2019

Course Taking and Teacher Data-Driven Decision Making Self-Efficacy and Anxiety: A Secondary Analysis

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ABSTRACT

COURSE TAKING AND TEACHER DATA-DRIVEN DECISION MAKING SELF-EFFICACYAND ANXIETY: A SECONDARY ANALYSIS

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An expanding culture of accountability in education has led to an influx in the amount and types of data teachers are expected to collect and use to increase student achievement. Research has identified data-driven decision making (DDDM) as a way for teachers to use educational data to promote more effective instruction and, ultimately, to improve student outcomes. Despite available data and research that supports the use of DDDM, using it to make instructional decisions is still a struggle for teachers. Therefore, this study looks at the relationship between DDDM-related coursework and teacher self-efficacy and anxiety for DDDM. In theory, DDDM-related coursework learning opportunities should provide teachers increased mastery experiences and, in turn, greater self-efficacy for DDDM and lower anxiety about the practice.

In order to investigate this relationship, this study used a secondary analysis of existing data to examine the extent to which teachers are taking DDDM-related courses and the relationships among the types of these courses taken by teachers and their DDDM self-efficacy and DDDM anxiety. Descriptive statistics and multiple regression analyses were conducted on each of two merged datasets (pre-service and in-service). Results from this study suggest that most pre-service and in-service teachers are taking DDDM-related courses and that some of these courses are associated with higher DDDM self-efficacy and lower DDDM anxiety in teachers. Findings contribute new evidence for connections between course-related learning opportunities and teacher self-efficacy beliefs.

NORTHERN ILLINOIS UNIVERSITY

DE KALB, ILLINOIS

DECEMBER 2019

COURSE TAKING AND TEACHER DATA-DRIVEN DECISION MAKING SELF-EFFICACY AND ANXIETY: A SECONDARY ANALYSIS

BY

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A THESIS SUBMITTED TO THE GRADUATE SCHOOL

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS

FOR THE DEGREE

MASTER OF SCIENCE

DEPARTMENT OF EDUCATIONAL TECHNOLOGY,

RESEARCH AND ASSESSMENT

Thesis Director:
Todd D. Reeves

ACKNOWLEDGEMENTS

A huge thank you goes out to my advisor, Dr. Todd Reeves, for the gift of his time, extensive access to his data, invaluable guidance, and supportive friendship. He led me step by step through the depth of material and twists and turns with expertise, patience, and humor. I have learned so very much and I will always be grateful.

I would also like to thank the rest of my thesis committee, Dr. Thomas Smith and Dr. Cynthia Campbell, for their knowledge, constructive comments, and hard questions.

Finally, I have a special thank you going out to my family and friends for their encouragement and unconditional support. To Josh and his family for all those evenings and weekends caring for the kids so I could continue making progress, to my parents and siblings for showing me that working hard makes challenging things possible, and to my village for all the love and laughs throughout.

DEDICATION

To my boys, Andrew and Devan, for all the adventures

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CHAPTER 1

INTRODUCTION

Since the passing of No Child Left Behind (NCLB, 2002) and the Individuals with Disabilities Education Improvement Act (IDEIA, 2004), an increased culture of accountability for schools through rigorous standards and high-stakes testing has developed. Schools are continuously inundated with data through assessment and accountability systems with an increased pressure on promoting student achievement. As the Every Student Succeeds Act (ESSA, 2015) replaces NCLB, a wider variety of indicators for determining student growth and achievement are acceptable. States can now choose a reliable indicator of student growth and must include an additional indicator of “school quality,” including student safety, chronic absenteeism, and student or teacher engagement (ESSA, 2015). Additional indicators and measures of progress increase the amount of data that are collected and available for professionals in the school community, including teachers, to analyze, interpret, and use to make instructional decisions.

Often the pressure to collect and use data from multiple sources to increase student achievement is placed on teachers. Teachers regularly need to use both academic data (e.g., achievement test scores, classroom-based formative or summative assessments, student academic work) and non-academic data (e.g., attendance, discipline, motivation) to identify gaps in student learning and strengths and weaknesses in the curriculum and to monitor and report student progress, validate patterns of need, and communicate and collaborate with other professionals (Reeves, Wei, Scheel, & Hamilton, 2018). As the emphasis for using data to support educational reforms continues, it is necessary to evaluate the progress teachers are making in their ability to utilize data effectively (Means, Chen, DeBarger, & Padilla, 2011).

Research has identified data-driven decision making (DDDM) as a way to use educational data to promote more effective instruction and, ultimately, to improve student outcomes. DDDM is a "systematic collection and use of many forms of data from a variety of sources in order to improve student performance" (Dunn, Airola, Lo, & Garrison, 2013a, p.222). Data can come from varied sources (e.g., instructional, administrative, demographic, behavioral, process) and can be used by all members of the educational community—especially teachers—to make decisions that affect student achievement (Mandinach, 2012). An increased interest from the educational community, school administrators, and teachers to use DDDM effectively has prompted attention in the research community to investigate the effects of DDDM and the process by which to promote its implementation (Marsh, Pane, & Hamilton, 2006). A growing body of research supports the use of DDDM (Carlson, Borman, & Robinson, 2011; Van Geel, Keuning, Visscher, & Fox, 2016) and continues to evaluate and delineate quality and effective methods/resources to use in the process (Mandinach, 2012).

Although DDDM likely has a relationship with increased student achievement, it is a method that may be quite different from the process of teaching many teachers have employed in the past. When evaluating their students, teachers often gave mandated assessments as required but continued to depend heavily on anecdotal information (Wayman, 2005). As pressure builds for teachers to use data in their decision making, they are expected to no longer make decisions based on their personal narratives, intuitions, or opinions (Mandinach, 2012), but rather to use their content and pedagogical knowledge triangulated with data-based interpretations to transform information into instructional decisions (Mandinach & Gummer, 2016).

This significant shift in focus requires teachers to have important skills for understanding data. Five primary phases of DDDM as outlined by Mandinach and Gummer (2016) include identifying problems and framing questions, using data, transforming data into information, transforming information into a decision, and evaluating outcomes. Teachers must have a prerequisite knowledge base in data literacy for teaching to work through the phases of DDDM (Mandinach & Gummer, 2016). Mandinach and Gummer (2016) have defined the construct of data literacy as “the ability to transform information into actionable instructional knowledge and practices by collecting, analyzing, and interpreting all types of data… to help determine instructional steps” (p.2). For example, to transform data into information, teachers must be able to interpret data, assessing patterns and trends within them.

Despite available data and strong research that supports the use of DDDM, using it to make instructional decisions is still a struggle for teachers (Wayman, & Jimerson, 2014). Due to the complexity of understanding data literacy, teachers struggle to apply such skills to use DDDM effectively. In a 2009 district survey administered by the United States Department of Education, 85% of districts reported a “lack of teacher preparation on how to use data for instructional decision making” as a barrier to spreading DDDM and that “districts believe that school staff needs further training and support” (Means, Padilla, & Gallagher, 2010, p.44). This conclusion was echoed in a U.S. Department of Education teacher survey in 2009 (Means et al., 2010). It is essential that research identify ways to train and develop data-literate teachers to use DDDM productively for it to become an effective way of increasing student achievement (Dunn, Airola, & Garrison, 2013).

In addition to a lack of data literacy in the implementation of DDDM practices, teachers' self-efficacy beliefs may affect their use of DDDM. Recently, theorists have posited a task-specific self-efficacy construct known as self-efficacy for data-driven decision making (DDDM), or "teachers' beliefs about their abilities to successfully engage in classroom-level DDDM" (Dunn et al., 2013a, p.223). Researchers have found relationships between teacher self-efficacy with DDDM and how often and effectively teachers use the method (Dunn et al., 2013b; Reeves, Summers, & Grove, 2016). When people have the appropriate skills necessary for accomplishing a task, self-efficacy expectations strongly influence behavior and effort in the face of challenges (Bandura, 1977). In the case of teachers, self-efficacy beliefs influence their classroom practice (Bandura, 1993), so it is important to investigate factors that may influence teacher DDDM self-efficacy.

Dunn et al. (2013a) have distinguished four domains of DDDM self-efficacy, including self-efficacy for identification and data access, data technology use, data analysis and interpretation, and application of data to instruction. Additionally, DDDM anxiety, or "trepidation, tension, and apprehension related to [one's] ability to successfully engage in DDDM," was indicated as a factor related to teacher use of DDDM (Dunn et al., 2013b, p. 90). Importantly, a better understanding of the variables that are associated with teacher DDDM self-efficacy and DDDM anxiety is necessary to effect change in self-efficacy and anxiety and, in turn, DDDM practices.

