.39$) than those in the control group. In addition, teachers demonstrated a positive attitude toward the intervention process.

After implementing the eight-step DDDM intervention (Figure 2), van der Scheer and Visscher (2016) considered changes in 62 primary teachers' perceptions of efficacy in three areas: classroom management, instructional strategies, and student engagement. Participants received DDDM professional learning across seven meetings and four coaching sessions during a single school year in this intervention. Using a delayed treatment design with two teacher groups, the researchers found that the intervention had a significant positive effect on perceived efficacy for instructional strategies and student engagement but not classroom management. Similarly, van der Scheer et al. (2017) investigated the intervention's effect on 34 primary teachers' capacity to differentiate instruction based on student data using a short interrupted time series design such that classroom lessons were recorded and rated both before and after the intervention. The authors found that DDDM-related skills such as data analysis and instructional grouping improved significantly with a large effect (0.93), and this improvement was unrelated to initial basic teaching skills.

Team Interventions Focusing Only on Factors Influencing Teacher Use of Assessment Data

Abrams et al. (2021) conducted a mixed methods study in a single school district to consider the effect of a professional learning program on teacher data literacy, efficacy, and collaboration implemented at six schools with nine teacher teams, totaling 28 teachers. The program consisted of a 3-day summer workshop and real-time team support for data use collaboration. The authors also investigated organizational factors that facilitate or constrain teachers' DDDM. A repeated measures analysis of variance was conducted using teacher surveys and supplemented with 15 principal interviews to better understand survey responses. Teacher perceptions from the survey suggest that the intervention improved all three outcomes. The authors noted that while teacher data literacy, efficacy, and collaboration significantly increased after the program, trust measures related to collaboration did not. Abrams et al. also found significant correlations between data literacy and other factors such that the use of technology and efficacy to identify, analyze, and act on data increased ($r = 0.53$, $r = 0.72$, and $r = 0.73$, respectively) while anxiety decreased ($r = -0.48$). In addition, interviews with principals revealed that leaders aimed to support teachers in using data to make instructional changes by building a culture of data use. First, leaders communicated their expectations for assessment and analysis. Second, leaders involved themselves in team meetings to model and facilitate expectations for collaboration around data use. Third, leaders provided resources to support their expectations.

Andersen (2020) conducted a longitudinal mixed-methods study in Denmark to investigate how a 1-year intervention (The Learning School) consisting of the student learning platform tjek.me, corresponding teacher team training, and facilitated team discussions affected attitudes and instructional decision-making. Data analysis was based on learning platform usage, surveys, and focus groups from 93 teachers across 11 schools. The researchers found that most teacher participants did not use platform data or indicate any change in their attitudes or actions. Instead, teachers continued to rely on their intuition regarding student achievement. The authors referred to inadequate professional development, a lack of systems for improving teaching and learning, and misdirected collaboration to explain their findings.

While not named as an intervention, Datnow et al. (2021) conducted a longitudinal qualitative nested case study of an instructional improvement project to determine how teachers' DDDM capacity is built through formative assessments of student thinking in mathematics. The project activities included teacher collaboration during department and grade-level team meetings on lesson plans, instructional approaches, and reviews of student thinking, instructional coaching, and workshops. These professional learning activities were designed to increase teacher capacity for data use and coherence of classroom instruction with external accountability expectations. Over 4 years, the authors led 165 teacher, administrator, and coach interviews. They also observed 200 teacher meetings or training sessions at four middle school campuses to gain insight into how teachers work together to improve teaching and learning. The authors found an improvement in how teachers used assessments of student thinking to adjust instruction over time and teachers' capacity for initiating and analyzing those assessments.

Ebbeler et al. (2016) used a mixed-methods design with questionnaires and case study interviews to determine if the eight-step data team intervention affected educators' use of data for accountability, instruction, and school development. They found that the intervention increased general awareness of the importance of using data and increased data use, but not significantly when compared to a control group. In another analysis of the intervention, Ebbeler et al. (2017) considered the extent to which participants' capacity and attitudes (beliefs) improved. Survey results indicated that data literacy and attitudes increased significantly with a medium effect (d = 0.60) for intervention participants compared to the control group. A knowledge test administered to the treatment group confirmed these findings, as pre and posttest results identified a small to medium effect (d = 0.32) on data literacy. Furthermore, interview participants acknowledged improved capacity and attitudes toward data. Researchers also found that educators were generally satisfied with the data use intervention.

