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A Study of Elementary Teachers' Data Driven Decision-Making Practices and School Performance

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by

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APPROVAL FOR SUCCESSFUL DEFENSE

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Dedication

This study is dedicated to my father, Brig. General John L. Kotcho (1937–1995).

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CHAPTER 1: INTRODUCTION

U.S. educators strive to prepare students to meet the demands and expectations of an ever-evolving world and a globalized 21st-century community. Educator accountability has increased under the Elementary and Secondary Education Act (ESEA; 1965), the No Child Left Behind Act (NCLB; 2001), and the Every Student Succeeds Act (ESSA; 2015). Teachers and principals are expected to make informed instructional decisions using a variety of data, and state officials must set goals for all schools under their jurisdiction and provide intervention plans for schools needing improvement. In an age of accountability and school reform, the call to improve the quality of education so that all students in America be taught to high academic standards that will prepare them to succeed in college and careers is prevalent (ESSA, 2015). It is essential that teachers and principals understand the fundamental nature of data-driven decision-making (DDDM) and remain committed to the values of DDDM.

Teachers and administrators may feel that they understand the importance of using data to make informed educational decisions; however, effective implementation remains challenging even under the best of conditions, in the best of schools, and with the best teachers. The NCLB Act of 2001 resulted in the measurement of student learning and achievement relying heavily on specific summative standardized testing data (Earl & Fullan, 2003; Park & Datnow, 2009). The NCLB Act placed the focus on meeting adequate yearly progress (AYP) and avoiding punitive actions as a result of low performance. Accountability for educators was limited to data that reflected compliance, with limited impact on improving teaching and learning (Mandinach, 2009); thus, a large disconnect was produced between the data used to demonstrate compliance and the data designed to inform teaching practices (Smith, 2009). The NCLB Act increased teacher accountability; however, the act failed to help educators understand how to use vital information to make gains with individual students over time. Educators' and policymakers' recognition of the NCLB Act's strict mandates initiated a shift, resulting in the adoption of the ESSA by the Obama administration. The ESSA upholds that all students—regardless of background, location, or socioeconomic standing—should receive an education that is connected to high standards and measured by statewide assessments designed to measure students' progress toward those standards (ESSA, 2015). The NCLB Act's strict policies have resulted in state officials providing rigorous plans to close the achievement gap and increase quality of instruction, equity, and learning outcomes.

This paradigm shift transferred the focus from only using data to hold educators accountable to prompting educators to engage in a continuous cycle of improvement using multiple sources of data (Mandinach, 2012). Paradigm shifts are complex and require that educators maintain a mindset that can be cultivated and redefined over time (Fullan, 2001). This change in thinking is paramount if educators are to implement DDDM practices into their daily work, thus influencing the learning outcomes of all students.

Background of the Study

DDDM is defined as "the systematic collection, analysis, examination, and interpretation of data to inform practice and policy in educational settings" (Mandinach, 2012, p. 1). The notion of using data to inform educational decisions is not novel; in fact, teachers and school leaders have used data in various forms and for a variety of reasons for decades. Educators face many changes, and reform efforts are designed to have a positive impact on student achievement while addressing teacher accountability and performance (Cramer et al., 2014). It is important to use evidence from relevant data to guide decision-making and espouse a conceptual framework for DDDM that embraces "an iterative inquiry cycle" (Mandinach, 2012 p. 4). Due to federal and state accountability mandates, school officials nationwide have increased their capacity to collect, analyze, and distribute data and make decisions based on collected data. Using data for the purpose of school improvement is not just an option, but a necessary part of school improvement (Earl & Katz, 2002); however, challenges remains with the timely availability of data, accessibility to the data, and teacher understanding of how these data can be transformed into action that impacts instructional decisions.

Prior scholars have focused on using data to assist with guiding organizational change that leads to school improvement (Fullan & Steigelbauer, 1991; Massell, 1998; Schmoker, 2000). Limited data are available on how teachers use DDDM to inform instruction; most prior literature addressed the administrative use of data (Schifter et al., 2014). The National Assessment for Educational Progress (NAEP) and the NAEP Mathematics and Reading Highlights report assessment results every 2 years for Grades 4, 8, and 12. In 2017, 40% of fourth-grade students performed at or above the proficient level in mathematics, whereas 37% of fourth-grade students performed at or above the proficient level in reading and 28% of fourth-grade students performed at or above the proficient level in writing (The Nation's Report Card, n.d.-b). Of the 149,400 students assessed, most states reported no significant change in students' math, reading, and writing scores. Moreover, the NAEP 2019 report indicated that 41% of fourth-grade students performed at or above the proficient level in mathematics, which illustrated no change between 2017 and 2019 (The Nation's Report Card, n.d.-a). Thirty-five percent of fourth-graders performed at or above the proficient level in reading, indicating a decrease in reading scores between 2017 and 2019. A large majority of U.S. students are not meeting the standard if solid academic performance and competency are measured by demonstrating at or above the proficient level on NAEP assessments. In particular, students performing at the 10th and 25th percentiles demonstrated a decrease in performance compared to subsequent assessment years. For example, scores of fourth-grade students in specific groups—such as students who participated in the national school lunch program, students attended city or public schools, and students with disabilities—decreased between 2017 and 2019.

The disparity between the standards-based and evidence-based efforts put forth over the past decades and the results of these efforts as measured by student achievement deserves continued attention. Although more studies are now addressing how educators use student data to improve instructional practices, most do not reflect causal links between the use of data and student achievement (Wayman et al., 2012). It is essential that educators contemplate their attitudes, understandings, and actions related to effective DDDM practices and consider how these actions impact student learning outcomes.

Problem Statement

Using data to support decision-making in schools is an essential practice in the United States. DDDM is the "systematic collection, analysis, and application of many forms of data from myriad sources in order to enhance student performance while addressing student learning needs" (Marsh et al., 2006, p. 1). As a result of the NCLB Act (2001) and ESSA (2015), schools are accountable to ensure a quality education for all students. Schools are provided with an abundance of data designed to support educators in improving instruction and increasing student learning outcomes. Data are provided to teachers; however, teachers may not understand how to use data effectively to improve instruction (Massell, 2001). Many teachers have not received training on how to use assessment data (Mandinach & Gummer, 2013). Without appropriate professional development, support, and leadership, teachers may struggle to use data to make sound decisions and take action in their classrooms.

Analyzing and using data for decision-making is not intuitive, and most published resources that provide guidance are designed for administrators (Schifter et al., 2014). Teachers are required to analyze state assessment data and use the findings to inform their instructional decisions; however, teachers' lack of training in how to use data to improve student learning outcomes is a long-term problem (Schifter et al., 2014). This study examines DDDM practices of elementary teachers and the relationship between student achievement; thus, the study findings could impact the structure and systems schools use to support the DDDM process.

Significance of the Study

This study provides additional insight into how teachers use data to inform classroom instruction. The importance of using evidence from relevant data to guide decision-making continues to be at the forefront of school reform and accountability; however, the degree to which teachers may be supported in a data-driven school culture, have access to relevant and timely data, or have the knowledge to act upon data effectively is unknown. The use of data is paramount, and educators must engage in a cycle of quality improvement and reflection. Despite this understanding, student achievement in the United States is mediocre at best. This mediocre achievement is reflected in the New Jersey Partnership for Assessment of Readiness for College and Careers (PARCC) spring state summary reports. PARCC results between 2015 and 2019 indicated limited improvement; the percentage of third-grade and fourth-grade students who meet or exceeded expectations hovered around 50% in both mathematics and English language arts (ELA). The results of this study will assist school administrators and teachers with implementing effective DDDM practices in their schools and facilitate teachers' use of DDDM practices to inform instruction that results in greater student learning outcomes.

Research Questions

The purpose of this quantitative survey study was to investigate elementary teachers' readiness for DDDM in four areas: assessments, acting upon data, school support systems, and school culture. Survey results were analyzed to address the study's five research questions. The research questions that guided this study were as follows:

1. Is there a relationship between overall teacher readiness with DDDM practices and New Jersey School Performance Report ELA and mathematics proficiency levels?
2. Is there a relationship between teacher readiness with assessment use and New Jersey School Performance Report ELA and mathematics proficiency levels?
3. Is there a relationship between teacher readiness to act upon data and New Jersey School Performance Report ELA and mathematics proficiency levels?
4. Is there a relationship between teacher readiness with the use of school support systems available for DDDM and New Jersey School Performance Report ELA and mathematics proficiency levels?
5. Is there a relationship between teacher readiness with DDDM school culture and New Jersey School Performance Report ELA and mathematics proficiency levels?

The purpose of this quantitative correlation study was to examine elementary school teachers' levels of readiness regarding DDDM practices. The study also determined the relationship between school achievement with schools that report high and low levels of DDDM practices.

This study provides insight into the self-reported levels of DDDM by elementary school teachers in noncharter suburban public elementary schools in northern New Jersey. The focus of this quantitative study was to examine the DDDM practices of elementary teachers and determine if DDDM practices impact school achievement. The knowledge gained from this study provides insight that will inform educational leaders and policymakers, add to the existing research base, and facilitate change.

Methodology

This quantitative survey research study included teachers currently employed in noncharter suburban public elementary schools in Morris and Somerset Counties, New Jersey. All schools selected for this study were listed as a public noncharter elementary school and offered third-grade through fifth-grade classes. I obtained permission to administer the Statewide Data-Driven Readiness Study Teacher Survey authored by McLeod and Seashore (2006; see Appendix A). The survey was transposed into the digital survey tool SurveyMonkey to safeguard and manage collected confidential survey data, and no identifiable personal information was collected from participants. Only certified noncharter public elementary school teachers who directly provided instruction in ELA and/or mathematics during the 2018–2019 school year were considered for this study. The 2018–2019 New Jersey School Performance Report ELA and mathematics proficiency percentage scores for each school were collected from the New Jersey Department of Education website; these scores are part of the public record. I used ANOVA analysis to measure the strength of variables for all research questions and investigated descriptive statistics using Statistical Package for the Social Sciences (SPSS) software.

Study Limitations

The following lists describe the inherent limitations and delimitations in this study.

1. The participants in this study were limited to public noncharter school elementary teachers in suburban public elementary schools in Morris and Somerset Counties, New Jersey. All schools offered third-grade through fifth-grade classes.
2. Participants must have taught ELA and/or mathematics in their current school during the 2018–2019 school year.
3. The study was limited to the sample size of the respondents in the study group.
4. The responses of participants were voluntary, self-reported beliefs.
5. School achievement data were collected from the 2018–2019 New Jersey School Performance Report. The ELA and mathematics proficiency scores used to measure overall school performance are published annually and posted on the New Jersey Department of Education website for public access.

Study Delimitations

1. This study did not include teachers who did not teach ELA and/or mathematics in their current school during the 2018–2019 school year.
2. This study focused specifically on surveying teachers' use of DDDM practices. Superintendents, principals, and other school administrators were not included in this study.
3. Teachers who did not have a valid New Jersey teaching certification were not included in this study.
4. Secondary school teachers were excluded from this study.
5. Mendham Township Elementary School teachers were not included in this study.

Definition of Terms

Accountability - The ESSA requires states to use a set of indicators to measure the performance of all schools. Under the ESSA, New Jersey is required to use the data contained in the accountability profiles to identify schools in need of support or improvement (New Jersey Department of Education, ESSA Accountabilities Profile Companion Guide, 2018).

Achievement gap - Achievement gaps occur when one group of students—such as students grouped by race, ethnicity, or gender—outperforms another group and the difference in average scores between the two groups is statistically significant (that is, larger than the margin of error; National Assessment of Educational Progress, n.d.).

AYP - AYP is the amount of yearly improvement each Title I school and district are expected to make to enable low-achieving children to meet high performance levels expected of all children (U.S. Department of Education, 2009a).

DDDM - DDDM refers to the systematic collection, analysis, examination, and interpretation of data to inform practice and policy in educational settings (Mandinach, 2012).

Data literacy - Data literacy for teaching refers to the knowledge and skills educators need to effectively use data to transform information into actionable instructional knowledge and practices (Ebbeler et al., 2016; Mandinach & Gummer, 2016).

Data teams - A data team is a group of teachers focused on collaborative learning by sharing experiences and critical reflections related to data use (Ebbeler et al., 2016).

Data systems - Data systems are electronic, computer-based tools that help educators examine and manage student data (Wayman et al., 2012).

Data warehouse - A data warehouse is where data are collected and organized into one electronic repository (Wayman et al., 2005).

New Jersey Student Learning Standards - New Jersey Student Learning Standards were adopted in 2016 and provide school districts with clear and specific benchmarks for student achievement in nine content areas.

New Jersey School Performance Reports - New Jersey developed a school accountability system required by the ESSA. The New Jersey School Performance Reports are published yearly for every public school in New Jersey. School demographics, student growth, academic achievement, climate, staff, and accountability indicators are published in the report.

PARCC - PARCC is a collaboration of states that share a commitment to developing new-era assessments that measure students' readiness for college and careers. Statewide assessment data for students in Grades 3–10 are aggregated to calculate participation and proficiency rates in two content areas: ELA/literacy and mathematics (New Jersey Department of Education, ESSA Accountabilities Profile Companion Guide, 2018).

Professional learning community (PLC) - A PLC is a group of teachers that is focused on collaborative learning by sharing experiences and critical reflections (Ebbeler et al., 2016).

NCLB Act – The NCLB Act was signed into law in 2002. This federal mandate clearly delineates benchmarks in achievement for all students to close the achievement gap with accountability, flexibility, and choice (NCLB, 2001).

ESSA - The ESSA was passed in December 2015 with bipartisan congressional support. It replaced the NCLB Act of 2002 and reauthorized the ESEA of 1965 (ESSA, 2015). The purpose of the ESSA is to ensure that all students have equitable access to high-quality educational resources and opportunities and to close educational achievement gaps (ESSA, 2015).

Student information system - Student information systems are computer-based tools that manage basic student information such as scheduling, course grades, and demographic information (Wayman et al., 2012).

Organization of Remaining Chapters

This dissertation is organized into five chapters. In Chapter 2, I provide a review of the relevant literature as it relates to the significance of the study and theoretical framework described in Chapter 1. The literature discussed in Chapter 2 is organized under specific themes that provide the basis of the research argument. The theoretical framework of DDDM, school uses of data, data literacy, leadership, data-driven culture, teacher capacity for data use, and the barriers to effectively using data are analyzed. In Chapter 3, I outline the research methodology and procedures required for conducting this study. In Chapter 4, I present the data analysis and significant findings. In Chapter 5, I summarize the findings, discuss implications of the findings, and provide recommendations for future research, policy, and practice.

Chapter Summary

The purpose of this study was to examine the DDDM practices of elementary teachers and determine if a relationship exists between these practices and student achievement. This study adds to the current body of research focused on the DDDM practices of elementary school teachers. Previous studies by Teigen (2009) and White (2008) investigated principals' beliefs related to DDDM; however, more recent studies by Anderson (2015) and Immen (2016) focused on teacher perceptions of DDDM to inform instructional practices.

In the current study, I examined elementary teachers' use of assessments and teachers' level of acting on data along with school support systems for using data and school data culture. Teachers must demonstrate high levels of data literacy to make sound instructional decisions;

teachers use data literacy skills to turn raw data into knowledge that drives classroom instruction and improves student learning outcomes.

CHAPTER 2: REVIEW OF THE LITERATURE

This review of the literature provides insights into the existing body of research on DDDM and teachers' readiness and use of DDDM practices. The review addresses (a) the historical overview and context of school reform and accountability, (b) the theoretical framework for DDDM, (c) teacher capacity for data use, (d) data literacy, (e) data use, and (f) factors that influence data use. I examine research that addressed these topics in more detail and thus support the purpose of the current study. The literature review closes with a discussion regarding the importance of prioritizing DDDM practices and data literacy in schools to support instructional improvement and student achievement. The literature review also addresses the gap in the research that exists regarding teachers' DDDM practices and school achievement.

Historical Overview of School Reform and Accountability

U.S. schools are required to monitor and assess the learning outcomes of students and analyze data to drive instructional decisions. These efforts continue to grow as the need to use data effectively remains paramount in an era of reform and accountability. The NCLB Act of 2001, the American Recovery and Reinvestment Act of 2009, and general 21st century educational policy and practice have shifted toward meeting AYP to measure student success and close the achievement gap (Mandinach et al., 2006). The focus on student outcomes and high-stakes standardized assessments requires educators to collect, analyze, and use data purposefully to improve overall instructional outcomes (Datnow & Hubbard, 2015). DDDM is an essential part of the educational process and has received a tremendous amount of attention through policymaking and financial support. DDDM was included within the four pillars of the American Recovery and Reinvestment Act of 2009 and the Race to the Top program (U.S. Department of Education, 2009b); this inclusion of DDDM signaled the importance of using data to inform practice and policy to improve learning outcomes and close the achievement gap (Mandinach, 2012; Young & Kim, 2010). The increasing focus on evidence-based practice and the use of DDDM is more complex than ever. For over a decade, DDDM has been a developing reform initiative both nationwide and internationally. DDDM is a vital component to the learning process (Mandinach, 2012; Mandinach & Gummer, 2013).

Using data is not a novel concept; currently, teachers must engage in the systematic analysis of data collected from a variety of sources, including high-stakes statewide standardized assessments, and incorporate their findings into their instructional decision-making (Kennedy & Datnow, 2011; Mandinach, 2012). The use of data for school improvement is no longer a choice yet teachers are not trained to use data to reflect on instruction or student progress (Earl & Katz, 2002). This increased focus on DDDM partially evolved out of the emphasis on rigor and the notion that it is no longer acceptable for teachers to base instructional decisions on opinions or experience alone. The art and science of teaching calls for the use of evidence to inform practice (Gage, 1978). The U.S. Department of Education mandates educators to use data to inform policy and practice; thus, teachers must also become data literate to use data effectively (Mandinach, 2012).

The ESSA was signed with bipartisan support in December 2015 and replaced the NCLB Act of 2001, subsequently reauthorizing the ESEA of 1965. The federal government set the long-term academic proficiency standards under the NCLB Act; however, the ESSA allows state officials to set their own standards regarding academic proficiency, high school graduation rates, and English language proficiency. One of the most significant changes made under ESSA was the requirement that state officials develop a school accountability system. State accountability systems must include the following elements.

- academic proficiency;
- graduation rates for high school;
- academic growth or another statewide indicator of academic progress for K–8;
- progress toward English language proficiency; and
- at least one other state-determined indicator of school quality or student success.