An influential factor for DDDM self-efficacy and anxiety may have to do with the learning opportunities and preparation coursework teachers engage in. While learning opportunities are necessary and potentially available for both pre-service and in-service teachers in DDDM (Greenberg & Walsh, 2012; Reeves et al., 2016), it is less apparent whether coursework associated with developing teachers' data literacy and capacity for using DDDM are influential and effective in raising DDDM self-efficacy and reducing anxiety. Research has found previous coursework specifically on skills needed for DDDM and greater DDDM self-efficacy in teachers to be associated with greater data use frequency by in-service teachers (Reeves et al., 2016). Both coursework and self-efficacy are related to data use; however, less is known about the relationship between coursework and DDDM self-efficacy and anxiety. The field can also benefit from additional population estimates of the scope and nature of DDDM-relevant coursework.

In order to find better ways to support teachers' ability to use data to make instructional decisions that improve student learning, examining the relationship between teacher learning opportunities through DDDM-related coursework and their self-efficacy and anxiety in DDDM is needed. The purpose of this study was to examine the relationship among pre-service and in-service teacher participation in DDDM-related courses and their DDDM self-efficacy and anxiety. Pre-service teachers were students enrolled in a teacher preparation program working toward initial teacher certification. In-service teachers were those working as a certified classroom, special education, or English as a second language teacher. DDDM-related coursework were courses that focused on educational assessment, data-driven decision making, data use, Response to Intervention/progress monitoring, teacher inquiry/teacher research/action research, research methods, or statistics.

Theoretically, one source of self-efficacy is mastery experiences (Bandura, 1977), which may well be afforded to teachers during course-based learning opportunities as well as accumulated teaching experience (Klassen & Chiu, 2010; Swackhamer, Koellner, Basile, & Kimbrough, 2009). This study involved a secondary analysis of existing, unduplicated data from a research program on teacher data use from multiple studies of in-service and pre-service teachers.

The research investigated the following research questions:

1. To what extent have pre-service and in-service teachers taken DDDM-related courses?
2. What is the relationship between the type of DDDM-related courses taken by pre-service and in-service teachers and their DDDM self-efficacy?
3. What is the relationship between the type of DDDM-related courses taken by pre-service and in-service teachers and their DDDM anxiety?

CHAPTER 2

THEORETICAL FRAMEWORK AND LITERATURE REVIEW

Cycle of Inquiry Framework

Mandinach and Gummer (2016) have developed a theory for data-driven decision making and data literacy for teaching. They describe a cyclical process of inquiry that encompasses the complex skills teachers need to combine pedagogy and content knowledge with an ability to use data. The inquiry cycle framework of data literacy includes five primary phases of data use for teaching: identify problems and frame questions, use data, transform data into information, transform information into a decision, and evaluate outcomes (Mandinach & Gummer, 2016). These phases are presented in a logical progression, but because the cycle is iterative, the progression is neither necessarily linear nor fixed (Mandinach & Gummer, 2016).

In each phase of the inquiry cycle, teachers require sets of knowledge and skills to apply DDDM (Mandinach & Gummer, 2016). For example, after articulating a problem of practice, teachers will use data as part of a continuous cycle to work towards solving the problem. To do so, teachers need knowledge and skills in understanding assessment, accessing quality data, and analyzing data for meaning. Teachers would then be able to use statistics and data displays to transform data into information. This can be followed by transforming such information into decisions and evaluating outcomes by monitoring student performance over time. The cycle continues as teachers examine the decisions they have made for effects and consider the need to begin a new cycle for solving the problem. The assessment, action research, statistics, and progress monitoring knowledge and skills that are part of the construct of data literacy are then a prerequisite knowledge base for progressing through the phases of DDDM (Mandinach & Gummer, 2016).

Data Literacy and Data Use in Teachers

In theory, with greater data literacy, teachers are better equipped to engage in DDDM effectively. The literature accepts that data literacy in teachers is essential for successful DDDM (Dunlap & Piro, 2016; Dunn et al., 2013a; Means, Padilla, DeBarger, & Bakia, 2009; Reeves & Chiang, 2017). Prior research also supports that teachers have difficulty with DDDM due to a lack of data literacy (Mandinach & Gummer, 2016; Prenger & Schildkamp, 2018; Wayman & Jimerson, 2014). However, research is less clear about the ways to best support teachers' data literacy development.

DDDM is the process of using data to make decisions that promote positive student outcomes. Because practice is necessary for learning and executing new skills independently, in theory, the more often one uses DDDM the more likely it is that one can use the practice successfully (Marzano, 2010). Research into how often teachers use data shows that there are several factors that contribute to or impede the frequency of data use. Literature on data use among teachers demonstrates that the practice varies greatly depending on factors such as access to data (Means et al., 2009; Wayman, Jimerson, & Cho, 2012), school leadership (Park & Datnow, 2009; Wayman, Midgley, & Stringfield, 2006), opportunities for collaboration (Keuning, Van Geel, Visscher, Fox, & Moolenaar, 2016), and self-efficacy in DDDM (Dunn, Airola, & Garrison, 2013). Investigating predictors for these factors that influence data use, including learning mechanisms associated with self-efficacy in DDDM, can further a better understanding of how to effect change in teacher DDDM practices.

Learning Opportunities for Pre-Service Teachers

The literature contains several studies investigating the process of building teachers' capacity to be data literate and use DDDM effectively. Interventions targeted at pre-service teachers were primarily delivered during or embedded within undergraduate coursework in assessment. Course-embedded interventions are task-specific learning opportunities delivered within a course but are not the primary focus of the course. There is evidence that learning opportunities for pre-service teachers can affect their data literacy and use of DDDM (Dunlap & Piro, 2016; Reeves & Chiang, 2017; Reeves & Honig, 2015). Dunlap and Piro (2016) studied pre-service teachers involved in a "Data Chat" intervention that included having pre-service teachers collaborate in content-specific groups to understand, analyze, and interpret test score data from actual classrooms. These participants showed gains in specific skills for analyzing data for instruction and understanding how to adapt their future teaching (Dunlap & Piro, 2016).

Another intervention that showed statistically significant, short-term changes in participants between pre- and posttest data show that a course-embedded intervention in data literacy can be a promising learning mechanism to develop data interpretation skills (Reeves & Chiang, 2017).

Learning Opportunities Targeted for In-Service Teachers

There is also evidence that learning opportunities for in-service teachers can affect their data literacy and use of DDDM (Dunn, Airola, & Garrison, 2013; Marsh, Sloan McCombs & Martorell, 2010; Reeves & Chiang, 2018; Van Geel et al., 2016). The implied impact of a two-week intensive training in classroom assessment, conducted by Dunn, Airola, and Garrison (2013), showed substantial growth in teachers' knowledge and understanding of concepts related to student academic performance, including assessment data literacy. A mixed-methods study on a statewide reading coach program showed that support from an instructional coach in DDDM practices is associated with higher student achievement (Marsh et al., 2010). In a study by Van Geel et al. (2016), teachers in five schools were given a two-year intervention training on DDDM. At the end of the intervention period, these schools showed improved student achievement with an effect of almost an extra month of school on average (Van Geel et al., 2016). Similarly, in an intervention study that focused on the effects on teachers, training activities on data literacy for teachers had a positive effect on school staff's capacity to use DDDM (Staman, Visscher, & Luyten, 2014). Such evidence suggests that learning opportunities contribute to long-term effects on teacher data literacy, use of DDDM, and ultimately student achievement.

Learning Opportunities for Both Pre-Service and In-Service Teachers

Online learning to develop data literacy skills in DDDM can be a useful opportunity for both pre-service and in-service teachers. An experimental study that investigated the effects of a fully online and asynchronous[1] (meaning that participants did not need to log on at the exact time as each other) intervention with teachers showed significant positive changes in self-efficacy for DDDM in both pre-service and in-service teachers, with lowered levels of anxiety for DDDM (Reeves & Chiang, 2018).

More research into the field of learning mechanisms for building teacher capacity and self-efficacy in DDDM is necessary. Coursework, embedded course interventions, and ongoing professional development are the primary ways in which teachers are taught to use the practice of DDDM for the classroom. It is important to initially determine whether coursework in data literacy is enough or whether extra-curricular learning opportunities are necessary to effectively use DDDM at the classroom level. This study contributes to this literature by helping to create a better understanding of the role formal course taking in data literacy has on promoting self-efficacy and reducing anxiety for DDDM in pre-service and in-service teachers.