Hubers et al. (2017) conducted a longitudinal mixed-methods study of the same intervention as Ebbeler et al. (2016) to investigate the sustainability of the intervention based on organizational context (vision and actual use) across six data teams comprised of school leaders and teachers. They found limited instances of vision and policy for sustainable implementation of the data team intervention. Furthermore, while implementation was more evident in daily practice, no new data teams were formed, and existing data teams did not complete the evaluation component of the intervention.

In their study of the eight-step data team intervention, van Geel et al. (2017) used data literacy pre and posttest results to conduct multivariate, multiple-level item response theory analysis and measure changes in individual learning and knowledge gaps between 1,182 participants from 83 schools based on their role, gender, age, and study cohort. Not only did the authors find significant increases in participant data literacy, but initial significant differences due to education level and role were minimized.

Kippers, Poortman, et al. (2018) studied a year-long intervention in which an external data coach used a structured approach to assist teams with data literacy components (purpose setting, data collection, data analysis, data interpretation, and instructional action) within the eight-step DDDM process. Two voluntary workshops were also provided to team members in conjunction with the intervention. Data collection included pre and posttest data, interviews, evaluations, and logs involving teacher teams from six sites. Results from the mixed-methods study indicate a significant increase in data literacy with a medium to a large effect (d = 0.71) when considering pre and posttest results from a data literacy assessment. Results varied by component, and the authors found that participants struggled most with setting a purpose (problem definition, formulating hypotheses) that was confirmed through qualitative sources.

Two replication studies of the eight-step data team intervention occurred in Switzerland and the United States. Schildkamp, Smit, et al. (2019) conducted a qualitative study on the enabling and hindering factors of data use and the perceived effects of collaborating to solve educational problems based on the design of Schildkamp and Poortman (2015). Participants from four schools in Switzerland provided information for the study through focus groups and interviews, and the data team facilitator was also interviewed. Their findings are congruent with the previous study. Enabling factors include relevant and quality data, literacy and content knowledge, a positive attitude, and collaboration of a heterogeneous group around a shared problem. In addition, school leaders can support the use of data by providing a culture of data use with clear goals and vision, encouraging participants to engage in decision-making, and providing facilitation. However, the authors noted that these can also be hindering factors if they are not balanced with the team’s needs. Moreover, the authors found that the perceived effectiveness of the data team was limited to awareness and did not extend to deeper inquiry or problem-solving.

Similarly, Jimerson et al. (2021) implemented the eight-step intervention in the United States where policy dictates daily time structure and emphasizes accountability. Data were collected from a third-grade professional learning team, including six teachers, an instructional specialist, and a principal. Qualitative data included recorded meetings, field notes, and interviews. The researchers also administered a data literacy assessment to participants. The authors found that a data-use culture established by leadership and based on trust with expectations connected to the campus vision, norms, and goals enables the DDDM model implementation while a lack of time, fidelity, capacity, urgency, and appropriate facilitation as well as the tendency to jump to action without deep inquiry hinders the work.

Individual Participant Interventions Including a Focus on Student Achievement

Förster et al. (2018) investigated the effects of an intervention to help teachers assess and individualize instruction on student reading achievement and progress over 2 years. The professional learning intervention was two-fold, including a series of learning about reading progress assessments and reading differentiation resources (The Reading Sportsman). The authors conducted a two-group quasi-experimental study using student reading achievement from 28 classrooms and questionnaires from the 13 treatment group teachers. The authors found that students in the treatment classrooms had significantly higher growth in reading fluency (effect size Year 1 $d = 0.30$, Year 2 $d = 0.31$) but saw no significant difference in reading comprehension between the two groups. In addition, the intervention appeared to have a more positive impact on low-achieving students’ reading fluency and comprehension than on high-achieving students. The authors also found that teachers used the data multiple times monthly to address individual student and whole-class instructional needs.