Annual state assessments are one source of information that can be used to make instructional decisions; however, annual state assessments do very little in helping teachers improve teaching and learning because summative assessments are typically administered toward the end of the academic year (Young & Kim, 2010). Data use and its impact on student achievement is of growing importance; thus, it is essential that teachers have the ability to transform numbers and statistics into instructional decisions that meet the needs of students (Love et al., 2008). A continuous cycle of improvement can be maintained through the use of relevant data. The process of transforming raw data into usable knowledge that will inform instructional decision-making in the classroom is crucial (Mandinach et al., 2006).

In 2002, the U.S. Department of Education created the Institute of Education Science with the purpose of providing scientific evidence on which to ground education and policy, (Institute of Education Science, 2011). Subsequently, the What Works Clearinghouse was created as a storehouse for high-quality research studies that educators could use when making decisions about intervention or practices. School officials were faced with the pressures of meeting AYP and meeting accountability benchmarks rather than improving individual students' knowledge and skills (Mandinach, 2012). This accountability data were seen as having no connection to improving teaching and learning (Mandinach, 2009; Smith, 2009). The gap between using data for compliance and using data to inform teaching and learning emerged and a call for balance ensued. The way educators looked at data shifted from data use for accountability to data use for the purpose of continuous improvement; teachers began using data to inform decisions that are aligned with appropriate strategies and the needs of individual students. The complex process of taking raw data and transforming it into actionable knowledge became prominent in education reform efforts.

Theoretical Framework for DDDM

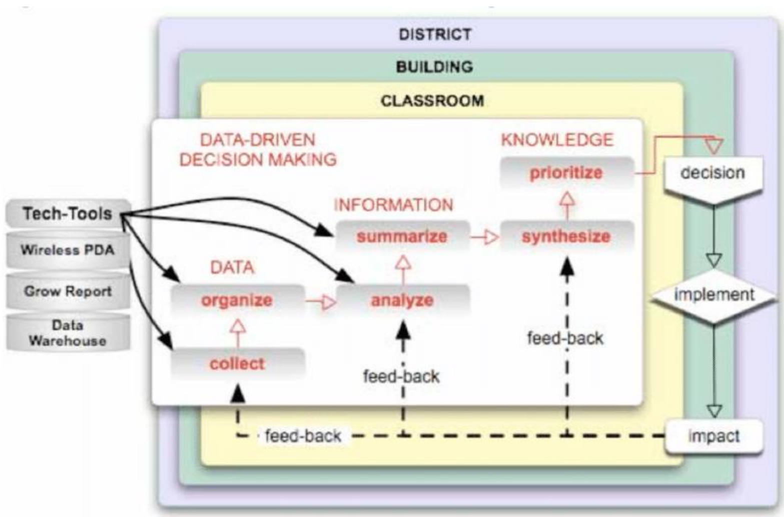
The shift to standards-based education and high-stakes accountability led to the NCLB Act. In recent years, the ESSA has pushed school officials to think differently about how to collect, analyze, and use data. Policymakers, administrators, and teachers are challenged to embrace a basic understanding of how data can inform decision-making for the purpose of raising student achievement. Mandinach et al. (2006) defined DDDM as the "systematic collection, analysis, examination, and interpretation of data to inform practice and policy in educational settings" (p. 8). The purpose of the DDDM process is to improve instruction and learning outcomes. DDDM intersects with all levels of the educational system and can be applied to classroom instruction and the development of school policy (Mandinach et al., 2006). Prior literature on the use of data in K–12 instructional settings has indicated that just making data available does not automatically improve teaching and learning. DDDM is more complex and involves translating evidence into information and actionable knowledge that administrators and teachers can use to address future problems (Spillane, 2012).

Multiple conceptual frameworks can be used to assist educators with the complex task of transforming raw data into usable information. The models included in this review used one of the following frameworks: management theory, organizational psychology, and social organization management theory (Ackoff, 1989; Breiter, 2003; Choo, 2002; Thorn, 2002).

Certain frameworks illustrate the process required to interpret, analyze, and act upon data. Mandinach et al. (2006) created a model framework for DDDM based on organization and management theory in the use of data. The framework is supported by the work of Ackoff (1989), Breiter (2003), Brunner et al. (2005), and Drucker (1989). Data, information, and knowledge move through a continuum (Ackoff, 1989). Data can be interpreted and translated into actionable knowledge that can be applied to making decisions. Data alone in any form do not have meaning until the person examining the data understand and make meaning of it. Data become information when meaning is realized. This information can illuminate the relationship between data and context, but does not result in further action. Knowledge is the relevant information collected that can be used to make decisions in the classroom (Mandinach et al., 2006). Figure 1 illustrates the process of moving data to knowledge.

Figure 1

Framework for DDDM



Note. From "A Theoretical Framework For Data-Driven Decision Making" [Paper presentation], by E. B. Mandinach, L. Rivas, D. Light, C. Heinze, and M. Honey, 2006, The Annual Meeting of the American Educational Research Association, San Francisco, CA, United States, p. 7. Copyright 2006 by the American Education Research Association.

The continuum illustrated in Figure 1 relies on six essential skills. In the data stage, the two skills are (a) collect and (b) organize. At the information stage, the two skills are (a) analyze and (b) summarize. At the knowledge stage, the two skills are (a) synthesize and (b) prioritize. The process within the framework may be applied at the district, building, or classroom levels when a problem is identified and data are needed to inform decisions. For example, a teacher can decide which data are meaningful to collect and then organize the data systematically. Organizing the data allows the teacher to understand and make sense of the data. After organizing the data, the teacher can analyze the information on either a micro or macro level depending on the issue. The analysis of information is summarized before synthesizing and prioritizing the new knowledge. Mandinach et al. (2006) described the outcome of this six-step process as a decision. Teachers may or may not implement changes based on a variety of reasons. The final stage of the framework indicates that the result of implementing a decision is the impact. The teacher must evaluate the impact of the decision and decide if it is necessary to revisit any of the six steps in the process. DDDM is an iterative process that requires the decision-maker to move through and possibly revisit the six steps to reach the results that will ultimately solve the educational problem (Mandinach et al., 2006).

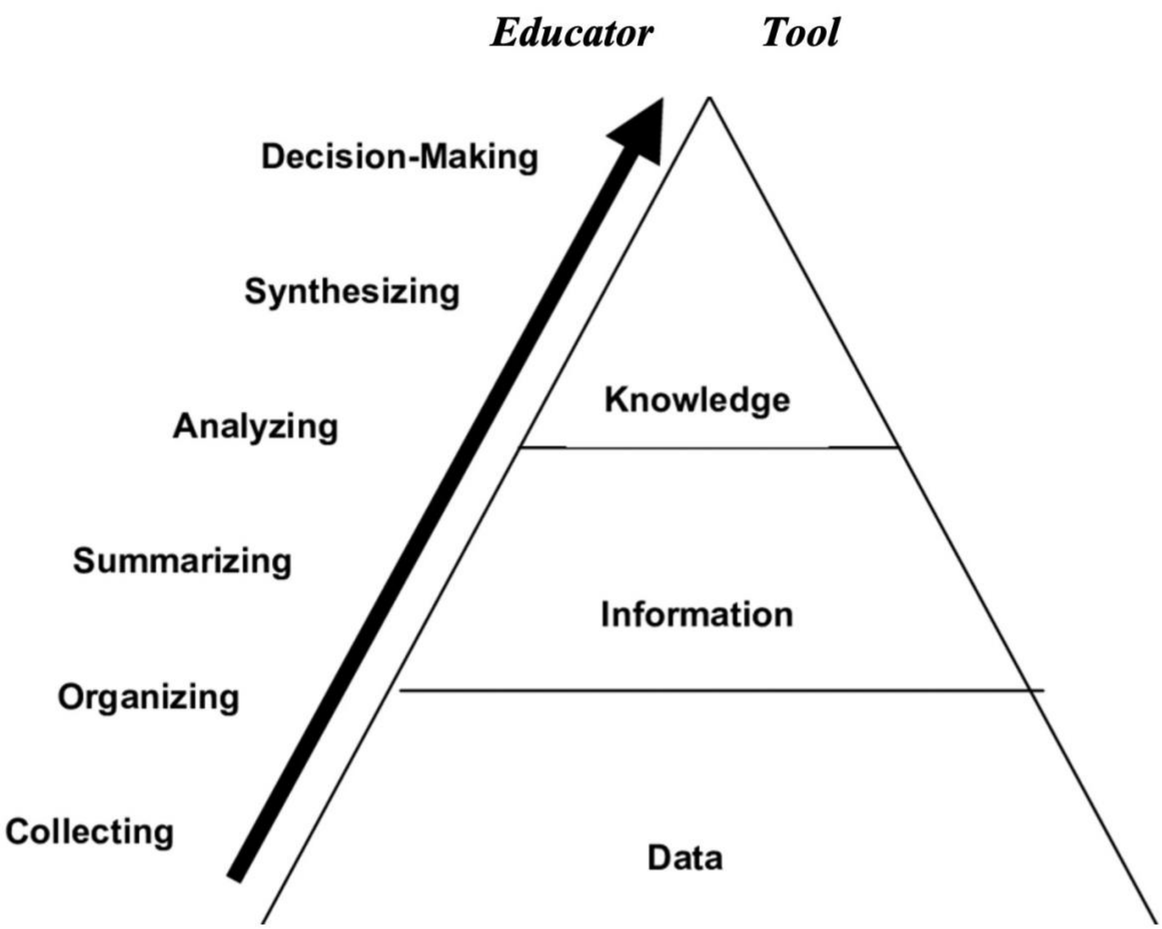
Transforming data into knowledge is at the heart of the decision-making process; however, little is known about the ways in which teachers and administrators use data to inform educational practices (Light et al., 2005). The Grow Network study examined how teachers working in the New York City school system used data to inform their decisions about teaching and learning. The Grow Network study was contracted by the New York City Board of Education to provide print and web-based reports for Grades 3–8 in ELA and mathematics to transform assessment results into instructional tools for teachers, principals, and parents

(Brunner et al., 2005). The Grow Network study was the largest study conducted on improving the quality of decision-making at multiple levels of a school system and included 1,200 schools, 500,000 students, 30,000 teachers, and 5,000 district and building leaders. The study results indicated that teachers used the data from the Grow Reports® to (a) plan lessons, (b) start conversations with students, parents, and administrators, and (c) plan their own professional development. Teachers also used the data to make decisions about the amount of instructional time, resources needed, practice opportunities, and homework. The Grow Network study provided important insights into the role of standardized assessments and DDDM in education (Light et al., 2005).

Light et al. (2005) presented a framework that illustrated how teachers should take the lead regarding DDDM to improve teaching and learning practices. Light et al.'s framework is built upon organization and management theory (Ackoff, 1989; Breiter, 2003; Choo, 2002; Thorn, 2002) and illustrates the process a teacher goes through to transform raw data into actionable knowledge (see Figure 2).

Figure 2

The Process of Transforming Data Into Knowledge



Note. Adapted from “Keeping Teachers in the Center: A Framework of Data-Driven Decision Making” [Paper presentation], by D. Light, D. H. Wexler, and J. Heinze, 2005, The Annual Meeting of the Society for Information Technology and Teacher Education, Phoenix, AZ, United States, p. 3. Copyright 2005 by the Association for the Advancement of Computing in Education.

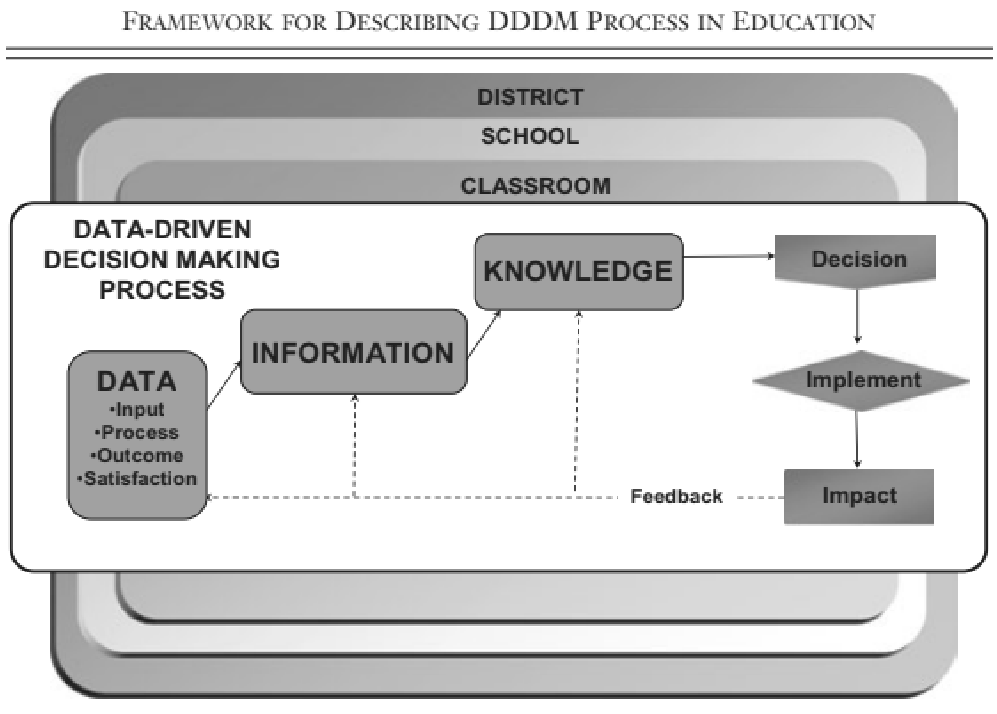
The educator moves through six steps, beginning with collecting and organizing data and summarizing, analyzing, and synthesizing information. These steps guide the educator toward decision-making. Light et al.’s (2005) model highlights the teacher as the essential element in DDDM and their relationship with the tools that help shape this process. These decision making steps include five areas of instructional practice: (an) instruction and lesson planning, (b) differentiation, (c) supporting conversation about students' learning, (d) teacher reflection on professional development, and (e) student self-directed learning (Brunner et al., 2005).

Data support the tools and technologies that affect the process of converting data into knowledge. Light et al. (2005) identified six traits that impact how teachers use data tools for educational decisions: (a) access and ease of use, (b) length of feedback loop, (c) comprehensibility of the data, (d) manipulation of the data, (e) utility and quality of the data, and (f) links to instruction. Light et al. indicated that data reports may help teachers better understand the data, thus moving the data into the information stage. Light et al.'s framework supported the Grow Network's findings; both Light et al. and the Grow Network asserted that teachers play an important role in the final stages of the data knowledge process. Educators' decisions are primarily guided by their own knowledge and pedagogy and data are used to help educators understand students' performance in the classroom.

It is assumed that DDDM improves teaching and learning; however, the process is not necessarily straightforward, and little attention has been paid to the various ways that educators use data to make decisions about teaching and learning. Ikemoto and Marsh (2007) developed a framework based on two RAND Corporation studies that examined the various ways educators use data to make decisions about teaching and learning. Ikemoto and Marsh discussed how DDDM varies based on the type of data and how educators analyze and act upon data. The authors used the data knowledge continuum modeled by Mandinach et al. (2006) to form their framework (see Figure 3).

Figure 3

Ikemoto and Marsh Framework for Describing DDDM Process in Education

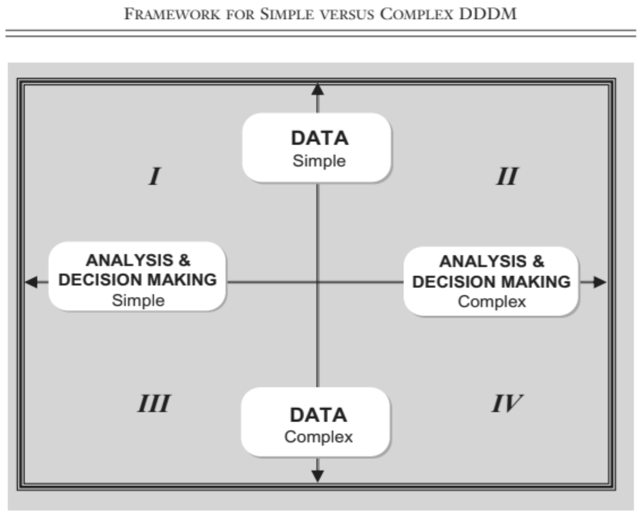


Note. From "Cutting Through the 'Data-Driven' Mantra: Different Conceptions of Data-Driven Decision Making," by G. S. Ikemoto and J. A. Marsh, 2007, p. 109. Copyright 2007 by RAND. Reprinted with permission

Ikemoto and Marsh's (2007) framework is thorough in its design; however, the framework does not address the diversity and subtleties of making decisions in real-life circumstances. The practice of DDDM can be messy and not as continuous as this framework outlines. Ikemoto and Marsh discussed how types of data can be simple or complex and posited that the types of analysis used in decision-making also varies from simple to complex. Figure 4 illustrates the four quadrants of DDDM models, and Figure 5 provides examples of DDDM models.

Figure 4

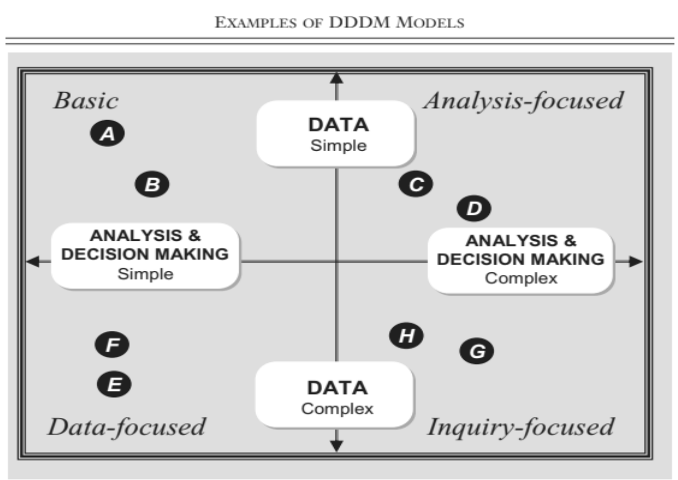
Ikemoto and Marsh Framework for Simple vs. Complex DDDM



Note. From “Cutting Through The “Data-Driven” Mantra: Different Conceptions Of Data-Driven Decision Making,” by G. S. Ikemoto and J. A. Marsh, 2007, p. 111. Copyright 2007 by RAND. Reprinted with permission.

Figure 5

Examples of DDDM Models



Note. From “Cutting Through The “Data-Driven” Mantra: Different Conceptions Of Data-Driven Decision Making,” by G. S. Ikemoto and J. A. Marsh, 2007, p. 113. Copyright 2007 by RAND. Reprinted with permission.