Social Cognitive Theory

Social cognitive theory presented by Bandura (1977), specifically his thoughts on self-efficacy, is part of the theoretical framework for this study. Chen, Gully, and Eden (2001) explained that

[1] Participants do not need to be logged on at the same time.

Bandura's theory describes how self-efficacy varies on three dimensions: level of difficulty, strength of the certainty of success, and generality. The general dimension of self-efficacy (GSE) describes the belief in one's overall competence in a variety of settings (Chen et al., 2001). As explained by Bandura (1977), a more task-specific focus on self-efficacy expectation refers to a person's belief that they will be successful when doing a task. Bandura (1977) describes four factors that affect a person's self-efficacy expectations: performance accomplishments, vicarious experience, verbal persuasion, and emotional arousal. Repeated success through performance accomplishments, or mastery experiences, raises strong self-efficacy expectations (Bandura, 1977). It is important that people do not just achieve success through easy tasks, but by mastering challenges in order to affect their self-efficacy beliefs. Bandura (1977) posits that people need to participate when introduced to something to develop the skills to do it. Then, by slowly removing assistance and following it up with "self-directed mastery" tasks, people will generalize their self-efficacy expectations to the specific task (Bandura, 1977). Coursework in data literacy may provide an opportunity for teachers to have mastery experiences with DDDM. This study examined the relationship between developing skills through coursework and a task-specific self-efficacy construct of teacher self-efficacy with DDDM.

Bandura (1993) posited that a teacher's self-efficacy affects how they approach the educational process and specific instructional practices. Teacher self-efficacy beliefs are "a judgement of his or her capabilities to bring about desired outcomes of student engagement and learning" (Tschannen-Moran & Hoy, 2001). Research indicates that teachers with a strong sense of self-efficacy are more likely to implement new practices (such as DDDM) than teachers with low self-efficacy (Guskey, 1988). Because of the significant impact it can have on teacher practices, the literature remains invested in exploring teacher self-efficacy as applied to such DDDM skills.

Much of the previous research on teacher self-efficacy was done as it relates to outcomes including job satisfaction (Klassen & Chiu, 2010; Schwarzer & Hallum, 2008; Skaalvik & Skaalvik, 2007), data use (Gallagher, Means, & Padilla, 2008; Reeves et al., 2016), and student achievement (Caprara, Barbaranelli, Steca, & Malone, 2006; Goddard, Hoy, & Hoy, 2000). Less research has examined demographic predictors of self-efficacy in teachers such as gender, age, and length of time teaching (Klassen & Chiu, 2010; Wolters and Daugherty, 2007). The literature continues to be limited in its contribution on the type of learning opportunities associated with elevating teacher self-efficacy expectations (Piro, Dunlap, & Shutt, 2014). Developing instruments to measure self-efficacy in teachers has furthered some of the literature, allowing researchers to examine predictors or correlates of specific constructs of teacher self-efficacy (Dunn et al., 2013a; Henson, 2001; Tschannen-Moran & Hoy, 2001).

Teacher Self-Efficacy for DDDM

DDDM self-efficacy, or teachers' belief in their ability to use DDDM to improve student outcomes, is a specific self-efficacy construct for teachers. Researchers have investigated some factors that contribute to higher DDDM self-efficacy in both pre-service and in-service teachers. Additionally, there is some literature on learning opportunities, including course-embedded interventions, that have raised levels of DDDM self-efficacy in teachers (Green, Schmitt-Wilson, & Versland, 2016; Piro, Dunlap, & Shutt, 2014; Reeves & Honig, 2015; van der Scheer &

Visscher, 2016). While investigators have studied each of these variables, research has not examined the relationship between semester-long DDDM-related coursework and DDDM self-efficacy in teachers. Because DDDM is associated with improved outcomes for students and considered by many to be a contemporary best practice, having a better understanding about the types of semester-long DDDM-related courses that foster increased teacher self-efficacy in the context of DDDM is important to continue to research and practice (Mandinach, 2012).

Pre-Service Teacher Self-Efficacy for DDDM

Research shows that pre-service teachers' DDDM self-efficacy can be affected by course-embedded interventions (Piro et al., 2014; Reeves & Honig, 2015). Participants in Piro et al.'s (2014) study showed increased self-efficacy and confidence in using data as an outcome of the collaborative instructional format of the intervention. Similarly, a moderately higher self-efficacy with DDDM was reported by pre-service participants in a course-embedded intervention on data literacy (Reeves & Honig, 2015). In both studies, these learning opportunities were course embedded and implemented for only a short period of time. It is important to investigate whether building capacity through semester-long courses in data literacy is also associated with increased DDDM self-efficacy among pre-service teachers.

In-Service Teacher Self-Efficacy for DDDM

A few studies have examined in-service teacher DDDM self-efficacy. One study by Dunn et al. (2013a) surveyed teachers who had participated in a DDDM intervention and found that teachers with more self-efficacy with DDDM were more likely to collaborate with colleagues to use DDDM more frequently and more effectively with their students. Literature on self-efficacy for DDDM for in-service teachers indicates that such can be affected by interventions in data literacy after beginning their professional careers. Similarly, van der Scheer and Visscher (2016) found teacher DDDM self-efficacy was significantly improved following an intensive intervention and that such effects continued for at least a year after the intervention. Greater effects on DDDM self-efficacy were seen when teachers were provided with learning opportunities that lasted for an extended period or had greater involvement by the administration (Green et al., 2016). It stands to reason that teachers with semester-long courses on data literacy would have increased DDDM self-efficacy. It is important to investigate any relationship between in-service teachers' DDDM self-efficacy and the type and frequency of DDDM-related coursework taken by a teacher.

Teacher Anxiety for DDDM

Additional research into DDDM has indicated that teachers find DDDM practices anxiety producing (Dunn et al., 2013b; Means et al., 2009). Emotional arousal caused by anxiety is another source of information that can affect an individual's perceived self-efficacy beliefs about their ability to deal with situations that are stressful (Bandura, 1977). Dunn et al. (2013b) found a significant, inverse relationship between DDDM anxiety and DDDM self-efficacy and that anxiety was an important factor to consider when investigating learning mechanisms of DDDM. Additional research measuring teachers' DDDM anxiety indicated that after receiving data literacy interventions, both pre-service and in-service teachers showed some lowered anxiety, though not statistically significant, for DDDM (Reeves & Chiang, 2017; Reeves & Honig, 2015). Because teacher anxiety for DDDM can contribute to resisting and avoiding the practice (Dunn, Airola, & Garrison, 2013), thereby providing teachers with less mastery experiences that in turn reduce self-efficacy (Bandura, 1977), examining the relationship between the type and frequency of DDDM-related coursework and teacher anxiety is an important step in understanding how learning mechanisms could affect teacher DDDM practice.

Coursework

Distribution of Coursework in Data Literacy

This study investigated undergraduate and graduate courses that have a focus on building teachers' data literacy and that could have a relationship with their DDDM self-efficacy and DDDM anxiety. In the context of the data literacy phases, as described by Mandinach and Gummer (2016), coursework in assessment, statistics, progress monitoring, research, and DDDM were appropriate for examining. Research into the distribution of the type and frequency of these types of formal teacher preparation courses was scarce.

The published research that did exist about teacher education coursework resulted in calls for future research. Reeves (2017b) and Reeves et al. (2016) looked at data literacy courses taken by pre-service and in-service teachers at both the undergraduate and graduate levels, respectively. When respondents were asked about the number of semester-length courses covering data literacy taken, about 85% of pre-service (Reeves, 2017a) and 63% of in-service respondents (Reeves et al., 2016) indicated that they had taken at least one assessment course. Specifically, pre-service participants had taken courses in research, progress monitoring, and/or DDDM at a rate of 61-65%. The percentage of in-service teachers who had taken these data literacy courses at the undergraduate level was much lower, at between 37 and 49% (Reeves et al., 2016). The percentage at the graduate level for in-service teachers was higher at 49-60%, but still less than the rate for pre-service respondents (Reeves et al., 2016). All these courses were taken at a lower rate for both pre-service and in-service respondents than assessment courses (Reeves, 2017a; Reeves et al., 2016). The sample sizes in these two studies included 142 pre-service and 329 in-service teachers, whereas the present study looked at differences in the number of DDDM-related courses taken by over 700 in-service and pre-service teachers. A larger sample size contributes to a better understanding of the distribution of these kinds of coursework in the population of teachers.