Peters et al. (2021) reanalyzed data from six previous general education classroom studies to determine if an identified positive impact of the 1-year DDDM intervention to improve reading fluency, comprehension, and motivation examined by Förster et al. (2018) was generalizable when considering only low-performing readers. The original studies used a quasi-experimental design to compare students’ reading achievement across three teacher groups: those with access to the Learning Progress Assessment, those with access to the Learning Progress Assessment and instructional materials, and those without access to either (control). The authors considered individual study results for 1,346 low-performing readers in 264 teachers' classes and analyzed the results as a whole. No significant effects were identified, but positive trends indicated that using the Learning Progress Assessment might help teachers improve reading outcomes for low-performing students.

In an intervention for DBI consisting of tools, learning modules, and collaborative supports, McMaster et al. (2020) provided assessment tools, learning modules, face-to-face workshops, and coaching to develop teachers' capacity for DBI implementation. The authors used a randomized control trial pre and posttest approach and collected data from 20 teachers and 53 students across two school districts. Teachers took knowledge and skills assessments and self-reported instructional changes while students were administered pre and postintervention writing assessments, and observations were conducted to measure implementation fidelity. The findings indicate significant improvement in the teacher treatment groups' knowledge and skills (g = 2.92). Teachers in the treatment group also demonstrated more teacher-guided writing instruction (g = 1.63), but other changes were not significant. Student outcomes connected to teachers in the treatment group improved but were not significantly different from those associated with control group teachers. In addition, fidelity was greatest for curriculum-based measurement (83.5%) followed by writing instruction (79.1%) and decision-making (52.1%).

Powell et al. (2021) conducted an exploratory study to evaluate the impact of the project Supporting Teaching of Algebra with Individual Readiness on math readiness, DBI implementation and efficacy, and organizational factors (culture, climate). The project's intervention included DBI professional development consisting of three sessions, monthly coaching, and instructional videos for individualized support. The authors used data from two surveys administered to 22 teachers and math outcome assessments from 56 middle school students with difficulty learning mathematics. The researchers found a significant pre to posttest change in teachers' perceptions of culture and climate. Concerning teachers' assessment perceptions, significant increases were identified in importance, understanding, and confidence (d = 0.56, d = 1.39, d = 1.07, respectively). While no significant differences were identified for the frequency of assessment use or DBI practices, students' mathematics achievement showed significant differences with small to large effects on four of five pre to posttest assessments (d = 0.16, d = 0.34, d = 0.74, d = 1.17).

In a study of influencing factors and student achievement, Supovitz and Sirinides (2018) investigated the impact of a feedback cycle on 64 teachers' views about the importance of data, self-reported proficiency in using data for instructional changes, perceptions of their learning about pedagogy and student thinking, instructional practice, and student mathematics performance. Treatment professional learning communities received emailed feedback from videotaped lessons for this experimental study (titled Linking Study). Teams also participated in facilitated dialog on video content and assessment data. The authors used data at multiple points in time from pre and postsurveys, lesson observation ratings, professional learning community exit slips, and student end-of-unit test outcomes to link teaching and learning by comparing means and group differences. Study results indicate that teachers' perceptions of data use importance, efficacy, and comfort working together did not change significantly. However, significance was found when considering what teachers perceive about their ability to link instruction to student needs; specifically, learning about teaching and understanding student thinking (g = 1.07–1.32, g = 0.86–1.42, respectively). Observation ratings support these findings as there were also significant differences between groups on instructional rigor and teacher-student interactions at the second time point (g = 0.86, g = 0.80, respectively). Student assessment results did not indicate any significant findings except for a small effect at the last time point for treatment students when controlling for pretest and grade level.

A randomized control study (van der Scheer & Visscher, 2018) was conducted to investigate the impact of the eight-step data team intervention on Grade 4 student achievement in mathematics. The authors use standardized math test scores to determine if 25 Grade 4 teachers' participation in the intervention improved student achievement compared to students of 33 control group teachers. Students' scores were analyzed at three points across the year and measured for growth. The researchers did not find significant differences between student achievement for those in the experimental groups' classes and those in the control group. However, low-performing students who received extended instruction in the experimental groups' classes showed statistically significant positive effects (d = 0.19) from pre to posttest scores.