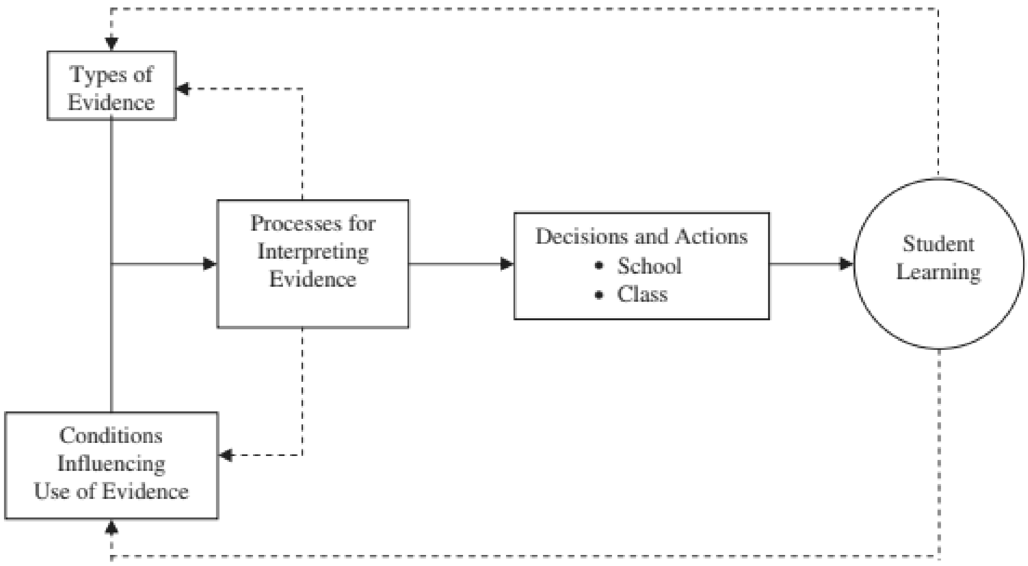
Ikemoto and Marsh named four types of DDDM models: basic (quadrant I), analysis-focused (quadrant II), data-focused (quadrant III), and inquiry-focused (quadrant VI). Basic DDDM uses simple data and simple analysis whereas inquiry-focused DDDM uses complex data and complex analyses.

Ikemoto and Marsh (2007) studied 10 school districts and identified common conditions that were most likely to support the use of data in schools. These conditions included (a) the accessibility and timeliness of data, (b) the perceived validity of data, (c) staff capacity and support for considering data, (d) the time available to interpret and act on evidence, (e) partnership with external organization in analyzing and interpreting data, (f) tools for both data collection and interpretation, and (g) an organizational culture and leadership that support the systematic collection of data (Ikemoto & Marsh, 2007).

Anderson et al. (2010) further explored the conditions and practices that influence data use. Anderson et al. focused on the use of data and conditions that influence data use by principals and teachers and reported on the strength of the relationship between data use and student achievement. Student learning was the dependent variable in Anderson et al.'s framework for understanding evidence-informed processes (see Figure 6). The types of evidence and conditions that impact the use of evidence are the variables. The variables influence the interpretation of evidence, which in turn impacts the decisions and actions of teachers and principals.

Figure 6

Framework for Understanding Evidence-Informed Processes



Note. From "Leading Data Use in Schools: Organizational Conditions and Practices at the School and District Levels," by S. Anderson, K. Leithwood, & T. Strauss, 2010, *Leadership and Policy in Schools, 9*(3), p. 292. (https://doi.org/10.1080/15700761003731492). Copyright 2010 by Routledge.

Anderson et. al. (2010) indicated that principal leadership shapes data use culture and impacts teachers' data use. However, a weak positive relationship was reported between student achievement and school and district data use. Gill et al. (2014) developed a framework for the process of DDDM based on strategic data use and previous findings regarding data use in education. Gill et al.'s framework was built to support the belief that the main goal of DDDM is improved student achievement and college readiness. DDDM includes three cohesive steps for improving student learning outcomes (see Figure 7).

Figure 7

DDDM The Theory of Action for DDDM in Education

Note. From "A Conceptual Framework for Data-Driven Decision Making" by B. Gill, B. C. Borden, and K. Hallgren, 2014, Mathematica Policy Research, p. 2. (https://www.mathematica.org/download-media?MediaItemId={953F2E9F-3195-47FD-BA06-2CAB60BB132E}). In the public domain.

The data infrastructure portion of Figure 7 illustrates the theory of action: assemble high quality raw data, conduct analysis that ensures resulting data are relevant and diagnostic, and use relevant and diagnostic data to inform instructional and operational decisions. These actions cannot take place without the organizational support of data infrastructure, analytic capacity, and a culture of DDDM (Gill et al., 2014). The framework illustrates that improved data infrastructure that includes technical hardware, internet connections, computers, and servers must be established for an educational institution to collect high-quality data. Connections must be made between different types of data to promote analysis. Easy access to data and timely delivery improves educators’ ability to use data to support decisions. Educational institutions should establish technical support assistance and professional development training for teachers and principals who are using the data to make decisions. Professional development training may include how to access, analyze, and use data to improve instructional practices. Establishing a strong DDDM culture of leadership and accountability systems are key to facilitating DDDM actions (Gill et al., 2014).

All of the frameworks presented in this review follow the theory that data become information that transforms into actionable knowledge that can be applied to a continuous cycle of improvement (Anderson et al., 2010; Brunner et al., 2005; Gill et al., 2014; Ikemoto & Marsh, 2007; Light et al., 2005; Mandinach et al., 2006). The remaining sections of this literature review address the themes that have emerged from the literature that significantly impact the success of DDDM in schools: teacher capacity for data use, data literacy, data use, acting upon data, and factors influencing data use.

Teacher Capacity for Data Use

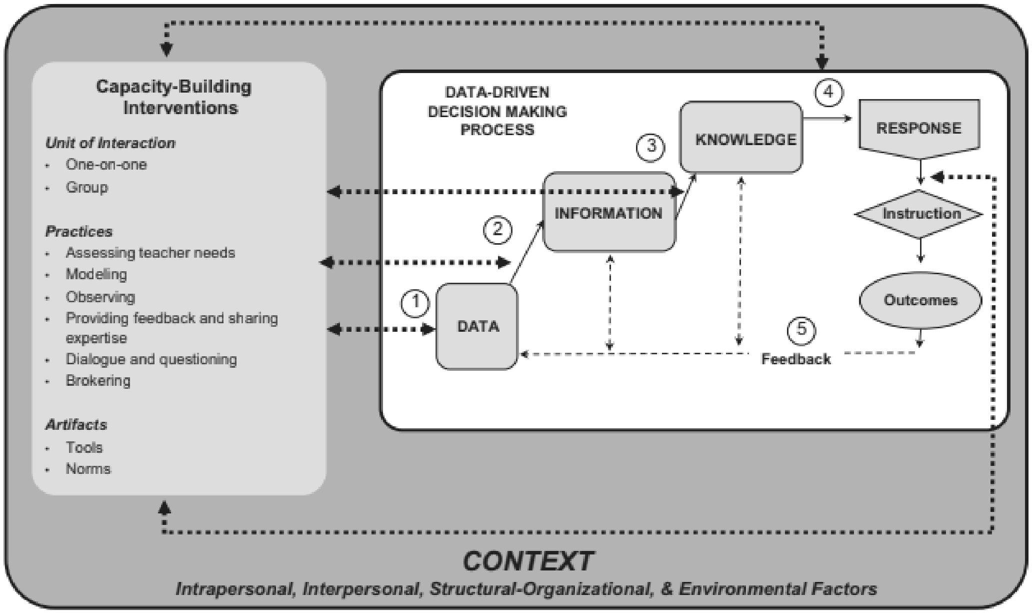
Evidence-based practice continues to be at the forefront of education reform. Educators are required to use multiple data sources to collect student information. Accountability requirements and meeting the needs of an increasingly diverse population of learners compounds the challenges of improving student achievement. It is believed that analyzing evidence regarding student learning will help teachers prioritize time and focus instruction on the individual needs of students (Hamilton et al., 2009). DDDM requires educators to effectively use data to inform their practice; however, teacher capacity for data use is dependent on teachers’ beliefs and attitudes. Teachers’ beliefs and capacity for data use are not always connected to practice; however, teachers’ beliefs about data seem to be the conduit between data and instructional decisions (Datnow & Hubbard, 2015). To use data effectively, teachers must develop the knowledge and skills needed to analyze and act upon knowledge to improve instruction. Not all educators are comfortable engaging with data, and many teachers lack the training needed to fully understand how to use data successfully to bring about positive student learning outcomes (Dunlap & Piro, 2016). The amount and type of data that are available to educators has increased over the past 2 decades, while developing teachers' capacity for and beliefs about using data has remained sluggish at best. Many teachers may feel unprepared, unconfident, and reluctant due to lack of support and lack of appropriate training on data use.

Teacher efficacy is defined as "teachers' beliefs in their abilities to organize and engage in the necessary behaviors to attain desired student outcomes" (Tschannen-Moran & Hoy, 2001, p. 783). Teacher's sense of efficacy for DDDM is defined as "teachers' beliefs in their abilities to organize and execute the necessary courses of action to successfully engage in classroom-level DDDM to enhance student performance" (Dunn et al., 2013). Teachers who have a strong sense of efficacy for teaching tend to overcome challenges associated with adopting new practices such as DDDM (Dunn et al., 2013). Teachers' confidence in their data skills impacts how teachers use data to inform their decisions in the classroom (U.S. Department of Education, 2019a). Knowing how to interpret data and knowing how to use data are two separate skills that must be supported and addressed in teacher training and professional development; however, few studies have addressed how leaders can support teachers' capacity for data use. District and school administrators face challenges in supporting teachers due to lack of expertise, tools, and time (Anderson et al., 2010; Cosner, 2011; Park & Datnow, 2009). Principals have difficulty supporting teachers' data use by proving general guidance and not examining past practice as a response to making improvements to future instruction (Cosner, 2011). Stronger theoretical frameworks are needed to understand educational interventions and actions that support teacher capacity for data use (Marsh & Farrell, 2015; Spillane, 2012; Young & Kim, 2010).

Marsh and Farrell (2015) developed a framework for understanding how to build teacher capacity for data use. The framework is built upon the foundation of sociocultural theory, meaning that learning is social. Learning takes place when individuals interpret information and make connections to experiences, attitudes, and beliefs in everyday situations (Vygotsky, 1978). A mentor–apprentice relationship supports learning by modeling and discussing activities that will improve the learner's capacity and performance (Collins et al., 1991). Marsh and Farrell suggested that it is beneficial to look through the lens of sociocultural learning when deciding how to best support teachers' use of data. March and Farrell's framework uses three types of capacity-building interventions that play a significant role in developing teachers' skills and knowledge of data use (see Figure 8). The three interventions are literacy coach, data coach, and data team. A literacy coach is a trained master teacher who can support small groups or one-on-one instruction at the building level to help teachers improve their students' literacy skills.

Figure 8

Capacity Building for DDDM



Note. From "How Leaders Can Support Teachers With Data-Driven Decision Making: A Framework For Understanding Capacity Building," by J. A. Marsh and C. C. Farrell, 2015, *Educational Management Administration & Leadership, 43*(2), p. 272. (https://doi.org/10.1177/1741143214537229). Copyright 2015 by Sage.

Data support may be one of the responsibilities of a literacy coach. A data coach provides school-based support with interpreting and using data (Lachat & Smith, 2005; Love et al., 2008). Data teams function similarly to PLCs, where teachers can work in small collaborative work groups typically led by a knowledgeable teacher. Working in small groups promotes increased data interpretation (Means et al., 2011). Data teams may also have a positive impact on teachers' beliefs, understanding, and practice (Gallimore et al., 2009; McDougall et al., 2007). Capacity-building interventions help teachers to (a) collect data, (b) organize and analyze into information, (c) transform information into actionable knowledge, (d) respond and adjust instruction, and (e) evaluate the effectiveness of the results. Marsh and Farrell's (2015) model suggests that capacity building is based on a learning process that allows educators to construct knowledge through social interaction, beliefs, prior knowledge, and experiences.

Data Literacy

The process of DDDM includes a complex series of steps that transform data into actionable knowledge. Instructional decisions are based on the knowledge and skills a teacher has to use the data effectively. However, the level of knowledge and skills a teacher needs to be considered data literate is unclear. Mandinach and Gummer's (2016) definition of data literacy is as follows.

> 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)

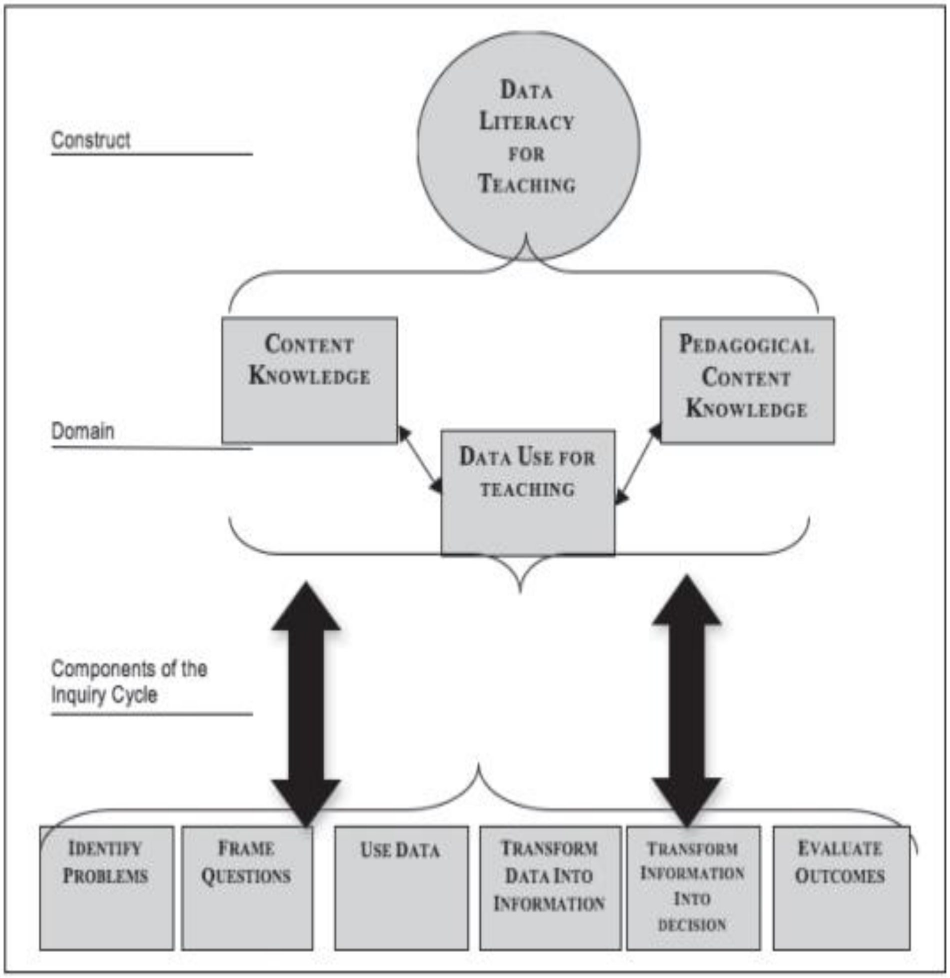
Over the past 40 years, school accountability in the United States has evolved from establishing basic minimum testing requirements for graduation to a large nationwide effort to improve learning outcomes through standardized state and federal testing requirements (Wayman & Jimerson, 2014). Educators are required to use data to inform instructional practice for the purpose of accountability and improving student learning outcomes; however, teachers have difficulty using data for this purpose and face issues such as lack of principal leadership, knowledge, data systems, and time (Anderson et al., 2010; Wayman et al., 2012; Mandinach & Jackson, 2012). DDDM has become part of the evaluation criteria for effective teaching (Ikemoto & Marsh, 2007), yet it is evident that teachers still feel unprepared to use data when making instructional decisions, and teachers often demonstrate low knowledge and skills regarding data use (Huguet et al., 2014). The following knowledge and skills are associated with data literacy.

- collecting and comparing multiple data points;
- using multiple sources of data and monitoring outcomes;
- using various types of assessment data to inform decisions;
- asking questions of the data to gain deeper understanding;
- working in data teams to examine data;
- identifying student learning gaps and adjusting instruction to fill gaps; and
- using student data to adjust instruction and practice (Mandinach & Gummer, 2013).

Gummer and Mandinach (2015) explained the nature of data literacy for teaching as complex and discussed the interconnectedness of disciplinary knowledge, teaching practices, and pedagogical content knowledge. Figure 9 illustrates the organization of the data literacy conceptual framework. Data use for teaching "incorporates knowledge and skills from other broad domains of teaching, including disciplinary content and pedagogical content knowledge" (Gummer & Mandinach, 2015, p. 13). Data literacy is demonstrated through the relationship between data use for teaching, disciplinary knowledge and practice, and pedagogical content knowledge. Within the domain of data use for teachers are the components of the inquiry process. The subcomponents and elements for each component of the inquiry process are presented in Figure 10.

Figure 9

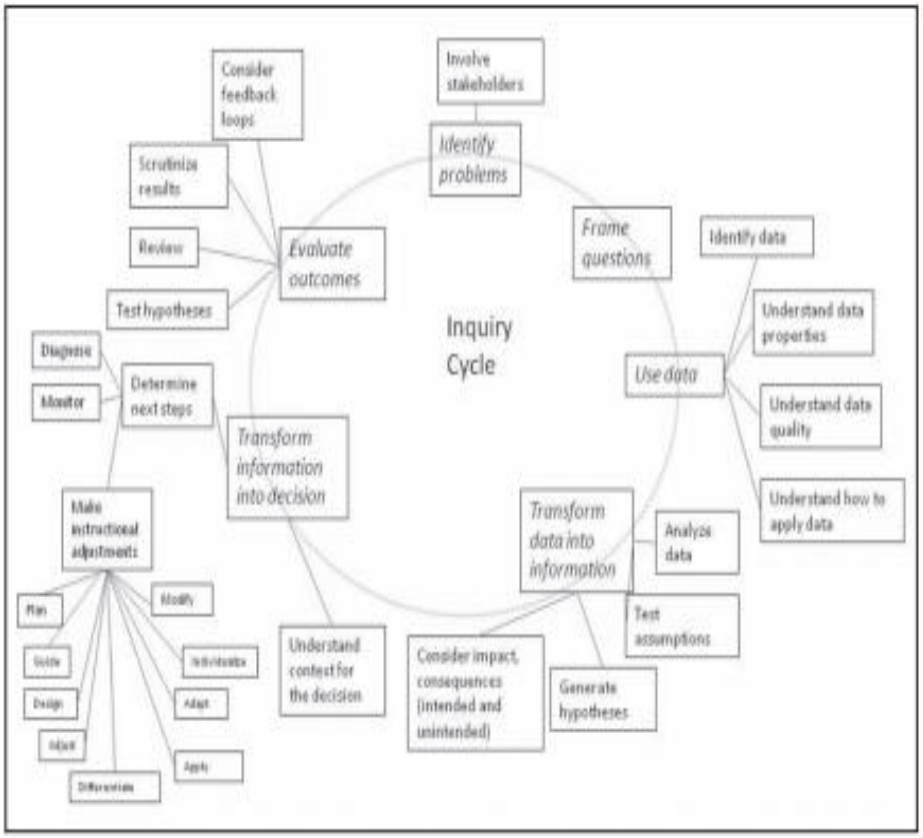
Organization of Data Literacy Conceptual Framework



Note. From "Building a Conceptual Framework for Data Literacy, "by E. Gummer and E. Mandinach, 2015, *Teachers College Record*, *117*(4), p. 13. Copyright 2015 by Teachers College, Columbia University.