Other studies have looked at course-taking patterns of teachers in data literacy. Mandinach, Friedman, and Gummer (2015) investigated course programs at schools of education around the United States and found that many institutions offer stand-alone courses in DDDM, but most of these courses focus on assessment literacy. While these schools of education are embedding data use concepts into existing courses, a predominant emphasis is on assessment and the use of assessment data (Mandinach et al., 2015). Greenberg and Walsh (2012) found only 21% of teacher preparation programs covered topics of assessment literacy adequately, less than 1% of programs covered analytic skills adequately, and fewer than 2% covered instructional decision making adequately. It is beneficial to understand the extent to which prospective teachers take courses that can provide them with the information and experiences in DDDM needed to enhance their DDDM self-efficacy.

Coursework and DDDM Self-Efficacy and Anxiety

While research has investigated in-service professional development and course-embedded pre-service interventions for their ability to affect teacher DDDM self-efficacy and anxiety, these relationships with types of semester-long DDDM-related coursework were missing in the literature. Investigators have examined other relationships between teacher preparation coursework and outcomes. Studies that have examined the general link between teacher coursework and student achievement are often inconclusive, but one study by Wayne and Youngs (2003) found a strong link between teachers with coursework in mathematics and higher student achievement in math. DDDM includes statistical and other mathematical knowledge skills, so teachers with additional DDDM-related coursework could have contributed to increases in student achievement due to a stronger sense of self-efficacy for DDDM.

In addition, research has linked data literacy coursework experiences to increases in data use and with increased DDDM self-efficacy (Reeves, 2017a; Reeves et al., 2016). While not stand-alone courses, Reeves and Chiang (2017) found that embedded learning opportunities within coursework can increase teachers' data literacy. Additionally, these course-embedded data literacy interventions are linked to increased DDDM self-efficacy and confidence (Dunlap & Piro, 2016; Reeves & Honig, 2015). After data literacy is taught to teachers through coursework, it is important to study teacher beliefs about their confidence in making data-driven decisions that improve student outcomes. Considering that all teachers must be a part of teacher preparation programs that may include coursework in assessment, research, statistics, progress monitoring, and DDDM, research is needed to examine the link between the types of coursework and DDDM self-efficacy in teachers.

Other Factors That May Influence DDDM Self-Efficacy in Teachers

To control for extraneous variables when looking at the relationship between course taking and DDDM self-efficacy and anxiety, this study included several control variables that overlap with both the primary independent and dependent variables. These teacher characteristic variables included age, gender, race, teaching experience, position, and school level. While there is a paucity of literature looking at associations with any of these teacher characteristics and specifically DDDM self-efficacy, researchers have examined the links between some of these factors and teacher self-efficacy or general self-efficacy (GSE). These variables had the possibility of being associated with course taking or DDDM self-efficacy, so for rigorous examination, this study explored whether these additional variables explained the findings.

Age and Years of Teaching Experience

Literature on GSE indicates that it changes with age (Gecas, 1989). Studies suggest that efficacy builds until middle age and then gradually declines (Gecas, 1989). One study on teacher self-efficacy did not support that age is a significant factor (Veldman, Admiraal, Mainhard, Wubbels, & Van Tartwijk, 2017) but that teaching experience may be a better predictor than age (Hughes, 2012). There is debate about when in their careers teachers are most self-efficacious. Wolters and Daugherty (2007) found that teacher self-efficacy increases with more experience, whereas Klassen and Chiu (2010) argued that the relationship is non-linear, with self-efficacy increasing from years 0 to 23 and then declining as years of experience increased. Alternatively, Hoy and Spero (2015) found significant increases in self-efficacy during student teaching but significant declines during the first year of teaching. Ghaith and Yaghi (1997) found that experience was negatively correlated with teacher self-efficacy. Consequently, it was important to control for age and experience variables in the present study.

Gender and Race

There is a general lack of racial and gender diversity in the teacher workforce in America that may be related to the types and distributions of DDDM-related coursework in teacher education programs. According to the National Center for Education Statistics, in the 2011-2012 school year, 82% of K-12 public school teachers were White, 7% were Black, and 8% were Hispanic; about 76% of all teachers were female (Goldring, Gray, & Bitterman, 2013). Additionally, teacher education faculty in 2007 was 78% White (Sleeter, 2017). In 2011-12, 16% of all Black teacher preparation program students were enrolled in historically Black colleges or universities and only 42% of Black students who started their programs in 2003-04 attained bachelor's degrees in education by 2008-09 (King, 2016). The greater proportion of White faculty and the production in greater proportion for White/female teachers in teacher education programs may have relationships with how programs are designed and how students are supported (Sleeter, 2017). Additionally, the attention to which a program works in courses on race and ethnicity, statistics and math, inquiry and research, and other curricula may be affected by the diversity of the faculty and students (Sleeter, 2017). Because race and gender may be related to the types of coursework and programs offered in teacher education programs, it was important to control for these factors in the present study analysis.

There is literature associating gender and race with self-efficacy constructs. In a review of literature, Gecas (1989) summarizes the research on associating gender and self-efficacy indicating that women have a lower sense of GSE, personal control, and mastery than men. When a specific construct of teacher self-efficacy was considered, female teachers showed lower classroom management self-efficacy and more work stress (Klassen & Chiu, 2010). Also, minority groups have historically shown lower levels of GSE (Gecas, 1989). In a comparison of self-efficacy among Black and White individuals, show that Black people report lower GSE, with a primary function of the difference based on racial discrimination and its consequences

(Gecas, 1989). When specifically looking at teachers, Guo, Justice, Sawyer, and Tompkins (2011) found significant differences in GSE between Black and White teachers. Additionally, evidence that culture plays a role in self-efficacy comes from studies showing significant differences in the GSE of Mexican Americans and Anglos due to specific differences in heritage beliefs (Gecas, 1989). It was important to take into consideration the possibility that factors of gender and race could have explained part of the findings of this study.

Teaching Position and School Level

Research has linked teacher position (i.e. subject area) and school level of a teacher (i.e., elementary) to teacher self-efficacy. Klassen and Chiu (2010) and Wolters and Daugherty (2007) found associations between teaching in elementary school and higher teacher self-efficacy than teachers in middle and high schools. Additionally, teachers in middle school and high school reported lower levels of self-efficacy for engaging students (Wolters & Daugherty, 2007). Conversely, teachers who that work with young children reported higher levels of self-efficacy for student engagement and classroom management (Klassen & Chiu, 2010). In Swackhamer et al. (2009), highly qualified, subject-specific teachers with additional coursework in math or science reported higher teacher outcome efficacy, or belief that the educational system can work for all students. Exploring the variables of teacher position and school level differences in regard to DDDM self-efficacy was important to better describe the findings.

CHAPTER 3

METHODS

Data Source

This study involved a secondary analysis of existing, unduplicated data from a research program on in-service and pre-service teacher data use. The study has an explanatory correlational design. Its purpose is to examine the relationship among pre-service and in-service teacher participation in DDDM-related courses and their DDDM self-efficacy and anxiety. Data for this study were merged from the five data sources described below, which each included data on in-service and/or pre-service teachers' DDDM self-efficacy, anxiety, and coursework. Because the variables were not the same for both pre-service and in-service teachers, a fully merged dataset comprising all five original datasets was then split into two separate datasets: pre-service teacher (PST) and in-service teacher (IST). In this section, sources for the data that were used for the present study will be discussed, but information on each measure, including the characteristics of (e.g., items, scales) and reliability and validity evidence for each, will be discussed in the Variables and Measures section.

In-Service Teacher Data Use Study

The first dataset includes data from a published study of 329 Illinois public school teachers from at least 71 schools across at least 54 districts. Data collection included contacting Illinois public school district principals with a request to distribute an electronic survey to their teachers. The survey was online and administered via Qualtrics. The survey included both researcher-developed and existing instruments to ask participants to report on their demographics, data use practices, assessment beliefs, DDDM self-efficacy and anxiety, and DDDM-relevant course taking (Reeves, Summers, & Grove, 2016).

Pre-Service Teacher Data Use Study

The second dataset includes data from a published study of 142 current/former K-12 pre-service teachers from Illinois and Massachusetts who completed a full-time student teaching experience within five years of study publication. Instrumentation was a Qualtrics online survey that included both researcher-developed and existing instruments to ask participants to report on their demographics, data use practices during student teaching, assessment beliefs, DDDM self-efficacy and anxiety, and DDDM-relevant course taking (Reeves, 2017a).