Team Interventions Including a Focus on Student Achievement

Lai and McNaughton (2016) summarized the impact of four school wide intervention replication studies on student achievement across various contexts. The intervention, the learning school model, included three phases of professional learning: collaborative analysis, content knowledge development, and sustainability. Their quasi-experimental study focused specifically on the data use component of the professional learning model and was conducted four times at 53 schools during 8 years. The authors indicated that learning school model data use professional learning resulted in statistically significant improvements across three studies in reading comprehension (d = 0.24–1.68), writing (d = 0.50–0.67), and high school qualifications (no effect size available) based on an analysis of nationally recognized achievement assessments. In addition, results indicate that older students experienced a higher impact on reading achievement, and students at lower performance levels had the largest gains. Furthermore, the authors noted that increased achievement was already evident after the data literacy component was completed, and schools were able to sustain impact after the intervention concluded.

Poortman and Schildkamp (2016) conducted a mixed-methods study to investigate their 2-year professional learning intervention (including a data analysis course) for data teams using a university data coach to guide the teams through a structured eight-step DDDM process. The authors conducted t tests and used descriptive statistics to analyze student achievement results. They also collected assessment data from the nine participating data teams to determine which teams solved their self-selected educational problem. Five teams solved their problems related to geography and English, and general secondary exam passing percentages suggested that the intervention improved student achievement. Significant increases in student achievement were identified for one team's focus on final senior exam grades (d = 0.45) and two teams' English exam grades (d = 0.54, d = 0.66).

Research by van Geel et al. (2016) and Staman et al. (2017) studied the eight-step data team intervention to determine its impact on primary student mathematics achievement. In van Geel et al. (2016), 4 years of math achievement from standardized tests aggregated at the student and school levels across 53 primary schools were studied, controlling for school and student characteristics such as school size and type, socioeconomic status (SES), gender, and age. Comparisons of pre and during-intervention achievement showed positive effects equivalent to an extra month of instruction; however, results varied across schools. Results also indicated that schools with large populations of low SES students experienced more benefit from the intervention. Staman et al. (2017) conducted a quasi-experimental involving 84 schools (42 control, 42 test) using multilevel analysis with students' posttest interim assessment scores as the dependent variable. Their findings indicate that while there was no main effect of the focus intervention on mathematics achievement, some students with lower scores and students in schools with larger populations of low SES students did see statistically significant positive interaction effects. Keuning et al. (2019) replicated van Geel et al.'s (2016) study in 39 elementary schools and found similar results: mathematics and spelling achievement generally increased during the eight-step data team intervention and varied across campuses. Schools with larger populations of low SES students saw higher effects in mathematics. Furthermore, students identified as low SES and high SES also saw larger effects than middle SES students. However, higher effects for spelling were not noted. In addition, the authors concluded that schools that focused on the same subject during both years of the intervention experienced larger intervention effects.

Conclusion

The purpose of this review was to evaluate and recommend interventions for continuous improvement of a PK–12 public school district's DDDM program for linking instructional adjustments to individual student assessment data. This review adds to the literature on DDDM actions, outcomes, and interventions. Specifically, three research questions were considered. The synthesis of the literature for the first research question concerning how assessments are defined and used for DDDM indicates that formative, summative, and interim assessments are categorized by and used for a variety of purposes, including ranking scores to identify student groups, identifying students' strengths and weaknesses around specific skills, analyzing student work to better match instructional strategies with student needs, and monitoring learning progress.

The findings for the second research question regarding factors that promote teachers' use of assessment data for DDDM show that teacher capacity, teacher attitudes and beliefs, collaboration, and leadership and context promote DDDM implementation when positive or increased and hinder when missing or insufficient.