Figure 10

Components of Inquiry Cycle in the Domain of Data Use for Teaching,



Note. From “Building a Conceptual Framework for Data Literacy, “by E. Gummer and E. Mandinach, 2015, *Teachers College Record*, *117*(4), p. 15. Copyright 2015 by Teachers College, Columbia University.

DDDM continues to emerge as an essential component of effective teaching practice. The importance of data literacy is reflected in the increased need to demonstrate student learning and growth to meet state standards. Standards for teachers and educational leaders now require the use of data and data literacy skills and knowledge in addition to using assessment to improve instruction. Data literacy is now embedded in policy and standards. For example, the most updated standards for teachers developed from the Interstate Teacher Assessment and Supports Consortium (InTASC; CCSSO’s Interstate Teacher Assessment and Support Consortium, 2010) stated that “Effective instructional practice requires that teachers understand and integrate assessment, planning, and instructional strategies in coordinated and engaging ways” (p. 9). In the InTASC Model Core Teaching Standards Standard 6, the term “assessment” includes seven understandings of data use that are considered to be essential knowledge for teachers (CCSSO’s Interstate Teacher Assessment and Support Consortium, 2010). These seven understandings are as follows.

- 6(j). The teacher understands the differences between formative and summative applications of assessment and knows how and when to use each.
- 6(k). The teacher understands the range of types of multiple purposes of assessment and how to design, adapt, or select appropriate assessments to address specific learning goals and individual differences, and to minimize sources of bias.
- 6(l). The teacher knows how to analyze assessment data to understand patterns and gaps in learning, to guide planning and instruction, and to provide meaningful feedback to all learners.
- 6(m). The teacher knows when and how to engage learners in analyzing their own assessment results and in helping to set goals for their own learning.
- 6(n). The teacher understands the positive impact of effective descriptive feedback for learners and knows a variety of strategies for communicating this feedback.
- 6(o). The teacher knows when and how to evaluate and report learner progress against standards.

- 6(p). The teacher understands how to prepare learners for assessments and how to make accommodations in assessments and testing conditions, especially for learning with disabilities and language learnings needs.

By definition, data literacy is the ability to understand and use data effectively to inform decisions (Mandinach et al., 2008). DDDM is important for school improvement, yet teachers are underprepared to use data to make effective educational decisions (Ikemoto & Marsh, 2007; Reeves & Chiang, 2018; Schildkamp et al., 2014; van Geel et al., 2016).

Data Use

Data use is now an essential characteristic of high-performing schools (Schaffer et al., 2012) because data use leads to increased student achievement (Datnow & Park, 2009; Lai et al., 2014). Formative and summative assessment data are the most common type of data used in education however, other data related to teacher observation, student demographics, questionnaires, and interviews are also used (Jimerson, 2014). Data literacy plays a critical role in effective data use and DDDM. Educators' data literacy is paramount for successfully implementing data use in schools (Schildkamp & Poortman, 2015). Data use is impacted by teachers' ability to (a) access, collect, and analyze data; (b) transform data into information; (c) transform information into action; and (d) evaluate outcomes (Ebbeler et al., 2016). In-service teachers often do not have adequate data literacy skills and require professional development regarding the use of data in schools (Marsh, 2012).

Four conditions facilitate teachers' use of data: collaboration, common understandings, triangulation, and time (Datnow et al., 2007; Wayman et al., 2012; Wayman & Jimmerson, 2014). Collaboration allows teachers to share perspectives and interpret data. PLCs, grade-level teams, and data teams are common examples of collaboration (Ebbeler et al., 2016; Schildkamp

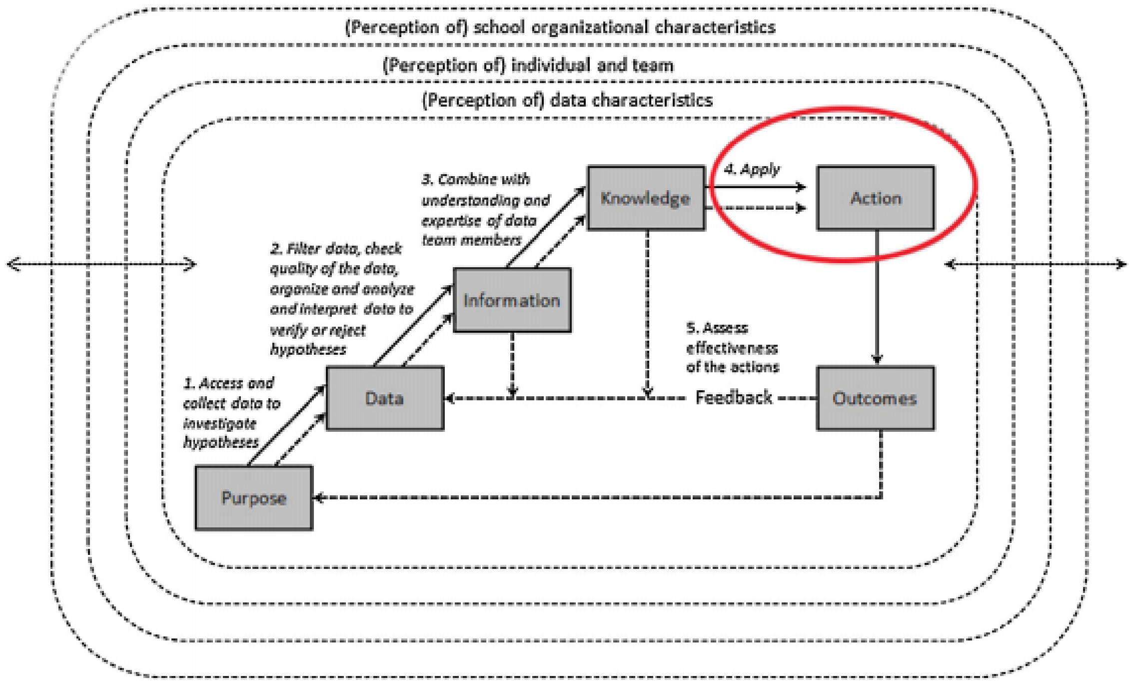
& Kuiper, 2010). Educators who share a common understanding about the goals of data use can build a foundation that leads to mutual learning and agreed upon outcomes. Additionally, using more than one method to collect data and multiple data elements allows for triangulation (Louis et al., 2010; Marsh et al., 2009). Adequate time to perform these collection tasks is essential for effective data use (Ikemoto & Marsh, 2007).

Acting Upon Data

Data use is an iterative process that is dependent on teachers accessing data, collecting data, analyzing data, and transforming data into useful information (Coburn & Turner, 2011; Marsh & Farrell, 2015). Ebbeler et al. (2016) examined the effects of a data use intervention on educators' use of knowledge and skills and developed a data use theory of action and addressed the factors that influence data use. Ebbeler et al.'s framework illustrates the connection between educators and data that leads to interventions that are implemented in the classroom (see Figure 11).

Figure 11

Data Use Theory of Action and Factors Influencing Data Use



Note. From "Data use theory of action, and factors influencing data use," by K. Schildkamp and C. Poortman, 2015, *Teachers College Record*, *117*(4), p. 2. Copyright 2015 by Teachers College, Columbia University.

The starting point for data use is identifying the problem or purpose. Data are then accessed, collected, and examined for quality. Next, the data team transforms data into information. The newly acquired knowledge can be applied to interventions and action related to classroom instructional practice. The data team evaluates the outcomes.

Educators act upon data in three areas: accountability, instruction, and school development (Breiter & Light, 2006; Coburn & Talbert, 2006; Schildkamp et al., 2019; Spillane et al., 2004; Wayman & Stringfield, 2006; Wohlstetter et al., 2008). Data can be used for accountability purposes as a result of state-mandated policy requirements. These data typically highlight overall school performance based on standardized test results; however, these types of data alone do not always equate to school improvement (Ebbeler et al., 2016). Data can be used to support instruction, bolster student achievement, and identify students' strengths or weaknesses. Data can also be used to differentiate lessons and follow student progress (Hamilton et al., 2009). Data use for school development can be applied to curriculum revisions, building goals, and identifying instructional methods (Breiter & Light, 2006; Coburn & Talbert, 2006).

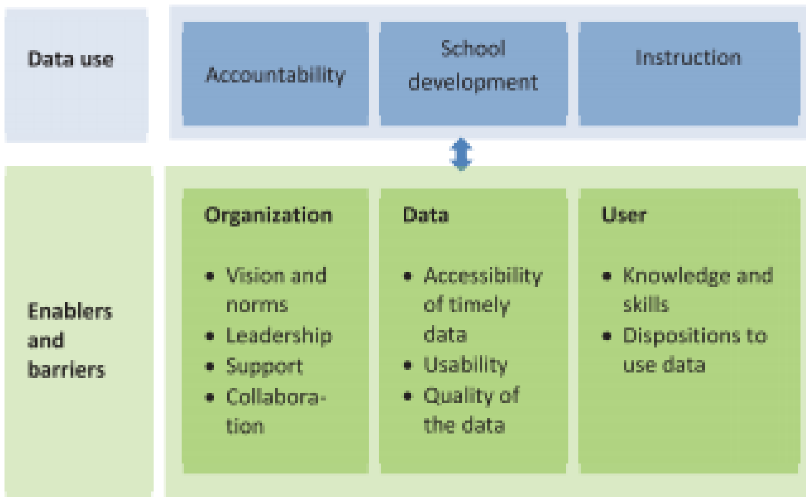
Factors Influencing Data Use

Data use is influenced by organizational characteristics, data, and user characteristics (Coburn & Turner, 2011; Datnow et al., 2013; Schildkamp & Kuiper, 2010; Schildkamp & Lai, 2013). School organizational characteristics that impact data start with a shared vision of learning, assessment, and good teaching practices. Data use is a priority in schools when strong structures for analyzing and interpreting data are evident (Datnow et al., 2007; Earl & Katz, 2006). It is important that school leadership and culture support data use in schools and that leaders provide opportunities for teachers to work with and collaborate on DDDM (Knapp et al., 2007; Wohlstetter et al., 2008; Young, 2006). Data teams, data coaches, and providing teachers with sufficient time to ask questions and consult with data experts are effective methods for improving teacher data use (Marsh et al., 2009).

The user characteristics of teachers also influence data use (Schildkamp et al., 2017). Teachers' knowledge, skills, and attitudes toward data (data literacy) impact how teachers analyze and interpret various forms of data. Data characteristics also influence use of data. Quality of data, usability, and accessibility of timely data all impact teachers' use of data to improve instruction (Breiter & Light, 2006; Halverson, 2010; Wayman & Stringfield, 2006). Figure 12 illustrates the factors that influence data use for accountability, school development, and instruction.

Figure 12

Types of Data Use and Influential Factors



Note. From "Factors Promoting and Hindering Data-Based Decision Making in Schools," by K. Schildkamp, C. Poortman, H. Luyten, and J. Ebbeler, 2017, *School Effectiveness and School Improvement*, *28*(2), p. 244. (https://doi.org/10.1080/09243453.2016.1256901). Copyright 2010 by Routledge.

Professional Development

Scholars have repeatedly found that in-service educators are not equipped with the knowledge and skills to effectively use data in schools (Marsh, 2012), and colleges provide little training for preservice teachers on data use and DDDM (Mandinach & Gumme, 2015). A PLC is a leading intervention used to improve teachers' ability to use data. A PLC is a group of teachers learning through collaboration and sharing of experiences and reflections. PLC's that focus on data are referred to as data teams (Ebbeler et al., 2016; Marsh & Farrell, 2015). PLCs are effective because teachers benefit from professional learning that is collaborative, engaging, contextual, job-embedded, intense, and coherent (Wayman & Jimerson, 2014). Additionally, teachers learn well collaboratively. Positive changes are more likely to take place when educators have the opportunity to exchange ideas and learn from one another (Desimone et al., 2002; Elmore, 2004). Engaging in professional learning is associated with implementation efforts and systemic changes in instructional practice (Desimone et al., 2002; Garet et al., 2001). Job-embedded learning allows teachers to experiment and use new learning immediately. The ability to apply new learning is vital, as because teachers make permanent changes in their practice when they experience positive outcomes (Fullan, 2007). Intensity refers to the duration and span of time needed for new learning to take hold. Longer duration of learning allows for increased learning within a sufficient time frame (Desimone et al., 2002; Elmore, 2004; Wei et al., 2009). Finally, professional learning that is connected to prior knowledge and aligned with teaching practice provides teachers with coherent learning experiences (Desimone et al., 2002).

Technology

It is essential that schools use data systems and develop strong data infrastructure for educators to effectively collect and use relevant and diagnostic data to support instructional practice (Gill et al., 2014). A data system is defined as any technology-based tool that assists educators with examining student data (Wayman et al., 2012). Wayman et al. (2012) examined how attitudes, leadership, and computer data systems influence data use. Three main types of data systems were used in the school districts studied: (a) student information systems that included basic demographic information, schedules, and grades; (b) assessment systems that organized test data; and (c) data warehouses that integrated data from many systems and provided longitudinal data on student performance. The educators in Wayman et al.'s study saw the value in using data to improve practice and viewed principal leadership and computer data systems as the two most common barriers. Difficulties relating to inefficient computer data systems affected attitudes toward data and use of data in all of the districts studied (Wayman et al., 2012).

Educators need integrated data that are easily accessible (Lachat & Smith, 2005; Mandinach et al., 2005; Means et al., 2011; Wayman & Stringfield, 2006). Effective data systems greatly improve data access and save time. Furthermore, efficient data systems increase collaboration and promote a common understanding of student achievement (Wayman & Stringfield, 2006). District policy must support the use of data systems and detail how data systems will be used to support classroom practice. Teachers with an improved access to data are able to use data in a timelier and relevant way (Gill et al., 2014). School district officials who prioritize the use of data must develop strong data systems, policy, and easily accessible and integrated data to support DDDM for school improvement (Wayman et al., 2012).

Summary

DDDM and data use in education have become essential to school improvement. Educators are required to collect, analyze, and transform data into information and actionable knowledge to support continuous improvement (Mandinach, 2012). Data use has shifted from using data only for compliance (NCLB, 2001) to using data for ongoing improvement and improved student outcomes (ESSA, 2015). This movement from accountability to a cycle of continuous improvement requires that data-driven practices be used at all levels of education. The availability and volume of accessible data is growing, and educators today must possess proficient data literacy skills to inform their teaching practice. Teachers must integrate data with context knowledge and experience and are expected to use evidence to determine instructional action (Shulman & Elstein, 1975).

This study addressed the gap in the literature regarding teacher readiness levels related to DDDM, assessment, school support systems, acting upon data, and school culture. The demand on educators to make sound, evidence-based decisions for school improvement has increased;

thus, educators’ data literacy and decision-making processes are more important than ever. Additionally, this study examined the relationship between teachers’ DDDM practices and school achievement. Through this study, I endeavored to provide additional insight to the existing body of research on DDDM and support future professional development initiatives in schools.

CHAPTER 3: METHODOLOGY

Intent of Study

The purpose of this nonexperimental, quantitative comparison research study was to examine the relationship between K–5 elementary school teachers' DDDM practices and school proficiency levels in math and ELA. The current study explored if significant differences exist between the level of school achievement (i.e., high, medium, and low achievement) and K–5 elementary teachers' level of readiness for implementing DDDM with assessment, acting upon data, and within support systems and school culture. The study findings provide insight that will facilitate and inform educational leaders and policymakers and add to the existing research base. This study also facilitates a greater understanding of elementary teachers' DDDM practices and the relationship between teachers' levels of data literacy and school achievement. More data are being made available to teachers in an effort to produce higher levels of learning and overall achievement; thus, a study that examines levels of overall school achievement and teachers' DDDM practices will support educators' understanding of how data literacy can impact the educational process. This chapter includes a description of the study's research design, population, research instruments, and methods for data collection and analysis.

Research Design

I used a nonexperimental, quantitative comparison research design to determine if group differences existed between teachers' levels of DDDM practices and overall school achievement. For the purpose of this study, the independent variables under study were teachers' level of DDDM practices in four subareas: assessment, acting upon data, support systems, and school culture. Data for these variables were supplied by the correlational design, and I used the survey tool to collect and assess teachers' levels of readiness for DDDM in each subarea. I then calculated an overall teacher readiness score for each school participating in the study. The overall school achievement in mathematics and ELA served as the dependent variables. Data for these variables were composed of the proficiency scores for mathematics and ELA for the 2018–2019 academic year. These data are archived and made available by the New Jersey Department of Education. These percentile data were grouped into three categories: high, medium, and low performance. I calculated an average score for each category.

Population

I selected the study participants from multiple noncharter suburban public elementary schools in Morris and Somerset Counties, New Jersey. Qualified participants held a valid New Jersey teaching certificate and had provided direct instruction in mathematics and/or ELA to students in any Grades K-5 during the 2018–2019 school year.

Teachers received an email invitation in the fall of 2020, along with a letter of consent and link to the electronic survey (see Appendix B). Introductory emails were also sent to superintendents/and or principals to assist in the recruitment of teacher participants from the elementary schools in their school district. One-hundred-ten teachers participated in this study, representing 56 schools in 30 school districts in Somerset and Morris Counties.

Research Instruments

I used the Statewide Data-Driven Readiness Study Teacher Survey to collect and assess participants' levels of DDDM practices. This survey tool was developed by Dr. Scott McLeod and Dr. Karen Seashore from the University of Minnesota. The tool was successfully used in McLeod and Seashore's (2006) Minnesota Statewide Data-Driven Decision Making Readiness Study, which included teachers, principals, superintendents, and school technology coordinators with a total participation of 4,267 Minnesota educators. In McLeod and Seashore's study, only

28% of the total population of teachers responded to the survey. This was the lowest percentage of respondents out of the four groups solicited.