Data Literacy Intervention Data

The next dataset includes data from a published study of 25 in-service teachers from four countries (88% US) and 14 states and 99 pre-service teachers from 29 states and 43 different teacher preparation programs. Instrumentation included two electronic surveys administered immediately before and after an online data literacy intervention that asked participants to report on their DDDM efficacy and anxiety, assessment beliefs, data use practices, and DDDM-relevant course taking (Reeves & Chiang, 2018).

Additional Data Literacy Intervention Data

The last two original datasets contain unpublished survey data of pre-service (*N*=214) and in-service (*N*=121) teachers' DDDM self-efficacy and anxiety, assessment beliefs, data use practices, and DDDM-relevant course taking. Data were collected during initial rounds of pretest-posttest data collection concerning an online data literacy intervention (that intervention reported in Reeves & Chiang, 2018), but findings related to these data remain unpublished.

Variables and Measures

PST Variables

The primary independent variables for the merged PST dataset pertained to the DDDM-related coursework taken by pre-service teacher participants: assessment, DDDM, RTI, teacher inquiry, research methods, and statistics. Pre-service teachers were students enrolled in a teacher preparation program working toward initial teacher certification. The dependent variables for the PST dataset were DDDM self-efficacy and DDDM anxiety. These measures are discussed in sections below.

The control variables for the PST dataset include age, sex, race, ethnicity, intended school level, and intended subject. The variable for age was continuous, on a ratio scale. Variables of sex, race, ethnicity, intended school level, and intended subject were categorical, on a nominal scale. Also, the school level each participant intends to primarily teach in the future was detailed by the Intended School Level variable. Levels for intended school level included *Pre-Kindergarten, Elementary school (K-5), Middle school (6-8), High school (9-12), Other,* and *Multiple*. In addition, the Intended Subject ariable identified the primary subject area the participant intends to teach in the future. Levels for intended subject included *All core subjects, English/language arts, Mathematics, Science, Social studies, Art, Music, Physical education, Foreign language, Other,* and *Multiple subjects*. Some variables were standardized or dummy coded before analysis.

IST Variables

The primary independent variables for the IST dataset were DDDM-related coursework taken by in-service participants in assessment, DDDM, RTI, teacher inquiry, research methods, and/or statistics. In-service teachers were participants working as a certified classroom, special education, or English as a second language teacher. The dependent variables for the IST dataset were DDDM self-efficacy and anxiety (discussed below).

The control variables for the IST dataset included age, sex, race, ethnicity, teaching experience, school level taught, and subject level taught. The variables for age and teaching experience were continuous and ratio level. Variables of sex, race, ethnicity, school level taught, and subject level taught were on categorical scales and nominal. The School Level Taught variable represented the school level the participant primarily teaches. Levels for school level taught included *Pre-Kindergarten, Elementary school (K-5), Middle school (6-8), High school (9-12), Multiple*, and *Cannot determine*. Also, the subject area the participant primarily teaches were categorized by the subject taught variable. Levels for subject taught included *All subject areas, English/language arts, Mathematics, Science, Social studies, Art, Music, Physical education, Foreign language, Other, Multiple subjects, and Cannot determine.* The following primary position labels were recoded as *Other*: agriculture, business, technology, economics, English language learning, family and consumer science, health, and life skills. Some variables were standardized or dummy coded before analysis.

Data-Driven Decision Making Self-Efficacy and Anxiety Measure

For both the PST and IST datasets, DDDM self-efficacy and anxiety data were measured using the Data-Driven Decision Making Efficacy and Anxiety Inventory (3D-MEA; Dunn et al., 2013a) and was used as the dependent variable in this study. This inventory uses 20 items to assess four task-specific areas of data-driven decision making self-efficacy: data identification and access (access), data technology use (technology), data analysis and interpretation (analysis), application of data to instruction (instruction), and task-specific data-driven decision-making anxiety (anxiety). In order to interpret 3D-MEA scores in these five task-specific areas, composite scores for each subscale (access, technology, analysis, instruction, and anxiety) were calculated from the mean of each to use in the analysis.

By calculating that the Cronbach's alpha for each rating scale ranged from 0.84 to 0.92, Dunn et al. (2013a) has provided strong prior evidence that the 3D-MEA scores show strong internal consistency reliability. There is also both content-related and internal-structure evidence provided for the instrument by Dunn et al. (2013a). With items based on Bandura's thoughts on self-efficacy in social learning theory and Tschannen-Moran and Hoy's (2001) model for teacher self-efficacy, Dunn et al.'s (2013a) instrument was developed to measure teacher DDDM self-efficacy and DDDM anxiety. Supported through cross-validation, a good model-data fit was found with a five-factor confirmatory factor analysis (CFA) model (Dunn et al., 2013b). Between the four DDDM efficacy areas of the measure, correlations were only at the small to moderate level ($.26 \leq r \leq .47$) for interfactor correlations (Dunn et al., 2013a). Additionally, when the 3D-MEA was compared with the Teachers' Sense of Efficacy Scale (Tschannen-Moran & Hoy, 2001), Dunn et al. (2013a) found correlation coefficients ranging from only –.02 to .27. This indicated that the 3D-MEA had discriminant validity from the general measure of teacher self-efficacy (Dunn et al., 2013a).

To look at the internal consistency of the 3D-MEA in this study, Cronbach's alpha was used for both the PST and IST datasets. Internal consistency reliabilities (αs) for the five 3D-MEA subscales ranged from .81 to .91 for the pre-service dataset and from .81 to .92 in the in-service dataset. The reliability estimates for each subscale in the datasets showed evidence of strong internal consistency.

Coursework Measure

For prior DDDM-relevant coursework, participants were asked to indicate how many undergraduate or graduate classes they had taken on each of six topics (Assessment, Data-driven decision-making/data use, Response to intervention/progress monitoring, Teacher inquiry/teacher research/action research, Research methods, and Statistics). A semester-length course included undergraduate and graduate level classes taken for one academic term by either a pre-service or in-service teacher. The final response format included options for no courses, one course, two courses, and three or more courses.

Data Management

Merged Dataset

A fully merged dataset comprising all five original datasets was initially compiled. After some preliminary cleaning (e.g., specification of variable labels), the one fully merged dataset was split into two separate datasets to use in this study: one dataset of pre-service teacher data (PST) and one dataset of in-service teacher data (IST). Two separate sets of analyses were carried out because the variables are not identical for both pre-service and in-service teachers. For example, pre-service teachers were asked what school level the participant intends to primarily teach, while the in-service participants were asked what school level they do primarily teach. Additionally, some items were only asked to one set of participants. For instance, years of teaching experience was logically only asked of in-service teachers. The process of merging the data and related analytic decisions are described below for the PST data, IST data, and primary measures.

PST Data Preparation and Merger

Much of the PST data initially were collected using a pretest/posttest format. If a respondent was missing either all items or individual items, these values were imputed from the posttest responses, if available. For example, one participant was missing a response for the number of assessment courses taken, so his response from the posttest was entered. This same decision rule was used for each of the variables to fill in missing data.

In one survey, participants were not asked what subject area the participants intended to teach but did indicate whether they had a subject-specific student teaching experience and the subject of that experience. This experience was assumed to be an indicator of preparation for teaching for the indicated subject in the future. These values were imputed for the intended subject variable for these participants.

Additionally, appropriate recoding was applied to the intended subject item responses for four participants. One individual indicated Bilingual Literacy and that was recoded as English/Language Arts. One respondent indicated Health and Physical Education and was recoded as just Physical Education. Because dual-language classrooms teach multiple subject areas in two different languages, an individual who indicated 1-5 Dual Language was recoded as All Core Subjects. Finally, one respondent indicated History, and this was recoded as Social Studies.

A similar assumption was made for the Intended School Level variable. In one survey, participants were not asked what school level they intended to teach but were asked in what grade level they had completed their student teaching experience. This experience was assumed to be an indicator of preparation for teaching a particular school level. These values were imputed for the Intended School Level variable for these participants. In addition, there were 15 responses for *Other* as the school level with text specifications. Only one text specifying "Literacy" as the grade level response was kept as *Other* as the school level of this response could not be confidently determined. The other 14 specified text responses indicated that *Multiple* was a more appropriate label and were recoded as such.