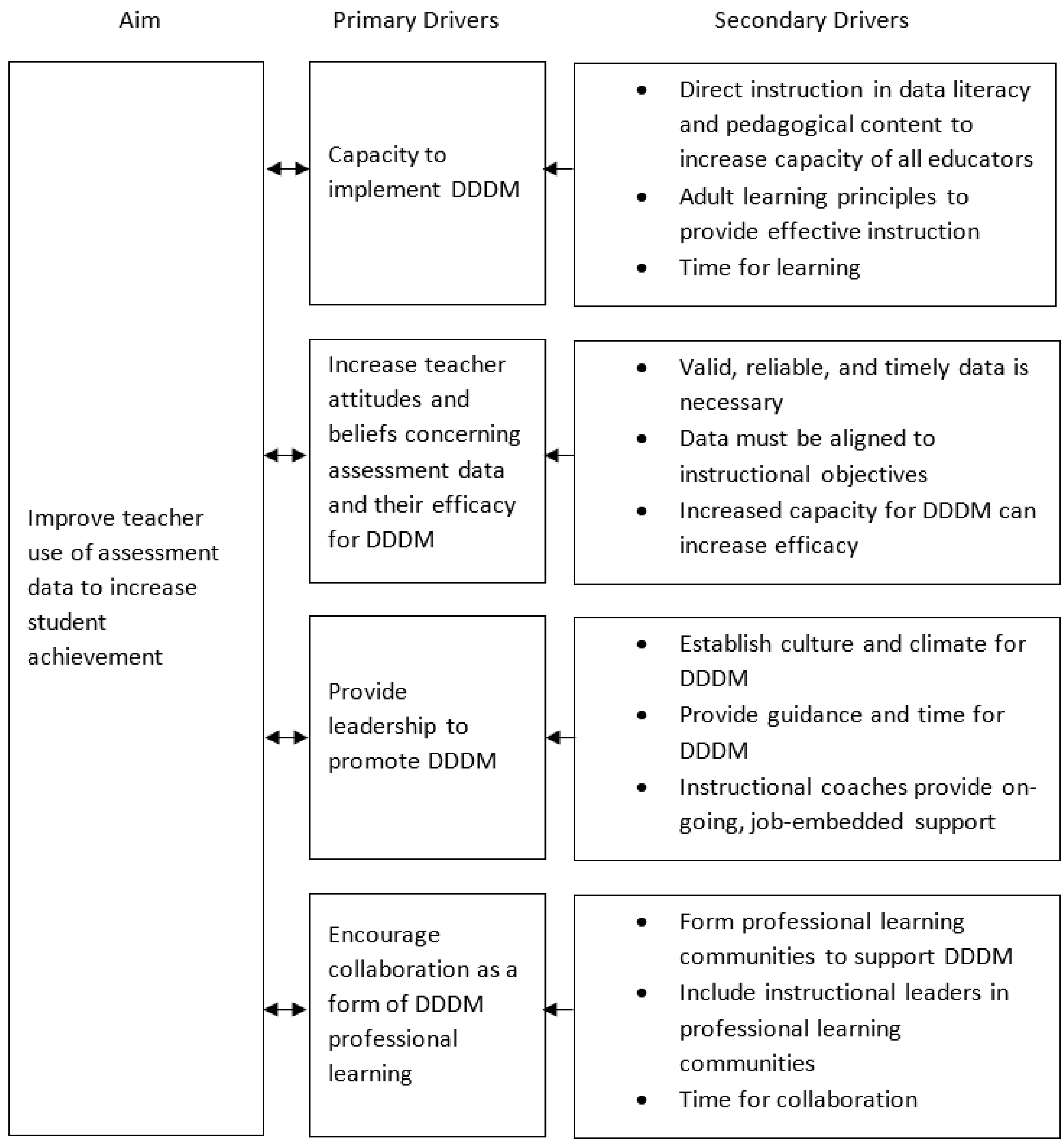
Finally, the third question about intervention strategies that are most promising for improving teachers' use of assessment data and student academic performance included the analysis of 25 studies. All of the interventions were implemented as professional learning opportunities such that workshops, meetings, or ongoing support were structured and designed within context to increase teacher capacity, attitudes, or beliefs. The most promising studies for improving student outcomes used collaborative teaming and coaching to provide job-embedded learning. The driver diagram in Figure 4 illustrates primary and secondary drivers with the aim of improving teachers' use of assessment data to increase student achievement in reading. Driver diagrams are improvement science tools that show and align organizational change options proven to achieve a desired aim (Bryk et al., 2017). Primary drivers are influencing factors, and secondary drivers are interventions needed for the desired change. After an evaluation, driver diagrams can be used to design an intervention and establish a working theory of improvement.

Limitations

Several limitations of this literature review should be considered. First, as with any literature review, all articles related to the topic could not be included due to resource limitations. Second, search methods and terms established the selected articles, meaning that variances in methods and terms could render different findings. Third, selecting only peer-reviewed articles from Quartile 1 journals may have been impacted by publication bias such that studies with nonsignificant results were less common. Finally, a single researcher conducted the review, which could also introduce researcher bias.

Figure 4

Driver Diagram to Improve Teacher Use of Assessment Data to Increase Student Achievement



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