The teacher survey included four subscales: assessment, acting upon data, support systems, and school culture (see Appendix C). The survey used a Likert-type scale rating ranging from *disagree strongly* to *agree strongly.* The Likert-type scale measured the respondents' opinions and asked respondents to rate items based on levels of agreement. I assigned a value to each level as follows: *disagree strongly* (1), *disagree moderately* (2), *disagree slightly* (3), *agree slightly* (4), *agree moderately* (5), and *agree strongly* (6). I then calculated and compared the sum of each subscale to answer Research Questions 2 through 5. I also calculated the total score for all four subscales to obtain an overall teacher data-driven readiness score. I answered Research Question 1 by analyzing the overall survey readiness score to teachers' school proficiency scores in math and ELA from the 2018–2019 New Jersey School Performance Report.

ELA and mathematics proficiency scores are reported annually on the New Jersey School Performance Reports. These reports are released and published by the New Jersey Department of Education and are a part of public record. I used the ELA and mathematics proficiency scores to inform this study. The proficiency scores reflect the percentage of students who meet or exceed expectations on the 2018–2019 New Jersey Student Learning Assessment.

Data Collection

I emailed the Statewide Data-Driven Readiness Study Teacher Survey to qualifying noncharter public suburban elementary schools in Morris and Somerset Counties, New Jersey during the fall of 2020. The survey was transposed into SurveyMonkey®. Participants received an email invitation that included a description of the study, a letter of solicitation/consent, and a link to the electronic survey. In addition, introductory emails were forwarded to district superintendents and/or principals to increase teacher participation in the study. The survey used a Likert-type scale of 77 items; three additional questions were included to ensure teacher respondents were qualified (see Appendix C). Teacher and administrators' emails were obtained using the New Jersey Department of Education School Directory and school district websites. The survey remained open until the desired number or participants was reached (N = 110). Reminder emails were forwarded to improve participation.

The New Jersey School Performance Reports are published annually in late winter and reflect data from the previous school year. I used the 2018–2019 New Jersey School Performance Report for all participating schools to inform this study. More current test data were not available due to the cancellation of standardized testing during the 2019–2020 school year due to the global pandemic.

Data Analysis

All teacher survey responses were collected using SurveyMonkey®. The survey data were retrieved and organized in a spreadsheet to reflect name of school, district, and number of participants. School proficiency scores in math and ELA were retrieved from the New Jersey School Performance Summary Reports and added to the spreadsheet for all schools. Math proficiency scores were grouped into the following categories: high (80%–100%) medium (44.5%–79.9%), and low (0%–44%). ELA proficiency scores were grouped into the similar categories: high (80%–100%), medium (57.9%–79.9%), and low (0%–57.8%). Proficiency bands are set by the New Jersey Department of Education and appear on the school's summary report. The Statewide Data-Driven Readiness Study Teacher Survey (McLeod & Seashore, 2006) includes four sub areas: assessments, acting upon data, support systems, and school culture. The survey measured the participants' responses to statements based on six levels of agreement. A value was assigned to each level as follows: *disagree strongly* (1), *disagree moderately* (2), *disagree slightly* (3), *agree slightly* (4), *agree moderately* (5), and *agree strongly* (6). A total score for all four subareas was calculated to obtain an overall teacher data-driven readiness score to answer Research Question 1. The data were uploaded in the statistical software IBM® SPSS® and a series of one-way ANOVAs were performed to determine if there was a significant difference between teacher readiness with DDDM practices and levels of school achievement in mathematics and ELA.

CHAPTER 4: RESEARCH FINDINGS

The purpose of this nonexperimental, quantitative comparison research study was to examine the relationship between K–5 elementary school teachers' level of DDDM practices and overall school achievement. Specifically, the study explored whether statistically significant differences existed between K–5 elementary teachers' readiness for implementing DDDM practices and level of school achievement in ELA and mathematics. I used the Statewide Data-Driven Readiness Study Teacher Survey (McLeod & Seashore, 2006) to determine teachers' DDDM readiness levels, which were treated as the continuous or interval variables. I used the 2018–2019 New Jersey School Performance Report ELA and math proficiency levels to determine high, medium, and low school achievement. The intent of this quantitative study was to examine if high DDDM readiness scores were related to high proficiency levels and if low DDDM readiness scores were related to low proficiency levels. In this chapter, I present the results and analysis of data for each of the following five research questions:

1. Is there a relationship between overall teacher readiness with DDDM practices and New Jersey School Performance Report ELA and mathematics proficiency levels?
2. Is there a relationship between teacher readiness with assessment use and New Jersey School Performance Report ELA and mathematics proficiency levels?
3. Is there a relationship between teacher readiness to act upon data and New Jersey School Performance Report ELA and Mathematics proficiency levels?
4. Is there a relationship between teacher readiness with the use of school support systems available for DDDM and New Jersey School Performance Report ELA and mathematics proficiency levels?

5. Is there a relationship between teacher readiness with DDDM school culture and New Jersey School Performance Report ELA and mathematics proficiency levels?

Results and Analysis of Findings

Sample

The sample for this study included 110 (n = 110) K–5 elementary teachers employed in noncharter public elementary schools in Morris County and Somerset County, New Jersey. Teacher participants represented 56 elementary schools in 30 school districts. All teacher participants provided direct instruction in mathematics and/or ELA to students in any grade from Grades K–5 during the 2018–2019 school year.

Results

I performed a series of one-way ANOVAs to determine if there was a significant difference between teacher readiness with DDDM practices and levels of school achievement in mathematics and ELA. The teacher survey used a Likert-type scale rating that ranged from *disagree strongly* to *agree strongly.* The Likert-type scale measured teachers' perceptions and asked respondents to rate items based on levels of agreement. A numerical value was assigned to each level of agreement as follows: *disagree strongly* (1), *disagree moderately* (2), *disagree slightly* (3), *agree slightly* (4), *agree moderately* (5), and *agree strongly* (6). I calculated the total score for all four subscales to obtain an overall teacher data-driven readiness score. I then calculated and compared the sum of each subarea to answer Research Questions 2 through 5. I answered Research Question 1 by analyzing the overall teacher readiness survey scores and their school's proficiency levels in math and ELA from the 2018–2019 New Jersey School Performance Report.

I performed a one-way ANOVA to determine if there was a significant difference between overall teacher readiness with DDDM practices and levels of school achievement in mathematics. The independent variable, school proficiency in mathematics, had three levels: low, medium, and high. The dependent variable, overall teacher readiness with DDDM practices, was treated as a continuous variable. Table 1 presents the descriptive statistics, and Table 2 indicates that there was no significant difference between overall teacher DDDM readiness practices and math proficiency level.

Table 1

Descriptive Statistics: Levels of Achievement and Teacher Agreement of Overall Data Practices

Proficiency levels	*N*	Mean	*SD*	Std. error
Low	12	292.42	41.069	11.855
Medium	76	296.09	43.890	5.035
High	22	312.09	51.828	11.050
Total	110	298.89	45.370	4.326

Table 2

ANOVA: Mathematics Proficiency Levels

Groups	Sum of squares	df	Mean square	F	Sig.
Between groups	4931.601	2	2465.800	1.202	.305
Within groups	219439.090	107	2050.833		
Total	224370.691	109			

Next, I performed a one-way ANOVA to determine if there was a significant difference between overall teacher readiness with DDDM practices and levels of school achievement in ELA. The independent variable, school proficiency scores in ELA, had three levels: low, medium, and high. The dependent variable, overall teacher readiness with DDDM practices, was treated as a continuous variable. Table 3 presents the descriptive statistics, and Table 4 indicates that there was a significant difference between overall teacher DDDM readiness and school ELA proficiency levels (*F*[2], 6.570, $p = .002$). Multiple comparison tables revealed that the significant difference was between high- and low-performing schools. Teacher survey scores in the high achievement group had a higher mean ($M = 323.81$, $SD = 46.830$) compared to teacher survey scores in the low achievement group ($M = 277.00$, $SD = 35.555$). Examination of Eta^2 revealed an effect size of .10, representing a large effect size (Cohen, 1988). According to Cohen (1988), .01 equals a small effect size, .05 equals a medium effect size, and .14 equals a large effect size.

Table 3

Descriptive Statistics: Levels of Achievement and Teacher Agreement of Overall Data Practices

Proficiency levels	*N*	Mean	*SD*	Std. error
Low	24	277.00	35.555	7.258
Medium	65	298.92	44.527	5.523
High	21	323.81	46.830	10.219
Total	110	298.89	45.370	4.326

Table 4

ANOVA: ELA Proficiency Levels

Groups	Sum of squares	*df*	Mean square	*F*	Sig.
Between groups	24540.837	2	12270.419	6.570	.002*
Within groups	199829.853	107	1867.569		
Total	224370.691	109			

Note. *$p < .05$.

I answered Research Question 2 by analyzing teacher readiness with assessment use and their school's proficiency levels in math and ELA from the 2018–2019 New Jersey School Performance Report. I performed a one-way ANOVA to determine if there was a significant difference between teacher readiness on assessment use and levels of school achievement in mathematics. The independent variable, school proficiency in mathematics, had three levels: low, medium, and high. The dependent variable, teacher readiness with assessment use, was treated as a continuous variable. Table 5 presents the descriptive statistics, and Table 6 indicates that there was no significant difference between teacher readiness regarding assessment use and levels of school math proficiency levels.

Table 5

Descriptive Statistics: Levels of Achievement and Teacher Agreement of Assessment Use

Proficiency levels	*N*	Mean	*SD*	Std. error
Low	12	46.58	21.981	6.345
Medium	76	40.16	17.591	2.018
High	22	43.82	20.866	4.449
Total	110	41.59	18.728	1.786

Table 6

ANOVA: Mathematics Proficiency Levels

Groups	Sum of squares	*df*	Mean square	*F*	Sig.
Between groups	564.296	2	282.148	.802	.451
Within groups	37666.295	107	352.021		
Total	38230.591	109			

Next, I performed a one-way ANOVA to determine if there was a significant difference between teacher readiness with assessment use and levels of school achievement in ELA. The independent variable, school proficiency in ELA, was conditional and had three levels: low, medium, and high. The dependent variable, teacher readiness with assessment use, was treated as a continuous variable. Table 7 presents the descriptive statistics, and Table 8 indicates that there was no significant difference between teacher readiness regarding assessment use and levels of school ELA proficiency scores.

Table 7

Descriptive Statistics: Levels of Achievement and Teacher Agreement of Assessment Use

Proficiency levels	*N*	Mean	*SD*	Std. error
Low	24	36.17	17.690	3.611
Medium	65	41.05	18.104	2.246
High	21	49.48	20.032	4.371
Total	110	41.59	18.728	1.786

Table 8

ANOVA: ELA Proficiency Levels

Groups	Sum of squares	*df*	Mean square	*F*	Sig.
Between groups	2031.158	2	1015.579	3.002	.054
Within groups	36199.433	107	338.312		
Total	38230.591	109			

I answered Research Question 3 by analyzing teacher readiness with acting upon data and their school's proficiency levels in math and ELA from the 2018–2019 New Jersey School Performance Report. I performed a one-way ANOVA to determine if there was a significant difference between teacher readiness with acting upon data and levels of school achievement in mathematics. The independent variable, school proficiency in mathematics, had three levels: low, medium, and high. The dependent variable, teacher readiness with acting upon data, was treated as a continuous variable. Table 9 presents the descriptive statistics, and Table 10 indicates that there was no significant difference between teacher readiness regarding acting upon data and levels of school math proficiency levels.

Table 9

Descriptive Statistics: Levels of Achievement and Teacher Agreement of Acting Upon Data

Proficiency levels	*N*	Mean	*SD*	Std. error
Low	12	77.42	7.501	2.165
Medium	76	80.36	10.383	1.191
High	22	84.36	10.896	2.323
Total	110	80.84	10.329	.985

Table 10

ANOVA: Mathematics Proficiency Levels

Groups	Sum of squares	*df*	Mean square	F	Sig.
Between groups	431.639	2	215.820	2.062	.132
Within groups	11197.415	107	104.649		
Total	11629.055	109			

Next, I performed a one-way ANOVA to determine if there was a significant difference between teacher readiness with acting upon data and levels of school achievement in ELA. The independent variable, school proficiency in ELA, had three levels: low, medium, and high. The dependent variable, teacher readiness with acting upon data, was treated as a continuous variable. Table 11 presents the descriptive statistics, and Table 12 demonstrates that there was a significant difference between teacher readiness with acting upon data and levels of school ELA proficiency levels (F[2], 5.942, p = .004). Multiple comparison tables revealed that the significant difference was between high- and low- performing schools. Teacher survey scores in the high achievement group had a higher mean (M = 86.43, SD = 10.225) compared to teacher survey scores in the low achievement group (M = 76.25, SD = 9.176). Examination of Eta^2 revealed an effect size of .09, representing a medium to large effect size (Cohen, 1988).

Table 11

Descriptive Statistics: Levels of Achievement and Teacher Agreement of Acting Upon Data

Proficiency levels	*N*	Mean	*SD*	Std. error
Low	24	76.25	9.176	1.873
Medium	65	80.72	10.030	1.244
High	21	86.43	10.225	2.231
Total	110	80.84	10.329	.985

Table 12

ANOVA: ELA Proficiency Levels

Groups	Sum of squares	*df*	Mean square	*F*	Sig.
Between groups	1162.396	2	581.198	5.942	.004*
Within groups	10466.658	107	97.819		
Total	11629.055	109			

Note. $*p < .05$

I answered Research Question 4 by analyzing teacher readiness with support systems and their school's proficiency levels in math and ELA from the 2018–2019 New Jersey School Performance Report. I performed a one-way ANOVA to determine if there was a significant difference between teacher readiness with support systems for DDDM practices and levels of school achievement in mathematics. The independent variable, school proficiency in mathematics, was conditional and had three levels: low, medium, and high. The dependent variable, teacher readiness with support systems for DDDM practices, was treated as a continuous variable. Table 13 presents the descriptive statistics, and Table 14 indicates that there was no significant difference between teacher readiness with support systems for DDDM practices and school math proficiency levels.

Table 13

Descriptive Statistics: Levels of Achievement and Teacher Agreement of Support Systems

Proficiency levels	*N*	Mean	*SD*	Std. error
Low	12	77.17	14.070	4.062
Medium	76	79.32	16.424	1.884
High	22	84.00	15.988	3.409
Total	110	80.02	16.102	1.535

Table 14

ANOVA: Mathematics Proficiency Levels

Groups	Sum of squares	*df*	Mean square	*F*	Sig.
Between groups	483.876	2	241.938	.932	.397
Within groups	27776.088	107	259.590		
Total	28259.964	109			

Next, I performed a one-way ANOVA to determine if there was a significant difference between teacher readiness with support systems for DDDM practices and levels of school achievement in ELA. The independent variable, school proficiency in ELA, was conditional and had three levels: low, medium, and high. The dependent variable, teacher readiness with support systems for DDDM practices, was treated as a continuous variable. Table 15 presents the descriptive statistics, and Table 16 indicates that there was a significant difference between teacher readiness with support systems for DDDM practices and levels of school ELA proficiency levels (F[2], 3.806, p = .025). Multiple comparison tables revealed that the significant difference was between high- and low-performing schools. Teacher survey scores in the high achievement group had a higher mean (M = 87.38, SD = 14.361) compared to teacher survey scores in the low achievement group (M = 74.50, SD = 14.981). Examination of Eta^2 revealed an effect size of .06, representing a medium effect size (Cohen, 1988). According to

Cohen (1988), .01 equals a small effect size, .05 equals a medium effect size, and .14 equals a large effect size.

Table 15

Descriptive Statistics: Levels of Achievement and Teacher Agreement of Support Systems

Proficiency levels	*N*	Mean	*SD*	Std. error
Low	24	74.50	14.981	3.058
Medium	65	79.68	16.344	2.027
High	21	87.38	14.361	3.134
Total	110	80.02	16.102	1.535

Table 16

ANOVA: ELA Proficiency Levels

Groups	Sum of squares	*df*	Mean square	*F*	Sig.
Between groups	1876.796	2	938.398	3.806	.025*
Within groups	26383.168	107	246.572		
Total	28259.964	109			

Note. $^{*}p < .05$

I answered Research Question 5 by analyzing teacher readiness with school culture for DDDM practices and their school's proficiency levels in math and ELA from the 2018–2019 New Jersey School Performance Report. I performed a one-way ANOVA to determine if there was a significant difference between teacher readiness regarding school culture for DDDM practices and levels of school achievement in mathematics. The independent variable, school proficiency in mathematics, was conditional and had three levels: low, medium, and high. The dependent variable, teacher readiness regarding school culture for DDDM practices, was treated as a continuous variable. Table 17 presents the descriptive statistics, and Table 18 demonstrates that was no significant difference between teacher readiness regarding support systems for DDDM practices and school math proficiency levels.

Table 17

Descriptive Statistics: Levels of Achievement and Teacher Agreement of School Culture

Proficiency levels	N	Mean	SD	Std. error
Low	12	91.25	11.177	3.227
Medium	76	96.26	13.242	1.519
High	22	99.91	14.593	3.111
Total	110	96.45	13.405	1.278

Table 18

ANOVA: Mathematics Proficiency Levels

Groups	Sum of squares	*df*	Mean square	*F*	Sig.
Between groups	590.368	2	295.184	1.663	.195
Within groups	18996.805	107	177.540		
Total	19587.173	109			

Next, I performed a one-way ANOVA to determine if there was a significant difference between teacher readiness regarding school culture for DDDM practices and levels of school achievement in ELA. The independent variable, school proficiency in ELA, had three levels: low, medium, and high. The dependent variable, teacher readiness regarding school culture on DDDM practices, was treated as a continuous variable. Table 19 presents the descriptive statistics, and Table 20 indicates that there was a significant difference between teacher readiness regarding school culture for DDDM practices and levels of school ELA proficiency levels (F[2], 4.086, p = .019). Multiple comparison tables revealed that the significant difference was between high- and low-performing schools. Teacher survey scores in the high achievement group had a higher mean (M = 100.52, SD = 14.476) compared to teacher survey scores in the low achievement group (M = 90.08, SD = 11.832). Examination of Eta^2 revealed an effect size of .07, representing a medium effect size (Cohen, 1988). According to Cohen (1988), .01 equals a small effect size, .05 equals a medium effect size, and .14 equals a large effect size.