Certain PST variables were modified during the data preparation process to improve later interpretation of results. Variables for sex, race, ethnicity and intended subject were dichotomized. Male was the reference category for sex. For race, responses of “White” were coded as “1”; all other responses were coded as “0”. Non-Hispanic was the reference category for ethnicity. Finally, pre-service teachers of math or science subjects were combined and coded as “1”, while all other responses were coded as “0”. In addition, because SPSS had assigned age scores beginning at 1 for 18, these scores were recoded as raw age scores to make 18 reflected as 18, 19 as 19, etc.

IST Data Preparation and Merger

In merging all five datasets, some data preparation and management were necessary for the IST dataset. To begin with, some of the IST data were collected using a pretest/posttest format. If a respondent was missing either all items or individual items, these values were assigned from the respondent’s posttest responses, if available. This same decision rule was used for each of the variables to fill in missing data.

Additionally, some teachers responded to items using the *Other* label, when it could be more appropriately recoded. Any teachers who identified *Other* as their primary position and specified that they were teachers for “Specials” (e.g., Music, Physical Education, Art) were recoded as C*lassroom teacher*. One teacher who responded with *Other* and specified that she was a “Life Skills” teacher was coded as *Special education teacher*. Also, text responses for any teachers who identified their primary grade level taught as *Other* were used to recode the responses into more suitable categories. Text responses of “K-5”, “K-3”, “K-1 Sped”, “5-8”, and “9-12” were recoded as *Multiple*. Three responses that did not specify with text were left as *Other*. In addition, any teachers who identified *Other* as their primary school level taught and specified with text were recoded appropriately if applicable.

In merging the data, irrelevant data for the present study were used to fill in missing data for pertinent variables in the IST dataset. For example, data collected from teachers on their primary grade level taught were not used for analysis but were used to impute school level taught values, if responses were available.

Certain IST variables were also modified during the data preparation process to improve later interpretation of results. Variables for sex, race, ethnicity and subject taught were dichotomized. In the same way as the PST dataset, male was the reference category for sex, non-White was the reference category for race, and non-Hispanic was the reference category for ethnicity. Teachers of math or science subjects were combined and coded as “1”; while all other responses were coded as “0” for the Subject Taught variable. As in the PST, age scores from SPSS were recoded as raw age scores to make 18 reflected as 18, 19 as 19, etc.

Data Preparation and Merging of Measures

Merging the Data-Driven Decision Making Self-Efficacy and Anxiety Measure Data

The 3D-MEA measure items and response values were identical in form on the data collection surveys for all five original datasets. Some of the 3D-MEA data were collected using a pretest/posttest format. If a respondent was missing either all items or individual items, these values were imputed from the posttest responses, if available. This same decision rule was used for each of the 3D-MEA items to fill in missing data.

Merging the Coursework Measure

The coursework measure was collected differently for some of the original datasets. In one of them, the survey item asked participants to indicate the number of undergraduate and graduate classes separately. In merging the data, those responses were combined to indicate a total number of undergraduate and graduate classes total. Because the highest value option available to respondents on any of the original surveys was *three or more courses*, no "combined" value could be higher than this. Additionally, one dataset also included a response option for having taken "partial or part of" a course. Those responses were recoded to indicate they had not taken any courses on that topic. If a respondent was missing either all items or individual items, it was imputed from the posttest responses, if available.

Additionally, to cut down on the number of variables in the multiple regression analysis, responses for each Course Taking variable were also dichotomized. If a participant had indicated taking one or more courses in a type of DDDM-related course, the response was coded as a “1”; respondents who had taken no courses of that type were recoded as “0”.

Participants

Pre-Service Participants

The pre-service teacher dataset (PST) included 412 participants who provided informed consent. While some individuals in the PST dataset were not pre-service teachers at survey completion, the participants were instructed to report concerning their coursework and DDDM self-efficacy and anxiety at that time. The analytic sample included participants from 132 different institutions in 38 different states, with the majority from Illinois (49%). Overall, about 90% of the sample were female, 86% were White, 4% percent were Black and 11% were Hispanic. In this sample, the percentage of White and female participants was higher than the national average. In 2015, 80% of bachelor’s degrees in education were awarded to females, and of prospective teachers enrolled in traditional programs, 74% were White (Snyder, de Brey, & Dillow, 2016). The mean participant age in the present study was 25.2 (*SD* = 6.7), with about 53% between the ages of 21 and 23 years old. Pre-service teachers intending to teach all pre-K-12 grade levels was represented in the PST dataset; about 69% intended to teach at the elementary level (K-5), about 10% at the middle-school level (Grades 6-8), about 10% at the high school level (Grades 9-12), and about 9% percent intended to teach in roles that span multiple levels (e.g., Grades 6-12). At 66%, the majority intended to teach all subject areas, with four percent intending to teach science and two percent in math.

In-Service Participants

The in-service teacher dataset (IST) includes 372 school teachers who served in an instructional role during the data collection period of March 2015-November 2017 and provided informed consent. Based on available data, IST participants were from 32 different states with the majority from Illinois (61%). Overall, about 81% of the sample was female, 84% were White, 7% were Black, and 4% were Hispanic. The average age of participants was 38.3 years (*SD* = 11.4) and the average length of teaching experience was 13 years (SD = 14.3). These demographics were closely related to the United States population of public school teachers at 82% White, 7% Black, 8% Hispanic, and 76% female (Goldring et al., 2013). The IST sample included 76% pre-K-12 classroom teachers with an additional 21% special education teachers and 3% English as a second language/bilingual teachers. All individual pre-K-12 grade levels were represented in the data; about 2% of the respondents served at the pre-K level, about 35% at the elementary level (Grades K-5), about 29% at the middle-school level, about 18% at the high-school level (Grades 9-12), and about 13% served in roles that span multiple levels (e.g., Grades 6-12). The majority taught all subject areas, at about 35%, and 13% math and 6% science.

Analysis

Missing Data

The study separately investigated the scope and nature of missing data for both the PST and the IST datasets. To begin with, Little's (1988) test for whether data are missing completely at random (MCAR) was conducted on all analysis variables, continuous and categorical. This provides an overall test of whether the missing values were missing completely at random in each dataset. In the PST data, the test failed to reject the null hypothesis that the data were missing completely at random, X^2 (51, N = 412) = 49.9, p = .52. In the IST data, the test did reject the null hypothesis for the Little's test, indicating that the data were not missing completely at random, X^2(144, N = 372) = 192.25, p < .01.

Additionally, using the SPSS "Missing Values Analysis" procedure (IBM Corporation, 2016), missing data were looked at to see if it was missing at random or missing not at random. These analyses included examining the percentage of missing data for each variable and comparing groups of cases with data and without data for each variable.

For both datasets, Table 1 shows the amount of valid and missing data for both the PST and IST datasets. In the PST data, the variable with the greatest percentage of missing data, the only one missing more than 5% of values, was for pre-service teachers' Intended Subject variable, with 9.5% missing. An indicator variable was created by SPSS for "missingness" (yes or no) in the Intended Subject variable. Subsequent independent-samples *t* tests were used to look at patterns of missing values in a variable that may be affecting scale variables in the

Table 1

Missing Data for Independent Variables in the Pre-Service (PST) and In-Service (IST) Datasets, N=412 N=372

	Preservice			Inservice		
Variable	Valid	Missing	% Missing	Valid	Missing	% Missing
Age	410	2	0.5	350	22	5.9
Sex	411	1	0.2	365	7	1.9
Race	410	2	0.5	353	19	5.1
Ethnicity	410	2	0.5	358	14	3.8
Intended Subject	373	39	9.5	-	-	-
Intended Level	404	8	1.9	-	-	-
Experience	-	-	-	372	0	0.0
Subject Taught	-	-	-	372	0	0.0
Level Taught	-	-	-	372	0	0.0
Courses						
Assessment	408	4	1.0	372	0	0.0
DDDM	409	3	0.7	372	0	0.0
RTI	411	1	0.2	372	0	0.0
Teacher Inquiry	412	0	0.0	372	0	0.0
Research	411	1	0.2	372	0	0.0
Statistics	410	2	0.5	372	0	0.0

Note. Intended Subject and Intended Level are variables only in the PST. Experience, Subject Taught, and Level Taught are variables only in the IST.

dataset. Because the intended subject variable was the only variable missing more than 5% of values, it was the only variable on which there was enough missing data to make a comparison between those who did and did not respond in relation to other variables. The *t* tests comparing missingness in the Intended Subject variable to that in the Age and 3D-MEA variables showed significance for sixteen of twenty 3D-MEA variables ($ps < .05$). Participants with missing values had higher mean scores for 15 of the 16 significant 3D-MEA variables.