Table 19

Descriptive Statistics: Levels of Achievement and Teacher Agreement of School Culture

Proficiency levels	*N*	Mean	*SD*	Std. error
Low	24	90.08	11.832	2.415
Medium	65	97.48	12.982	1.610
High	21	100.52	14.476	3.159
Total	110	96.45	13.405	1.278

Table 20

ANOVA: ELA Proficiency Levels

Groups	Sum of squares	*df*	Mean square	*F*	Sig.
Between groups	1389.886	2	694.943	4.086	.019
Within groups	18197.287	107	170.068		
Total	19587.173	109			

Note. $^{*}p < .05$

Summary

This study explored whether statistically significant relationships existed between K–5 elementary teachers' readiness for implementing DDDM practices and levels of school proficiency in ELA and mathematics. I performed a series of one-way ANOVAs to determine if there was a significant difference between teachers' readiness with DDDM practices and levels of school achievement in mathematics and ELA.

A significant relationship was present between teachers' reporting high levels of overall DDDM practices and high levels of school achievement in ELA in all subareas of the survey except assessment. The relationship was significant at $p < .002$. Further analysis of the descriptive data indicated that the greatest difference existed between the mean scores in ELA for high- and low-performing schools. The data revealed no significant relationship between teachers' overall DDDM readiness practices and mathematics proficiency level.

CHAPTER 5: DISCUSSION AND CONCLUSION

The purpose of this nonexperimental, quantitative comparison research study was to examine the relationship between K–5 elementary school teachers' DDDM practices and school proficiency levels in ELA and mathematics. Mandinach (2012) defined DDDM as the systematic collection, analysis, examination, and interpretation of data to inform practice and policy in educational settings. Similarly, Marsh et al. (2006) defined DDDM as the "systematic collection, analysis, and application of many forms of data from myriad sources in order to enhance student performance while addressing student learning needs" (p. 8). Using data to support decision-making in schools is an essential practice in the United States. Data are provided to teachers; however, teachers may not understand how to use data effectively to improve instruction (Massell, 2001). Analyzing and using data for decision-making is not intuitive, and most published resources that provide guidance are designed for administrators (Schifter et al., 2014). Although teachers are required to analyze state assessment data and use the findings to inform their instructional decisions, teachers' lack of training in how to use data to improve student learning outcomes is a long-term problem (Schifter et al., 2014).

The research questions in this study focused on investigating elementary teachers' DDDM practices, specifically in the areas of assessment, acting upon data, use of support systems, and school culture. The study results indicated that teachers reporting overall high levels of DDDM practices had high student achievement in ELA; however, no significant relationship existed between teachers' levels of DDDM practices and student achievement in mathematics. The study results also revealed a significant positive relationship between teachers' DDDM practices and ELA proficiency in all subareas, (acting upon data, use of support systems, school culture) except assessment. Interestingly, no significant relationships were found between teachers' DDDM practices in any subareas and mathematics.

This chapter provides a discussion of the implications of the study findings that answer the five research questions, the connections related to the theoretical framework and existing research on DDDM in schools, and the study conclusions. The conclusions discussed are grounded in the study findings reported in Chapter 4 and either support or add to the existing research presented in the literature review. The chapter concludes with (a) a discussion of the limitations of the study; (b) recommendations for further research, policy, and teacher practice; and (c) a concluding summary.

Research Questions

This section details the answers to each of the study's research questions using the study findings. The results and analysis appear after each research question.

Research Question 1

Research Question 1 was as follows: Is there a relationship between overall teacher readiness on DDDM practices and New Jersey School Performance Report ELA and mathematics proficiency levels?

Using the New Jersey School Performance Report proficiency levels, the Statewide Data-Driven Readiness Study Teacher Survey, and descriptive statistics, results from this analysis revealed a significant relationship between overall teacher readiness with DDDM practices and ELA proficiency. The relationship was significant at the .002 level between high- and low-performing schools; therefore, the null hypothesis was accepted. The data suggest that teachers with overall high use of DDDM practices have high ELA performance. Teacher data readiness survey scores in the high ELA achievement group had a higher mean (M = 323.81, SD = 46.830) compared to teacher survey scores in the low ELA achievement group (*M* = 277.00, *SD* = 35.555). From these results, it can be inferred that as teachers' overall understanding and use of data increases, so does student achievement in ELA. These results correspond with the theoretical frameworks presented in Chapter 2, particularly the theory that data become information that transform into actionable knowledge that can be applied to a continuous cycle of improvement (Anderson et al., 2010; Brunner et al., 2005; Gill et al., 2014; Ikemoto & Marsh, 2007; Light et al., 2005; Mandinach et al., 2006).

The results of the ANOVA analysis suggest that no significant relationship exists between overall teacher readiness with DDDM practices and mathematics proficiency. Analysis of the descriptive statistics indicated that although teachers with overall high use of DDDM practices and high math proficiency level have the highest mean, no significance was found between high and low groups. Therefore, the null hypothesis was rejected.

Research Question 2

Research Question 2 was as follows: Is there a relationship between teacher readiness with assessment use and New Jersey School Performance Report ELA and mathematics proficiency levels?

Using the New Jersey School Performance Report proficiency levels, the Statewide Data-Driven Readiness Study Teacher Survey, and descriptive statistics, results from this analysis revealed no significant relationship between teachers' readiness with assessment use and ELA or mathematics proficiency levels; therefore, the null hypotheses were accepted for both. Data literacy plays a critical role in effective data use and understanding how to use assessments to improve student achievement. The absence of a significant relationship between ELA and mathematics proficiency levels and teachers' assessment use may indicate a gap in knowledge, lack of skills, and general attitudes towards assessment use. This disparity may also indicate that the quality, usability, and accessibility of timely data impact teachers' use of data to improve instruction (Breiter & Light, 2006; Halverson, 2010; Wayman & Stringfield, 2006).

Research Question 3

Research Question 3 was as follows: Is there a relationship between teacher readiness to act upon data and New Jersey School Performance Report ELA and mathematics proficiency levels?

Using the New Jersey School Performance Report proficiency levels, the Statewide Data-Driven Readiness Study Teacher Survey, and descriptive statistics, results from this analysis revealed a significant relationship between teachers' readiness to act upon data and ELA proficiency levels. The difference was significant at the .004 level between high- and low-performing schools; therefore, the null hypothesis was accepted. This finding supports the data use theory of action and factors influencing data use framework (Schildkamp & Poortman, 2015), which illustrates the connection between educators and data that leads to interventions implemented in the classroom. The study data imply that schools with high levels of teacher readiness to act upon data may possess the ability to access, collect, and examine the quality of data and then transform the data into information that can be applied to interventions and action related to classroom instructional practice. In addition, the data imply that teachers reporting high levels of readiness to act upon data may meet more regularly in teams to review data, review effectiveness of instructional practices, and make changes to instruction to improve student learning outcomes. To the contrary, no significant relationship was found between teacher readiness to act upon data and mathematics proficiency levels; therefore, the null hypothesis was accepted.

Research Question 4

Research Question 4 was as follows: Is there a relationship between teacher readiness with the use of school support systems available for DDDM and New Jersey School Performance Report ELA and mathematics proficiency levels?

Using the New Jersey School Performance Report proficiency levels, the Statewide Data-Driven Readiness Study Teacher Survey, and descriptive statistics, results from this analysis revealed a significant relationship between teachers' readiness with the use of school support systems and ELA proficiency levels. The relationship was significant at the .025 level between high- and low-performing schools; therefore, the null hypothesis was accepted. This finding may indicate that schools that frequently use support systems for DDDM may have a shared vision on learning, assessment, and good teaching practices. This study finding supports the findings of Ikemoto and Marsh (2007), who identified common conditions that are most likely to support the use of data in schools. These conditions include (a) the accessibility and timeliness of data, (b) the perceived validity of data, (c) staff capacity and support for considering data, (d) the time available to interpret and act on evidence, (e) partnership with external organization in analyzing and interpreting data, (f) tools for both data collection and interpretation, and (g) an organizational culture and leadership that supports the systematic collection of data (Ikemoto & Marsh, 2007). In addition, the data suggest that teachers with high levels of use of support systems for DDDM have (a) easy access to multiple sources of high quality and accurate assessment data and (b) the ability to monitor student progress with adequate technology. Teachers with high levels of use of support systems for DDDM may also understand how to create effective assessments and interpret data appropriately. To the contrary, no significant relationship was found between teachers' readiness with the use of school support systems and mathematics proficiency levels; therefore, the null hypothesis was accepted.

Research Question 5

Research Question 5 was as follows: Is there a relationship between teacher readiness with DDDM school culture and New Jersey School Performance Report ELA and mathematics proficiency levels?

Using the New Jersey School Performance Report proficiency levels, the Statewide Data-Driven Readiness Study Teacher Survey, and descriptive statistics, results from this analysis revealed a significant relationship between teachers' readiness with DDDM school culture and ELA proficiency. The relationship was significant at the .019 level between high- and low-performing schools; therefore, the null hypothesis was accepted. This result indicates that teachers reporting high levels of DDDM school culture may routinely use data to uncover problems and inform instructional practice to make improvements. In addition, the results suggest that supportive leadership exists and there is a strong sense of trust among teachers and administrators. The results also imply that establishing a strong DDDM culture of leadership and accountability systems are key to facilitating DDDM actions (Gill et al., 2014). Teachers reporting high levels of DDDM school culture may also have easy access to data, which improves their ability to use data to support decisions. In addition, schools with high levels DDDM school culture may have received technical support assistance and professional development training for teachers and principals who are using the data to make decisions. For these reasons, more study is needed to further examine the impact of these conditions on teachers' DDDM practices. To the contrary, no significant relationship were found between teachers' readiness with DDDM school culture and mathematics proficiency levels; therefore, the null hypothesis was accepted.

The purpose of this study was to examine the relationship between teachers' DDDM readiness and student achievement in both ELA and mathematics. The findings indicate different results in these two subject areas, which is intriguing because both subjects are highly prioritized in elementary curriculum. This prioritization may be related to mandatory state standardized testing and accountability requirements. Elementary teachers are considered generalists, meaning they are required to teach all subjects: ELA, mathematics, science, and social studies. The length of the school day and number of days per year is set by the state, whereas the amount of instructional time teachers spend on each subject is typically determined by the local board of education and school administration. Interestingly, the amount of instructional time spent on ELA and mathematics is not equal. This discrepancy indicates that the average instruction time allocated for ELA at the elementary level is much greater than math instruction (Milyutin, 2019). This trend may reveal an intriguing bias toward ELA versus mathematics instruction. According to a study from the Illinois Department of Education (2017), the average daily third-grade ELA instructional time in Illinois public schools was 132 minutes compared to 72 minutes in math (as cited in Rado, 2017). Although instructional time may be a factor that contributes to a teachers' overall DDDM readiness, further study would be needed to examine this idea.

Another consideration is the focus on instructional methods and use of assessments with mathematics. There are significant differences in the way teachers assess ELA and mathematics. Elementary teachers may have more training and skills with assessing reading and writing than math. The New Jersey Student Learning Standards for math require teachers to teach math differently than how they may have learned it themselves. Furthermore, the New Jersey Student

Learning Standards for math focus on engaging students in multistep problem solving, adaptive reasoning, fluency, and conceptual understanding. This shift in pedagogy has changed the methods teachers use to teach math, which may also impact how teachers use math assessment data to make instructional decision. Additional research on how teachers are responding to the shifts in math standards, best practices in elementary math instruction, and how best to support math teachers is warranted.

Conclusions

The results of this study revealed that significant relationships existed between K–5 elementary teachers' self-reported readiness on overall DDDM practices and high student achievement levels in ELA. These findings also indicated that teachers reporting high levels of DDDM practices also had high student achievement in ELA; therefore, the null hypothesis was rejected, and the alternative hypothesis was accepted.

Further inquiry and analysis determined that no significant relationships existed between teachers' readiness with overall DDDM practices and achievement in mathematics. Based on this finding, the null hypothesis was accepted. Additional analyses examined subareas of DDDM practices and their relationships to ELA and mathematics performance. The results of this study indicated that there significant relationships did exist between ELA achievement and teachers' levels of acting upon data, using school support systems, and school culture. Therefore, the null hypothesis was rejected, and the alternative hypothesis was accepted. No significant relationship was discovered between ELA achievement and the subarea of assessment. Therefore, the null hypothesis was accepted. Additionally, no significant relationships were discovered between mathematics achievement and teachers' readiness levels of assessment, acting upon data, using school support systems, and school culture. Therefore, the null hypotheses for all subareas were accepted.

Limitations of the Study

This research study was limited to quantitative data collected from one survey: The Statewide Data-Driven Readiness Study Teacher Survey (McLeod & Seashore, 2006). All data gathered from the participants were self-reported. Additional qualitative methods such as focus groups, interview, or observation were not used and may be considered for further research.

Participants were limited to K–5 elementary teachers who provided direct instruction in ELA and/or math during the 2018–2019 school year to students in any Grades K–5. Although the teachers' perceptions were valid, a time gap existed due to the lack of standardized testing data for the 2019–2020 school year; all state standardized testing was suspended as a result of the global pandemic. More recent standardized testing data coupled with more timely survey responses would help reduce this time gap and therefore provide more immediate reflection.

Teacher survey data were collected from a relatively small group of teachers representing 56 New Jersey elementary schools in 30 school districts in two counties. The study did not account for a school's special characteristics, teachers' experience or educational levels, enrollment size, English language learners, special education population, or other school demographics.

Recommendations for Further Study

This study adds to the existing body of research on DDDM practices and supports the foundational work of previous studies and theoretical frameworks on DDDM. The following are recommendations for further study not addressed within the confines of this research.

1. The participants in this study were solicited from two neighboring New Jersey suburban counties of similar size and demographics. Of the total number of participants ($n = 110$), teacher survey responses represented 56 elementary schools in 30 school districts. Future studies with a larger sample size would improve the reliability of the results. Additionally, researchers of future studies should include urban school districts to add to the existing research.
2. This study revealed significant relationships between high levels of teachers' DDDM readiness and ELA achievement in all subareas except assessment. This variation in the research deserves further investigation to examine how teachers use assessment and transform that information into practice.
3. No significant relationships existed between teachers' readiness with DDDM practices and mathematics. This is a compelling discovery that is worthy of further examination. Elementary teachers predominantly teach all subject areas, including ELA and mathematics. A mixed-methods study using focus groups, interviews, or observations to gain more qualitative data about teachers' readiness with DDDM practices in the area of mathematics may provide additional insight to help determine what influences teachers' DDDM practices with mathematics.
4. This study focused specifically on surveying teachers' readiness with DDDM practices. Superintendents, principals, and other school administrators were not included in this study. As discussed in the review of the literature, developing a DDDM school culture is an essential component of successful DDDM practice. School leadership has a significant role in this process.

Further study to examine the DDDM practices of principals using the Statewide Data-Driven Decision Making Principal Survey (McLeod & Seashore, 2006) would provide greater insight into the relationship between school leadership and DDDM practices.

5. As illustrated by Gill et al. (2014), strong data infrastructure is needed to support DDDM practices. Gill et al.'s framework illustrates that improved data infrastructure that includes technical hardware, internet connections, computers, and servers must be established for an educational institution to collect high-quality data. Connections must be made between different types of data to promote analysis. Easy access to data and timely delivery improves educators' ability to use data to support decisions. Educational institutions should establish technical support assistance and professional development training for teachers and principals who are using the data to make decisions. Further study of the current state of technical data infrastructure in elementary and secondary schools should be conducted.
6. According to the existing research on DDDM, 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. However, the level of knowledge and skills a teacher needs to be considered data literate is unclear. Further study on data literacy in schools and levels of teacher data literacy would provide additional insight.
7. Developing teachers' capacity for DDDM is an essential part of effective practice. Knowing how to interpret data and how to use data are two separate

skills that must be supported and addressed in teacher training and professional development; however, few studies have addressed how leaders can support teachers' capacity for data use. Further study on how school leaders can support teachers' capacity for data use would provide more information to help guide educational leaders.

8. Examining the relationship between instructional time provided for mathematics in elementary schools and mathematics proficiency would help educators and policymakers better understand the impact instruction time has on teachers' use of DDDM practices.
9. The New Jersey Student Learning Standards for math require teachers to teach math differently than how they may have learned it themselves. The New Jersey Student Learning Standards for math focuses on engaging students in multistep problem solving, adaptive reasoning, fluency, and conceptual understanding. This shift in pedagogy has changed the methods teachers use to teach math, which may also impact how teachers use math assessment data to make instructional decisions. Additional research on how teachers are responding to the shifts in math standards, professional development opportunities on best practice in elementary math instruction, and how best to support math teachers is warranted.

Recommendations for Policy and Practice

Current research on DDDM strongly emphasizes the importance of data literacy. Standards for teachers and educational leaders now require data literacy skills and knowledge in addition to using assessment to improve instruction. Data literacy is now embedded in policy and standards at the higher levels of the educational spectrum; however, data literacy must also exist at the district and building levels. Educational leaders who desire to improve teaching and learning must develop the essential skills and knowledge needed to engage in effective DDDM practices and provide professional development opportunities that foster the acquisition of these skills in their teachers.

Educators are required to use data to inform instructional practice for the purpose of accountability and improving student learning outcomes; however, teachers have difficulty using data for this purpose and face issues such as lack of knowledge, data systems, time, and principal leadership (Anderson et al., 2010; Mandinach & Jackson, 2012; Wayman et al., 2012). To provide teachers with the appropriate support, building principals would benefit from adopting strategies that help develop data literacy among staff.

The ability to understand and use data effectively to inform decisions is a complex process and is important for school improvement. Creating collaborative space and time for teachers is a vital part of successful DDDM. Teachers learn well together and would benefit from professional learning that is collaborative, engaging, and meaningful. Creating collaborative data teams to provide opportunities for teachers to ask questions, examine quality data, identify problems or learning gaps, and adjust instruction will help to improve instructional practice and increase students’ learning outcomes.

REFERENCES

Ackoff, R. L. (1989). From data to wisdom. *Journal of Applied Systems Analysis*, *16*(2), 3–9.

American Recovery and Reinvestment Act of 2009, Pub. L. No. 111–5. (2009).

Anderson, S., Leithwood, K., & Strauss, T. (2010). Leading data use in schools: Organizational conditions and practices at the school and district levels. *Leadership and Policy in Schools*, *9*(3), 292–327. https://doi.org/10.1080/15700761003731492

Breiter, A. (2003). *Information - Knowledge - Sense-making: A theoretical analysis from management / business literature* [Unpublished manuscript].

Breiter, A., & Light, D. (2006). Data for school improvement: Factors for designing effective information systems to support decision-making in schools. *Educational Technology & Society*, *9*(3), 206–217.