In the IST data, the two variables with more than 5% of values missing were Age and Race, with 5.9% and 5.1% respectively. Only indicator variables for "missingness" in Race and Age were created by SPSS because they were the only variables to contain enough missing data to make a comparison. The indicator variables were used in subsequent *t* tests comparing their missingness with that in the scale variables for the IST dataset: Age, Teaching Experience, and 3D-MEA variables. Independent-samples *t* tests showed a significant effect for Age and Teaching Experience ($t(22) = -3.1$, $p < .05$), Race and Teaching Experience ($t(19) = -2.5$, $p < .05$), and Race and one 3D-MEA (19) variable ($t(21) = -2.6$, $p < .05$). No other variables had significant effects. Participants with missing values had higher mean scores for all three variables.

Multiple Imputation

Multiple imputation was used for missing data in both datasets because of the advantages of using all available data and preserving sample size and statistical power (Rubin, 1996). Additionally, given the significant result in the IST dataset for Little's test for MCAR, multiple imputation was chosen as the most appropriate and defensible approach for handling missing data. The SPSS "Impute Missing Data Values" process was used to conduct the imputation using the automatic imputation method (IBM Corporation, 2016).

To perform the imputations, variables were selected for the imputation model. For the PST, Age, Intended School Level, all 20 3D-MEA variables, and the dichotomized variables for Sex, Race, Ethnicity, Intended Subject, and all 6 Course Taking variables were included in the model. For the IST dataset, Subject Taught and School Level Taught variables replaced Intended Subject and Intended Level Variables. Teaching experience was also added to the IST model. All other imputed variables were the same for the IST imputation process. All variables included in the imputation models were also themselves imputed if necessary. For both datasets, the course variables were imputed dichotomously (*no course, one or more courses*) because the imputation models were too complex to run otherwise.

To apply the multiple imputation process, a few constraints were imposed to prevent SPSS from imputing impossible or inapplicable values. For both datasets, 18 was specified as the minimum value for Age, and 3D-MEA variables were given only the measure's possible range of one to five with rounding to one. Specifically for the IST data, Teaching Experience was given a minimum value of one.

The first attempt to apply multiple imputation for the PST data produced an error. This was due to the limited number of cases identified as preschool teacher in the Intended Teaching Level variable. This was rectified by limiting the levels of the Intended Teaching Level variable. This included recoding the singular intended preschool teacher with the intended elementary teachers. Due to the same issue in the IST dataset, the seven preschool teachers were recoded with the elementary teachers. The subsequent attempt to apply multiple imputation individually for both datasets was successful. For both the PST and the IST datasets, this created five separate datasets for each.

Descriptive Statistics Analyses

Descriptive statistical analyses were conducted first to understand the variables in each dataset and answer the present study's first research question. To begin with, frequency distributions were used to describe the independent variables of semester-long coursework and the dependent variables of DDDM self-efficacy and anxiety for both the PST and IST datasets. Additionally, frequency distributions were done on categorical control variables including Sex, Race/Ethnicity, School Level Taught (intended-PST, primary-IST), and Subject Taught (intended-PST, primary-IST). Graphical representations of categorical variables including frequency tables and bar charts were made to describe each sample set. Also, frequency distributions were done on continuous control variables of Age and Teaching Experience (IST only) for each sample set.

Multiple Regression Analyses

Multiple regression was used to examine the relationship between DDDM self-efficacy/DDDM anxiety and DDDM-related courses using linear regression analysis in SPSS (IBM Corporation, 2016).

To improve interpretation of results, certain variables were modified after multiple imputation but before the multiple regression analysis. In the PST data, dummy variables were derived for the Intended Teaching Level variable. In the IST data, dummy variables were created for the Teaching School Level variable in the same way. The raw Age variable in both the PST and IST datasets was standardized for the multiple regression analysis. The Teaching Experience variable was also standardized for the IST dataset.

For both the PST and IST datasets, separate regression analyses were applied for each of the four subscales of DDDM self-efficacy and for the one subscale of DDDM anxiety of the 3D-MEA. Standardized scores for each subscale of the 3D-MEA were used as the dependent variable in each analysis. For interpretive purposes, 3D-MEA subscale composite scores were standardized before the regression analysis. Covariates included in the regression analyses were standardized age scores and dummy variables for sex, race, ethnicity, intended teaching subject, and intended school level for the PST data, while the IST included subject taught, school level taught instead of intended variables and also included teaching experience. The primary variables for both datasets included in the regression were the dichotomized DDDM-related course variables. For each type of course (assessment, DDDM, RTI, teacher inquiry, research, statistics), the responses were recoded “1” if the participant had taken at least one course in the course type and “0” if they had not taken any courses in that course type. Only these dichotomized Course Taking variables were included in the regression, because too many dummy variables for courses would have made the regression models too complex.

Results for regression coefficients are pooled by SPSS. In the absence of pooled results from SPSS for other aspects of the analysis, all omnibus ANOVA results (e.g., F, R^2) were from Imputation 1 (all other imputations were examined for noteworthy differences and are reported in the next section). For Imputation 1, the *p* values for each of the five ANOVAs were less than .05, indicating statistical significance. They were also significant for all other imputations, unless noted.

Analyses of Pearson correlations among variables was utilized to examine the variables for collinearity issues. Pooled correlation results are compiled and produced by SPSS. There were no excessive correlations between predictors that would indicate multicollinearity issues ($r > .8$) in either the PST or IST data. The highest correlation in the PST data was between the DDDM course variables of teacher Inquiry (teacher inquiry/teacher research/action research) and Research (research methods) at ($r = .538$, $p < .001$) and was also high in the IST data at ($r = .532$, $p < .001$). Given that the course title options showed some similarity, this increased correlation is logical. The highest correlation in the IST data was between Age and Teaching Experience at ($r = .74$, $p < .001$). This relationship is logical in that a person’s experience is related to age.

Histograms, probability plots, and scatterplots were used to examine the residuals for each regression analysis. Histograms, probability plots, and scatterplots are not pooled by SPSS, so all conclusions are based on the first imputation results (though each imputation result was examined for noteworthy differences). Histograms were examined for indications of nonnormality of residuals. In the PST data, the histograms for the residuals for technology showed some slight right skewness and those for analysis and instruction were somewhat kurtotic. In the IST data, the histograms for the residuals for technology showed some slight right skewness and those for access, analysis, and instruction were somewhat kurtotic. Despite these small observations, multiple regression is robust to these violations when the sample size is large (Williams, Grajales, & Kurkiewicz, 2013). Inspection of the probability plots in the PST and IST data revealed no issues except some slight skewness for analysis, instruction, and for technology in the PST only, and access in the IST only. All probability plots in both datasets are approximately linear, supporting the condition that the error terms are normally distributed. An examination of all scatterplots showed no fan shapes or lack of homoscedasticity for either the PST or the IST data.

CHAPTER 4

RESULTS

Descriptive Statistics

<u>Course Taking Variable Descriptive Statistics</u>

Table 2 contains the pooled descriptive statistics examined on the dichotomized DDDM-related course variables in both the PST and IST data used in the regression analysis. In the sample of 412 pre-service teachers, the highest proportion of pre-service teachers had taken assessment courses. With a mean percentage of 78.4%, almost 80% of pre-service teachers had taken at least one course in assessment. Other courses that showed most pre-service teachers had taken a course in them were Response to Intervention/progress monitoring (RTI) at 69.9%, research methods (research) at 54.3%, and teacher inquiry/teacher research/action research (teacher inquiry) at 53.2%. The two courses that showed less than half of pre-service teachers had taken a course in them were data-driven decision making/data use (DDDM), at 48.3%, and statistics, with the lowest average percentage of teachers at 45.2%

For in-service teachers, the participation rate in each of the six courses was over 50%. The highest percentage of in-service teachers had taken assessment courses at 82.3%. A high percentage of in-service teachers had taken courses in research (79%), teacher inquiry (72.8%), or statistics (68.5%). The lowest percentage of teachers in the in-service sample, but still at a majority, were those who had taken courses in RTI (59.7%) or DDDM (56.2%).

Table 2

Proportion of Pre-Service (PST) and In-Service (IST) Teachers with One or More Classes per Course Type, N= 412, N=372

	Pre-Service		In-Service	
Course Type	P	*SD*	P	*SD*
Courses				
Assessment	0.78	0.41	0.82	0.38
DDDM	0.48	0.50	0.56	0.50
RTI	0.70	0 .46	0.60	0.49
Teacher Inquiry	0.53	0.50	0.73	0.45
Research	0.54	0.50	0.79	0.41
Statistics	0.45	0.50	0.69	0.46

Note. Proportions are from dichotomized variables. All values are pooled results.