Brunner, C., Fasca, C., Heinze, J., Honey, M., Light, D., Mandianach, E., & Wexler, D. (2005). Linking data and learning: The Grow Network Study. *Journal of Education for Students Placed at Risk*, *10*(3), 241–267. https://doi.org/10.1207/s15327671espr1003_2

CCSSO's Interstate Teacher Assessment and Support Consortium. (2010). *Model core teaching standards: A resource for state dialogue* (ED566116). ERIC. https://eric.ed.gov/?id=ED566116

Choo, C. W. (2002). *Information management for an intelligent organization: The art of environmental scanning* (3rd edition). Information Today.

Coburn, C. E., & Turner, E. O. (2011). Research on data use: A framework and analysis. *Measurement: Interdisciplinary Research & Perspective*, *9*(4), 173–206. https://doi.org/10.1080/15366367.2011.626729

Coburn, C., & Talbert, J. (2006). Conceptions of evidence use in school districts: Mapping the terrain. *American Journal of Education*, *112*(4), 469–495. https://doi.org/10.1086/505056

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences*. L. Erlbaum Associates.

Collins, A., Brown, J., & Holum, A. (1991). Cognitive apprenticeship: Making thinking visible. *American Educator*, *15*(3), 6–11, 38–46.

Cosner, S. (2011). Teacher learning, instructional considerations and principal communication: Lessons from a longitudinal study of collaborative data use by teachers. *Educational Management Administration & Leadership*, *39*(5), 568–589. https://doi.org/10.1177/1741143211408453

Cramer, E. D., Little, M. E., & McHatton, P. A. (2014). Demystifying the data-based decision-making process. *Action in Teacher Education, 36*(5–6), 389–400. https://doi.org/10.1080/01626620.2014.977690

Datnow, A., Park, V., & Wohlstetter, P. (2007). Achieving with data: How high performing school systems use data to improve instruction for elementary students. Los Angeles: University of Southern California, Rossier School of Education, Center on Education, Center on Educational Governance.

Datnow, A., Park, V., & Kennedy-Lewis, B. (2013). Affordances and constraints in the context of teacher collaboration for the purpose of data use. *Journal of Educational Administration*, *51*(3), 341–362. https://doi.org/10.1108/09578231311311500

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

Desimone, L. M., Porter, A. C., Garet, M. S., Yoon, K. S., & Birman, B. F. (2002). Effects of professional development on teachers' instruction: Results from a three-year longitudinal study. *Educational Evaluation and Policy Analysis*, *24*(2), 81–112. https://doi.org/10.3102/01623737024002081

Drucker, P. F. (1989). *The new realities: In government and politics, in economics and business, in society and world view.* Harper & Row.

Dunlap, D., & Piro, J. S. (2016) Diving into data: Developing the capacity for data literacy in teacher education. *Cogent Education, 3*(1), Article 1132526. https://doi.org/10.1080/2331186X.2015.1132526

Dunn, K. E., Airola, D. T., Lo, W. J., & Garrison, M. (2013). What teachers think about what they can do with data: Development and validation of the data driven decision-making efficacy and anxiety inventory. *Contemporary Educational Psychology, 38*(1), 87–98. https://doi.org/10.1016/j.cedpsych.2012.11.002

Earl, L. M., & Katz, S. (2002). Leading schools in a data rich world. In K. Leithwood, P. Hallinger, G. C. Furman, K. Riley, J. MacBeath, P. Gronn, & B. Mulford (Eds.), *Second international handbook of educational leadership and administration* (pp. 1003–1022). Springer. http://dx.doi.org/10.1007/978-94-010-0375-9_34

Earl, L. M., & Katz, S. (2006). *Leading schools in a data-rich world: Harnessing data for school improvement*. Corwin Press.

Earl, L., & Fullan, M. (2003). Using data in leadership for learning. *Cambridge Journal of Education*, *33*(3), 383–394. https://doi.org/10.1080/0305764032000122023

Ebbeler, J., Poortman, C. L., Schildkamp, K., & Pieters, J. M. (2016). Effects of a data use intervention on educators' use of knowledge and skills. *Studies in Educational Evaluation*, *48*, 19–31. https://doi.org/10.1016/j.stueduc.2015.11.002

Elementary and Secondary Education Act of 1965, Pub. L. No. 89–10. (1965).

Elmore, R. F. (2004). *School reform from the inside out: Policy, practice, and performance*. Harvard Education Press.

Every Student Succeeds Act. 20 U.S.C. § 6301 (2015).

Fullan, M. (2001). *Leading in a culture of change.* Jossey-Bass

Fullan, M. (2007). *Leading in a culture of change: Personal action guide and workbook*. Jossey-Bass.

Fullan, M., & Stiegelbauer, S. (1991). The new meaning of educational change. *School Effectiveness and School Improvement*, *2*(4), 336–343. https://doi.org/10.1080/0924345910020406

Gage, N. L. (1978). *The scientific basis of the art of teaching*. Teachers College Press.

Gallimore, R., Ermeling, B., Saunders, W., & Goldenberg, C. (2009). Moving the learning of teaching closer to practice: Teacher education implications of school-based inquiry teams. *Elementary School Journal*, *109*(5), 537–553. https://doi.org/10.1086/597001

Garet, M. S., Porter, A. C., Desimone, L., Birman, B. F., & Yoon, K. S. (2001). What makes professional development effective? Results from a national sample of teachers. *American Educational Research Journal*, *38*(4), 915–945. https://doi.org/10.3102/00028312038004915

Gill, B., Borden, B. C., & Hallgren, K. (2014). *A conceptual framework for data driven decision making* [Report]. Mathematica Policy Research. https://www.mathematica.org/download-media?MediaItemId={953F2E9F-3195-47FD-BA06-2CAB60BB132E}

Gummer, E., & Mandinach, E. (2015). Building a conceptual framework for data literacy. *Teachers College Record*, *117*(4), 1–22.

Halverson, R. (2010). School formative feedback systems. *Peabody Journal of Education*, *85*(2), 130–146. https://doi.org/10.1080/01619561003685270

Hamilton, L., Halverson, R., Jackson, S. S., Mandinach, E., Supovitz, J. A., & Wayman, J. C. (2009). *Using student achievement data to support instructional decision making. IES practice guide. NCEE 2009-4067* (ED506645). ERIC. https://files.eric.ed.gov/fulltext/ED506645.pdf

Huguet, A., Marsh, J., & Farrell, C. (2014). Building teachers' data-use capacity: Insights from strong and developing coaches. *Education Policy Analysis Archives*, *22*, 52–54. https://doi.org/10.14507/epaa.v22n52.2014

Ikemoto, G. S., & Marsh, J. A. (2007). *Cutting through the "data-driven" mantra: Different conceptions of data-driven decision making.* RAND.

Immen, K. C. (2016). *Making data-driven decisions: Teacher perceptions about using student assessment data to inform instruction* (Publication No. 10167992) [Doctoral dissertation, Seattle University]. ProQuest Dissertations & Theses Global.

Institute of Education Sciences. (2011). *WWC procedures and standards handbook.* What Works Clearinghouse.

Jimerson, J. B. (2014). Thinking about data: Exploring the development of mental models for "data use" among teachers and school leaders. *Studies in Educational Evaluation*, *42*, 5–14. https://doi.org/10.1016/j.stueduc.2013.10.010

Kennedy, B. L., & Datnow, A. (2011). Student involvement and data-driven decision making. *Youth & Society*, *43*(4), 1246–1271. https://doi.org/10.1177%2F0044118X10388219

Knapp, M. S., Copland, M. A., & Swinnerton, J. A., (2007). Understanding the promise and dynamics of data-informed leadership. *Yearbook of the National Society for the Study of Education*, *106*(1), 74–104. https://doi.org/10.1111/j.1744-7984.2007.00098.x

Lachat, M. A., & Smith, S. (2005). Practices that support data use in urban high schools. *Journal of Education for Students Placed at Risk*, *10*(3), 333–349. https://doi.org/10.1207/s15327671espr1003_7

Lai, M. K., Wilson, A., McNaughton, S., & Hsiao, S. (2014). Improving achievement in secondary schools: Impact of a literacy project on reading comprehension and secondary schools qualifications. *Reading Research Quarterly*, *49*(3), 305–334.

Light, D., Wexler, D. H., & Heinze, J. (2005, March 1). *Keeping teachers in the center. A framework of data-driven decision-making* [Paper presentation]. The Annual Meeting of the Society for Information Technology and Teacher Education, Phoenix, AZ, United States.

Louis, K. S., Dretzke, B., & Wahlstrom, K. (2010). How does leadership affect student achievement? Results from a national US survey. *School Effectiveness and School Improvement*, *21*(3), 315–336. https://doi.org/10.1080/09243453.2010.486586

Love, N., Stiles, K. E., Mundry, S., & DiRanna, K. (2008). *A data coach's guide to improving learning for all students: Unleashing the power of collaborative inquiry.* Corwin Press.

Mandinach, E.B., Friedman, J.M., & Gummer, E.S. (2015). How can schools of education help to build educators' capacity to use data: A systematic view of the issue. *Teachers College Record*, 117(4).

Mandinach, E. B. (2009, October). *How LEAs use data to inform practice: The opportunities for and challenges to use in schools and districts* [Conference session]. NEI Research and Evaluation that Inform Leadership for Results Conference, Louisville, KY, United States.

Mandinach, E. B. (2012). A perfect time for data use: Using data-driven decision making to inform practice. *Educational Psychologist*, *47*(2), 71–85. https://doi.org/10.1080/00461520.2012.667064

Mandinach, E. B., & Gummer, E. (2013). A systematic view of implementing data literacy in educator preparation. *Educational Researcher*, *42*(1), 30–37. https://doi.org/10.3102/0013189X12459803

Mandinach, E. B., & Gummer, E. S. (2016). What does it mean for teachers to be data literate: Laying out the skills, knowledge, and dispositions. *Teaching and Teacher Education*, *60*, 366–376. https://doi.org/10.1016/j.tate.2016.07.011

Mandinach, E. B., & Jackson, S. S. (2012). *Transforming teaching and learning through data-driven decision making.* Corwin Press.

Mandinach, E. B., Honey, M. Light, D., Heinze, C, & Nudell, H. (2005, April 1). *Data-driven instructional decision-making using technology-based tools* [Paper presentation]. The Annual Meeting of the American Educational Research Association, Montreal, Quebec.

Mandinach, E. B., Honey, M., Light, D., & Brunner, C. (2008). A conceptual framework for data-driven decision-making. In E. Mandinach & M. Honey (Eds.), *Data-driven school improvement: Linking data and learning* (pp. 1331). New York, NY: Teachers College Press.

Mandinach, E. B., Rivas, L., Light, D., Heinze, C., & Honey, M. (2006, April 1). *The impact of data-driven decision making tools on educational practice: A systems analysis of six school districts* [Paper presentation]. The Annual Meeting of the American Educational Research Association, San Francisco, CA, United States.

Mandinach, Ellen & Gummer, Edith. (2015). Data-Driven Decision Making: Components of the Enculturation of Data Use in Education. Teachers College Record. 117. 1-8.

Marsh, J. A., & Farrell, C. C. (2015). How leaders can support teachers with data-driven decision making: A framework for understanding capacity building. *Educational Management Administration & Leadership*, *43*(2), 269–289. https://doi.org/10.1177%2F1741143214537229

Marsh, J. A., Pane, J. F., & Hamilton, L. S. (2006). *Making sense of data-driven decision making in education: Evidence from recent RAND research.* RAND Corporation. https://www.rand.org/pubs/occasional_papers/OP170.html

Marsh, J. A., Sloan McCombs, J., & Martorell, F. (2009). How instructional coaches support data-driven decision making. *Educational Policy*, *24*(6), 872–907. https://doi.org/10.1177/0895904809341467

Marsh, J.A. (2012). Interventions promoting educators’ use of data: Research insights and gaps. *Teachers College Record*, 114(11), 1-48

Massell, D. (1998). *State strategies for building capacity in education: Progress and continuing challenges* (ED426490). ERIC. https://files.eric.ed.gov/fulltext/ED426490.pdf

Massell, D. (2001). The theory and practice of using data to build capacity: State and local strategies and their effects. In S. H. Fuhrman (Ed.), *From the capitol to the classroom: Standards-based reform in the states* (pp. 148–169). University of Chicago Press.

McDougall, D., Saunders, W., & Goldenberg, C. (2007). Inside the black box of school reform: Explaining the how and why of change at getting results schools. *International Journal of Disability Development and Education*, *54*(1), 51–89. https://doi.org/10.1080/10349120601149755

McLeod, S., & Seashore, K. (2006). *Data driven decision making readiness survey*. Teachers. Minneapolis, MN: University of Minnesota.

Means, B., Padilla, C., DeBarger, A., & Padilla, C. (2011). *Teachers' ability to use data to inform instruction: Challenges and supports* (ED516494). ERIC. https://files.eric.ed.gov/fulltext/ED516494.pdf

Milyutin, E. (2019, August 19). *Why don't we spend more time teaching math?* District Administration. https://districtadministration.com/da-op-ed-why-dont-we-spend-more-time-teaching-math/

National Assessment of Educational Progress. (n.d.). *Achievement gaps.* Retrieved September 1, 2021, from https://nces.ed.gov/nationsreportcard/studies/gaps/

The Nation's Report Card. (n.d.-a). *Explore results for the 2019 NAEP reading assessment.* Retrieved September 1, 2021, from https://www.nationsreportcard.gov/reading/?grade=4

The Nation's Report Card. (n.d.-b). *2017 NAEP mathematics & reading assessments: Highlighted results at grades 4 and 8 for the nation, states, and districts.* Retrieved September 1, 2021, from https://www.nationsreportcard.gov/reading_math_ 2017_highlights/

New Jersey Department of Education, ESSA Accountabilities Profile Companion Guide. ESSA Accountability. (2018).https://www.state.nj.us/education/title1/accountability/progress/18/.

New Jersey Department of Education. New Jersey Student Learning Standards: Mathematics. (2020, June). http://www.njintouch.state.nj.us/education/aps/cccs/math/.

No Child Left Behind Act of 2001, Pub. Law No. 107-110. (2001).

Park, V., & Datnow, A. (2009). Co-constructing distributed leadership: District and school connections in data-driven decision-making. *School Leadership and Management*, *29*(5), 477–494. https://doi.org/10.1080/13632430903162541

Rado, D. (2017). Teaching time in Math on the rise, while English declines. *Chicago Tribune*. www.chicagotribune.com/news/breaking/ct-met-math-english-instruction-time-20171128-story.html

Reeves, T. D., & Chiang, J.-L. (2018). Online interventions to promote teacher data-driven decision making: Optimizing design to maximize impact. *Studies in Educational Evaluation*, *59*, 256–269. https://doi.org/10.1016/j.stueduc.2018.09.006

Schaffer, E., Reyonolds, D., & Stringfield, S. (2012). Sustaining turnaround at the school and district levels: The high reliability schools project at Sandfields Secondary School. *Journal of Education for Students Placed at Risk*, *17*(1–2), 108–127. https://doi.org/10.1080/10824669.2012.637188

Schifter, C. C., Natarajan, U., Ketelhut, D. J., & Kirchgessner, A. (2014). Data-driven decision making: Facilitating teacher use of student data to inform classroom instruction. *Contemporary Issues in Technology and Teacher Education*, *14*(4), 419–432. https://citejournal.org/volume-14/issue-4-14/science/data-driven-decision-making-facilitating-teacher-use-of-student-data-to-inform-classroom-instruction/

Schildkamp, K., & Lai, M. K. (2013). Conclusions and a data use framework. *Data-Based Decision Making in Education*, 177–191. https://doi.org/10.1007/978-94-007-4816-3_10

Schildkamp, K., & Kuiper, W. (2010). Data-informed curriculum reform: Which data, what purposes, and promoting and hindering factors. *Teaching and Teacher Education*, *26*(3), 482–496. https://doi.org/10.1016/j.tate.2009.06.007

Schildkamp, K., & Poortman, C. (2015). Factors influencing the functioning of data teams. *Teachers College Record*, *117*(4).

Schildkamp, K., Karbautzki, L., & Vanhoof, J. (2014). Exploring data use practices around Europe: Identifying enablers and barriers. *Studies in Educational Evaluation*, *42*, 15–24. https://doi.org/10.1016/j.stueduc.2013.10.007

Schildkamp, K., Poortman, C. L., Ebbeler, J., & Pieters, J. M. (2019). How school leaders can build effective data teams: Five building blocks for a new wave of data-informed decision making. *Journal of Educational Change*, *20*(3), 283–325. https://doi.org/10.1007/s10833-019-09345-3

Schildkamp, K., Poortman, C., Luyten, H., & Ebbeler, J. (2017). Factors promoting and hindering data-based decision making in schools. *School Effectiveness and School Improvement*, *28*(2), 242–258. https://doi.org/10.1080/09243453.2016.1256901

Schmoker, M. J. (2000). The results we want. *Educational Leadership*, *57*(5), 62–65.

Shulman, L. S., & Elstein, A. S. (1975). Studies of problem solving, judgment, and decision making: Implications for educational research. *Review of Research in Education*, *3*, 3–42. https://doi.org/10.2307/1167252

Smith, N. (2009, October). *Data accuracy in longitudinal data systems* [Conference Session]. The Special Education Data Accountability Center Retreat, Rockville, MD, United States.

Spillane, J. P. (2012). Data in practice: Conceptualizing the data-based decision-making phenomena. *American Journal of Education*, *112*(2), 113–241. https://doi.org/10.1086/663283

Spillane, J. P., Halverson, R., & Diamond, J. B., (2004). Towards a theory of leadership practice: A distributed perspective. *Journal of Curriculum Studies*, *36*(1), 3–34. https://doi.org/10.1080/0022027032000106726

Teigen, B. N. (2009). *A systematic examination of data-driven decision-making within a school division: The relationships among principal beliefs, school characteristics, and accreditation status* [Doctoral dissertation, Virginia Commonwealth University]. VCU Scholars Compass. https://scholarscompass.vcu.edu/cgi/viewcontent.cgi?article=2956&context=etd

Thorn, C. (2002). Data use in the classroom: The challenges of implementing data-based decision-making at the school level. In I. D. Selwood, A. Fung, & C. D. O'Mahoney (Eds.), *Management of education in the information age* (pp. 21–30). Springer.

Tschannen-Moran, M., & Hoy, A. W. (2001). Teacher efficacy: Capturing an elusive construct. *Teaching and Teacher Education*, *17*(7), 783–805. https://doi.org/10.1016/s0742-051x(01)00036-1

U.S. Department of Education (2009a). *Guidance on standards, assessments, and accountability*. https://www2.ed.gov/policy/elsec/guid/standardsassessment/guidance_pg5.html

U.S. Department of Education. (2009b). *Race to the Top program: Executive summary* (ED557422). ERIC. https://files.eric.ed.gov/fulltext/ED557422.pdf

U.S. Department of Education. (n.d.). *Every Student Succeeds Act (ESSA)*. Retrieved September 1, 2021, from https://www.ed.gov/essa?src=ft.%20(2018).%20 https://www.nj.gov/education/title1/accountability/progress/18/ESSACompanionGuide.docx.

U.S. Department of Health, Education, and Welfare, Office of Education, Profile of ESEA: The elementary and secondary Education act of 1965, titles I, II, III, IV, V (1967). Washington, D.C.

van Geel, M., Keuning, T., Visscher, A. J., & Fox, J. (2016). Assessing the effects of a school-wide data-based decision-making intervention on student achievement growth in primary schools. *American Educational Research Journal*, *53*(2), 360–394. https://doi.org/10.3102/0002831216637346

Vygotsky, L. (1978). *Mind in society: The development of higher psychological processes*. Harvard University Press.

Wayman, J. C., & Jimerson, J. B. (2014). Teacher needs for data-related professional learning. *Studies in Educational Evaluation*, *42*, 25–34. https://doi.org/10.1016/j.stueduc.2013.11.001

Wayman, J. C., & Stringfield, S. (2006). Technology-Supported involvement of entire faculties in examination of student data for instructional improvement. *American Journal of Education*, *112*(4), 549–571. https://doi.org/10.1086/505059

Wayman, J. C., Cho, V., & Spikes, D. D. (2012). District-wide effects on data use in the classroom. *Education Policy Analysis Archives*, *20*(25), 1–28.

Wayman, J. C., Stringfield, S., & Yakimowski, M. (2005). *Teachers using data to improve instruction: Exemplary practices in using data warehouse and reporting systems* [Paper presentation]. The 2005 Annual Meeting of the American Educational Research Association, Montreal, Canada. .

Wei, R. C., Darling-Hammond, L., Andree, A., Richardson, N., & Stelios, O. (2009). *Professional learning in the learning profession: A status report on teacher development in the United States and abroad*. National Staff Development Council.

White, V. C. (2008). *Relationships among principals' beliefs about data-driven decision making, principal and school characteristics, and student achievement in elementary schools* (Publication No. 3347189) [Doctoral dissertation, University of Florida]. ProQuest Dissertations & Theses Global.

Wohlstetter, P., Datnow, A., & Park, V. (2008). Creating a system for data-driven decision-making: Applying the principal-agent framework. *School Effectiveness and School Improvement*, *19*(3), 239–259. https://doi.org/10.1080/09243450802246376

Young, V. M., & Kim, D. H. (2010). Using assessments for instructional improvement: A literature review. *Education Policy Analysis Archives*, *18*(19), 1–40.

Young, V.M. (2006). Teachers' use of data: Loose coupling, agenda setting, and team norms. *American Journal of Education*, 112(4): 521-548.

Appendix A: Statewide Data-Driven Readiness Study Teacher Survey Permission

Julianne Kotcho <jkotcho@mendhamtwp.org>

Request:Survey Tool

Scott McLeod <dr.scott.mcleod@gmail.com> Mon, Sep 17, 2018 at 11:50 PM
Reply-To: dr.scott.mcleod@gmail.com
To: jkotcho@mendhamtwp.org

Hi Julianne,

You are welcome to use one or more of the DDDM surveys and/or modify them as desired with proper attribution. Please see http://www.dangerouslyirrelevant.org/copyright. I would like to request a PDF copy of any writings (articles, dissertation, etc.) that emerge from your use of the surveys. See the attached. Also, several dissertations have used the DDDM surveys so make sure you find those for your literature review!

Thanks for the kind words about my last book. My next one comes out this week! :)

Good luck with your study!
[Quoted text hidden]

9 attachments

mcleod-2007-mnsdc-powerpoint-20268.pdf
1383K

MNPrincipalSurvey.pdf
20K

2017-FALL-DOCTORALDISSERTATION-BIGNER.pdf
2026K

MNSuperintendentSurvey.pdf
21K

MNTeacherSurvey.pdf
20K

MNTechCoordinatorSurvey.pdf
19K

Makaravage_Dissertation.pdf
2128K

Hughes_Dissertation.pdf
3072K

Bailey_Dissertation.pdf
3160K

Appendix B: Informed Consent/Letter of Solicitation

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Informed Consent/Letter of Solicitation

November, 2020

Dear New Jersey Elementary School Teacher:

Researcher's Affiliation:
Julianne Kotcho is a doctoral candidate at Seton Hall University, College of Education and Human Services, Executive Ed.D Program, Educational Leadership, Management, Policy, Administration and Supervision.

Purpose of the Study & Duration:
Ms. Kotcho is conducting a study entitled, *A Study of Elementary School Teachers' Data-Driven Decision Making Practices and School Performance.* The purpose of the study is to explore the relationship between teachers' data-driven decision making practices and school achievement. The estimated time of participation for subjects in this study is approximately 15-20 minutes.

Description of Procedures:
Qualifying participants must have a current New Jersey Standard Teaching Certificate and taught ELA and/or Math in any grades 3-5, in their current school during the 2018-2019 school year. Subjects will receive an email invitation to voluntarily complete the *Statewide Data-Driven Readiness Study ~ Teacher Survey* via SurveyMonkey®. Subjects agree to participate by entering and submitting the completed survey online. Subjects may opt-out of participation by a) not completing the survey b) starting survey and selecting to EXIT survey prior to submitting.

Survey Instrument:
The survey instrument used in this study is the *Statewide Data-Driven Readiness Study ~ Teacher Survey*, developed by McLeod, S., & Seashore, K. (2006) This Likert scale survey includes 77 questions in 4 subareas: Assessment, Acting Upon Data, Support Systems, and School Culture. Sample question: "I use data from student assessments to set instructional targets and goals" Disagree Strongly, Disagree Moderately, Disagree Slightly, Agree Slightly, Agree Moderately, Agree Strongly.

Statement of Voluntary Participation:
Participation in this study is voluntary. Potential subjects may choose to participate by proceeding to enter, complete and submit the survey. Subjects may opt-out by not entering the survey or exiting the survey without submitting.

Statement of Anonymity:
Participation is this study is anonymous. The participants' employer school name will be collected. This information will be de-identified before files are shared with other researchers to ensure that, by current scientific standards and known methods, no one will be able to identify you from the information shared. The results of the research may be shared with the research community at large to advance knowledge however, no personal information or school names will be used. The identities of the participants are not associated with responses in any published format.

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Statement of Confidentiality:
All data will be securely stored to maintain confidentiality. Data will be secured on an encrypted USB drive. The encrypted USB drive will remain locked and stored with the researcher. The primary investigator will incorporate adequate safeguards into the research design such as keeping all data and information securely stored and following a system to ensure that no data is breached during or after the research process. Note: There is always a possibility of hacking of online material.

Statement of Record Keeping:
Data collected from the survey tool will be kept confidential and accessible only to the researcher conducting the study.

Participation Risks:
Participating in this study presents minimal risks to subjects however, it is possible that participants may experience anxiety or loss of self-esteem that could result from teachers reflecting on their own behaviors or attitudes toward data-driven decision making practices when completing the survey.

Direct & Indirect Benefits:
There are no direct benefits associated with participating in this study as it is not therapeutic or biomedical in nature. Indirect benefits associated with participation in this study are, contributing to the current knowledge based regarding Data Driven Decision Making practices, sharing experiences and practices that will benefit other education professionals and reflecting upon researched based data driven decision making practices during and after survey study.

Remuneration:
No payment or other type of remuneration will be given to participants in this study.

Explanation of Risk:
Participation in this study present minimal risk to the subjects.

Alternative Procedures:
No alternative procedures or courses of treatment are needed to participate in this study.

Contact Information:
For additional information or answers to questions regarding this research study:

1) Julianne Kotcho, Principal Investigator/Researcher, julianne.kotcho@student.shu.edu
2) Dr. Monica Browne, monica.browne@shu.edu
3) Seton Hall University Internal Review Board(IRB) (973)-761-9334 or irb@shu.edu.

If you wish to participate, please click the “I Agree” link embedded in the introductory email and you will be taken to the survey. If you do not wish to participate, please exit the browser.

Sincerely,

Julianne Kotcho, Doctoral Candidate, Seton Hall University

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Appendix C: Statewide Data-Driven Readiness Study Teacher Survey

STATEWIDE DATA-DRIVEN READINESS STUDY
- Teacher Survey -

Thank you for participating in this survey. Please note that Questions 1 to 20 ask you about four different kinds of assessment s: A) yearly assessments from the state, B) yearly assessments from other sources, C) common periodic assessments created in conjunction with other teachers, and D) other (i.e., not teacher-created) periodic assessments.

	Yes	No
1. **I receive state assessment results each year. IF NO, SKIP TO QUESTION 6**	O	O

STATE ASSESSMENTS	Disagree Strongly	Disagree Moderately	Disagree Slightly	Agree Slightly	Agree Moderately	Agree Strongly
2. State assessment results are timely enough to adequately inform my instruction	O	O	O	O	O	O
3. State assessment results are detailed enough to adequately inform my instruction	O	O	O	O	O	O
4. State assessments are aligned with state curriculum standards	O	O	O	O	O	O
5. State assessment results are easy to understand and interpret	O	O	O	O	O	O

	Yes	No
6. **I receive other yearly assessment results (e.g., Terranova, ITBS, NWEA) each year. IF NO, SKIP TO QUESTION 11**	O	O

OTHER YEARLY ASSESSMENTS	Disagree Strongly	Disagree Moderately	Disagree Slightly	Agree Slightly	Agree Moderately	Agree Strongly
7. Results from these other yearly assessments are timely enough to adequately inform my instruction	O	O	O	O	O	O
8. Results from these other yearly assessments are detailed enough to adequately inform my instruction	O	O	O	O	O	O
9. These other yearly assessments are aligned with state curriculum standards	O	O	O	O	O	O
10. Results from these other yearly assessments are easy to understand and interpret	O	O	O	O	O	O

	Yes	No
11. **I collaborate with other teachers to create and use common periodic assessments to monitor student progress during the school year. IF NO, SKIP TO QUESTION 16**	O	O

COMMON PERIODIC ASSESSMENTS	Disagree Strongly	Disagree Moderately	Disagree Slightly	Agree Slightly	Agree Moderately	Agree Strongly
12. Results from these common assessments are timely enough to adequately inform my instruction	O	O	O	O	O	O
13. Results from these common assessments are detailed enough to adequately inform my instruction	O	O	O	O	O	O
14. These common assessments are aligned with state curriculum standards	O	O	O	O	O	O
15. Results from these common assessments are easy to understand and interpret	O	O	O	O	O	O

STATEWIDE DATA-DRIVEN READINESS STUDY
- Teacher Survey -

	Yes	No
16. **I use other (i.e., not teacher-created) periodic assessments (e.g., Scantron, STAR, DIBELS, CBM) to monitor student progress during the school year. IF NO, SKIP TO QUESTION 21**	O	O

OTHER PERIODIC ASSESSMENTS	Disagree Strongly	Disagree Moderately	Disagree Slightly	Agree Slightly	Agree Moderately	Agree Strongly
17. Results from these other periodic assessments are timely enough to adequately inform my instruction	O	O	O	O	O	O
18. Results from these other periodic assessments are detailed enough to adequately inform my instruction	O	O	O	O	O	O
19. These other periodic assessments are aligned with state curriculum standards	O	O	O	O	O	O
20. Results from these other periodic assessments are easy to understand and interpret	O	O	O	O	O	O

ACTING UPON DATA	Disagree Strongly	Disagree Moderately	Disagree Slightly	Agree Slightly	Agree Moderately	Agree Strongly
21. Teacher teams meet regularly to look at student data and make instructional plans	O	O	O	O	O	O
22. When I meet with other teachers, we usually focus on student learning outcomes	O	O	O	O	O	O
23. Teachers in this school work collaboratively to improve curriculum and instruction						
24. Teachers are given adequate time for collaborative planning	O	O	O	O	O	O
25. Teachers in this school regularly discuss assumptions about teaching and learning	O	O	O	O	O	O
26. I use assessment data to identify students who are not experiencing academic success	O	O	O	O	O	O
27. I know what instructional changes to make when data show that students are not successful	O	O	O	O	O	O
28. I use assessment results to measure the effectiveness of my instruction	O	O	O	O	O	O
29. In this school I am encouraged to try out new teaching strategies	O	O	O	O	O	O
30. I use data to verify my assumptions about the causes of student behavior and performance	O	O	O	O	O	O
31. I have clear criteria for determining the success of instructional activities	O	O	O	O	O	O
32. If I propose a change, I bring data to support my proposal	O	O	O	O	O	O
33. I make changes in my instruction based on assessment results	O	O	O	O	O	O
34. Our district's goals are focused on student learning	O	O	O	O	O	O
35. Our school improvement goals are clear, specific, measurable, and based on student data	O	O	O	O	O	O
36. Teachers and principals have access to good baseline data from which to set annual instructional goals	O	O	O	O	O	O
37. I use data from student assessments to set instructional targets and goals	O	O	O	O	O	O

STATEWIDE DATA-DRIVEN READINESS STUDY
- Teacher Survey -

SUPPORT SYSTEMS	Disagree Strongly	Disagree Moderately	Disagree Slightly	Agree Slightly	Agree Moderately	Agree Strongly
38. I can easily access the information I need from school and district data systems	O	O	O	O	O	O
39. Teachers and parents communicate frequently about student performance data	O	O	O	O	O	O
40. Student performance data available to me are accurate and complete	O	O	O	O	O	O
41. Student performance data are easily available to the individuals that need them	O	O	O	O	O	O
42. Parents and community members know what our school is doing and what is needed to improve student achievement	O	O	O	O	O	O
43. Successful educational practices are widely shared in the district	O	O	O	O	O	O
44. My school uses multiple data sources to assess the effectiveness of educational programs	O	O	O	O	O	O
45. Teachers have significant input into data management and analysis practices	O	O	O	O	O	O
46. I know how to use technology to monitor student progress	O	O	O	O	O	O
47. I have adequate access to the technology necessary to monitor student progress	O	O	O	O	O	O
48. My professional development has helped me use data more effectively	O	O	O	O	O	O
49. I have received adequate training to effectively interpret and act upon yearly state assessment results	O	O	O	O	O	O
50. Professional development has improved my skill in developing classroom assessments	O	O	O	O	O	O
51. Teachers have significant input into plans for professional development and growth	O	O	O	O	O	O
52. Student achievement data are used to inform school and district improvement initiatives	O	O	O	O	O	O
53. Whole-school staff meetings focus on measured progress toward data-based improvement goals	O	O	O	O	O	O
54. Student achievement data are used to determine teacher professional development needs and resources	O	O	O	O	O	O
55. School and classroom improvement efforts are aligned with state standards	O	O	O	O	O	O
56. Student achievement data are used to determine resource allocation	O	O	O	O	O	O

STATEWIDE DATA-DRIVEN READINESS STUDY
- Teacher Survey -

SCHOOL CULTURE	Disagree Strongly	Disagree Moderately	Disagree Slightly	Agree Slightly	Agree Moderately	Agree Strongly
57. As a school we have open and honest discussions about data	O	O	O	O	O	O
58. I have the knowledge and skills necessary to improve student learning	O	O	O	O	O	O
59. Student achievement data are used primarily for improvement rather than teacher evaluation	O	O	O	O	O	O
60. Administrators in this school trust the professional judgments of teachers	O	O	O	O	O	O
61. Administrators model data-driven educational practices	O	O	O	O	O	O
62. My school adequately supports teachers' use of data to improve classroom instruction	O	O	O	O	O	O
63. My building's administrator(s) buffer my school from distractions to our school improvement efforts	O	O	O	O	O	O
64. My success as an educator should be determined primarily by my impact upon student learning	O	O	O	O	O	O
65. I routinely use data to inform my instructional practices and understand student needs	O	O	O	O	O	O
66. Teachers in this school have a sense of collective responsibility for student learning	O	O	O	O	O	O
67. My school uses data to uncover problems	O	O	O	O	O	O
68. I conduct self-assessments to continuously improve performance	O	O	O	O	O	O
69. I am a valued member of my school's data-driven reform efforts	O	O	O	O	O	O
70. I have access to high-quality student assessments to evaluate student progress	O	O	O	O	O	O
71. My success or failure in teaching students is primarily due to factors beyond my control rather than to my own efforts and ability	O	O	O	O	O	O
72. Using data has improved the quality of decision-making in my school	O	O	O	O	O	O
73. By trying different teaching methods, I can significantly affect my students' achievement levels	O	O	O	O	O	O
74. There is a strong sense of trust among teachers and administrators in my school	O	O	O	O	O	O
75. If we constantly analyze what we do and adjust to get better, we will improve	O	O	O	O	O	O
76. I feel some personal responsibility when our school improvement goals are not met	O	O	O	O	O	O
77. Students in our school believe that they will succeed at learning if they keep trying	O	O	O	O	O	O

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October 30, 2020

Julianne Kotcho
Seton Hall University

Re: Study ID#2020-120

Dear Julianne,

At its October 2020 meeting, the Research Ethics Committee of the Seton Hall University Institutional Review Board reviewed and approved your research proposal entitled "A Study of Elementary School Teachers' Data Driven Decision Making Practices and School Performance" as resubmitted. This memo serves as official notice of the aforementioned study's approval. Enclosed for your records are the stamped original Consent Form.

The Institutional Review Board approval of your research is valid for a one-year period from the date of this letter. During this time, any changes to the research protocol, informed consent form or study team must be reviewed and approved by the IRB prior to their implementation.

You will receive a communication from the Institutional Review Board at least 1 month prior to your expiration date requesting that you submit an Annual Progress Report to keep the study active, or a Final Review of Human Subjects Research form to close the study. In all future correspondence with the Institutional Review Board, please reference the ID# listed above.

Thank you for your cooperation.

Sincerely,

Mara Podvey
Mara C. Podvey, PhD, OTR
Associate Professor
Co-Chair, Institutional Review Board

Phyllis Hansell
Phyllis Hansell, EdD, RN, DNAP, FAAN
Professor
Co-Chair, Institutional Review Board

Office of the Institutional Review Board
Presidents Hall · 400 South Orange Avenue · South Orange, New Jersey 07079 · Tel: 973.275.4654 · Fax 973.275.2978 ·
www.shu.edu
WHAT GREAT MINDS CAN DO

Seton Hall University
Institutional Review Boar
OCT 3 0 2020
Approval Date
Expiration Date
OCT 3 0 2021

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Informed Consent/Letter of Solicitation

October, 2020

Dear New Jersey Elementary School Teacher:

Researcher's Affiliation:
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Sincerely,

Julianne Kotcho, Doctoral Candidate, Seton Hall University

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