There were some similarities and differences between the pre-service and in-service course taking proportions. Figure 1 displays the comparative course taking percentages between pre-service and in-service teachers. Similarly, the highest percentage of teachers for both pre-service and in-service teachers was in taking assessment courses at 78% and 82% of teachers respectively. The percentage for taking DDDM courses was also relatively similar at 48% of pre-service and 56% of in-service teachers. DDDM courses also had one of the lowest or the lowest percentages of teachers taking the courses for both sets of teachers. An RTI course was only type of course that had a higher percentage of pre-service teachers having taken it than in-service teachers. The biggest spreads in percentage of teachers having taken at least one course in the course type were teacher inquiry, research, and statistics, with a 15-20% difference in each.

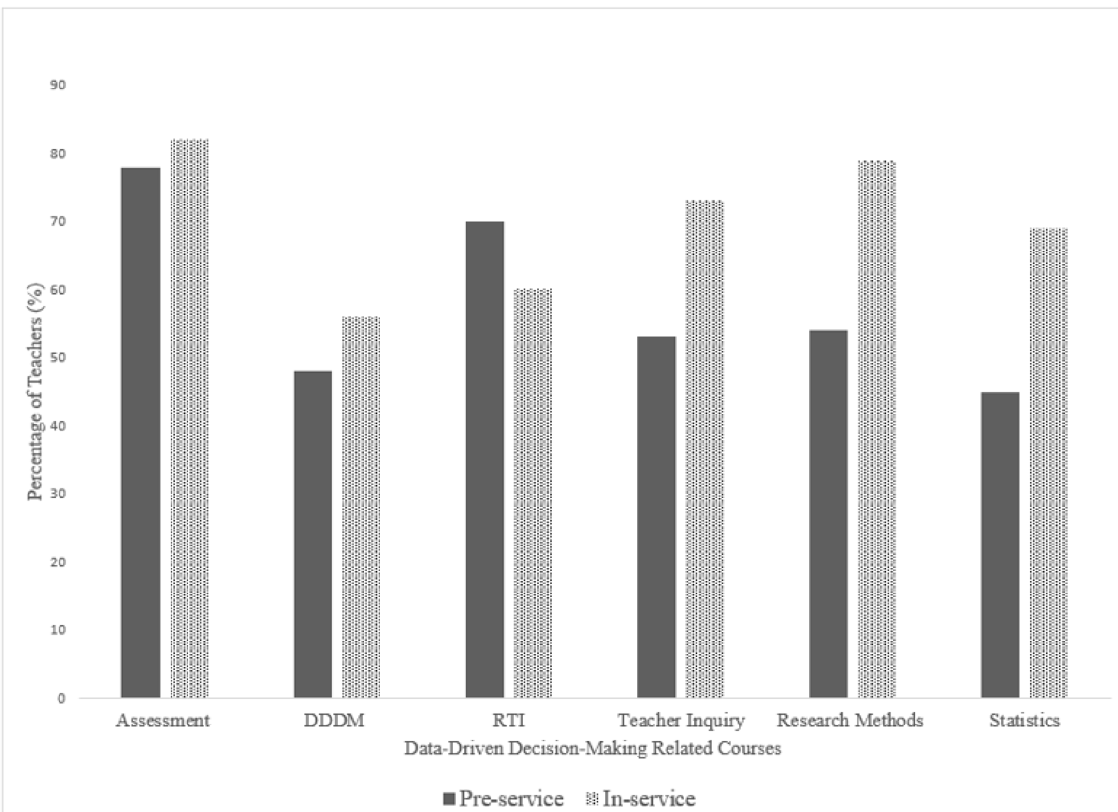

Figure 1. Percentages of Course Taking by Pre-Service and In-Service Teachers. This figure shows a comparison of teacher DDDM-related course taking patterns of teachers. $N = 412$; $N = 372$.

Course Taking Item Descriptive Statistics

Table 3 contains percentages of teachers for each response category for each of the undichotomized DDDM course variables in the PST and IST datasets. The imputation model was too complex with undichotomized Course Taking variables added to the model; therefore, these results do not include imputed values. Among PST, teacher inquiry courses had the highest percentage of teachers having taken three or more courses, while research courses had the highest percentage of teachers in the IST dataset. Statistics courses were the least commonly taken by pre-service teachers, whereas DDDM courses were least common among the sample's in-service teachers.

3D-MEA Self-Efficacy Descriptive Statistics

Table 4 contains the pooled descriptive statistics for the 3D-MEA variables from both the PST and IST datasets. The lowest mean values for the 3D-MEA variables in both the PST and the IST datasets were for DDDM self-efficacy for data technology use ($M = 3.29$, $SD = 0.96$; $M = 3.23$, $SD = 1.09$, respectively). The highest mean scores for the 3D-MEA variables in both the PST and IST datasets were for DDDM self-efficacy for application of data to instruction ($M = 3.71$, $SD = 0.69$; $M = 3.70$, $SD = 0.75$, respectively). DDDM anxiety mean composite scores were higher for pre-service teachers ($M = 2.88$, $SD = 0.88$) and lower for in-service teachers ($M = 2.62$, $SD = 0.91$).

Table 3

Percentage of Teachers Endorsing Specific Course Variable Items in the Pre-Service (PST) and In-Service (IST) Datasets
N=412, N =372

Course Type		0	1	2	3 or more	Missing
Assessment						
	PST	21.1%	52.2%	15.5%	10.2%	1.0%
	IST	17.7%	28.8%	26.9%	26.6%	0.0%
DDDM						
	PST	51.5%	33.0%	10.2%	4.6%	0.7%
	IST	43.8%	23.9%	15.1%	17.2%	0.0%
RTI						
	PST	30.1%	35.7%	22.1%	11.9%	0.2%
	IST	40.3%	29.0%	15.6%	15.1%	0.0%
Teacher Inquiry						
	PST	46.8%	27.2%	12.4%	13.6%	0.0%
	IST	27.2%	25.0%	23.9%	23.9%	0.0%
Research						
	PST	45.6%	27.9%	12.9%	13.3%	0.2%
	IST	21.0%	30.1%	20.2%	28.8%	0.0%
Statistics						
	PST	54.6%	34.7%	8.3%	1.9%	0.5%
	IST	31.5%	39.0%	17.2%	12.4%	0.0%

Note. Results are from pre-imputed data.

Table 4

Descriptive Statistics for 3D-MEA Composite Scores in the Pre-Service (PST) and In-Service (IST) Datasets
N=412, N=372

	Pre-Service		In-Service	
3D-MEA Subscale	*M*	*SD*	*M*	*SD*
Access	3.32	0.91	3.44	0.91
Technology	3.29	0.96	3.23	1.09
Analysis	3.65	0.76	3.64	0.89
Instruction	3.71	0.69	3.70	0.75
Anxiety	2.88*	0.88*	2.62	0.91

Note. *Pooled mean and standard deviation.

Covariate Descriptive Statistics

The pooled descriptive statistics of each covariate independent variable in the regression analyses are shown in Table 5. A greater proportion of the PST dataset participants in the sample are female or Hispanic than in the IST dataset. Also, the IST dataset has a greater percentage of math/science teachers and teachers at the middle, high, or multiple levels than pre-service teachers in the PST dataset sample who intend to teach math/science or intend to teach at levels other than elementary.

Table 5

Descriptive Statistics for Pre-Service (PST) and In-Service (IST) Categorical Covariate Independent Variables, N= 412, N=372

	Pre-Service		In-Service	
Variable	P	*SD*	P	*SD*
Sex				
Female	0.90	0.30	0.82	0.38
Race				
White	0.86	0.34	0.88	0.33
Ethnicity				
Hispanic	0.11	0.31	0.05	0.21
Intended Subject				
Math/Science	0.06	0.24	-	-
Intended Level				
Middle	0.10	0.31	-	-
High	0.10	0.30	-	-
Multiple	0.09	0.29	-	-
Subject Taught				
Math/Science	-	-	0.19	0.40
Level Taught				
Middle	-	-	0.30	0.46
High	-	-	0.18	0.39
Multiple	-	-	0.14	0.35

Note. All values are pooled results. Intended Subject and Intended Level are variables only in the PST. Experience, Subject Taught, and Level Taught are variables only in the IST.

Multiple Regression Findings

Multiple Regression Analysis Results for Pre-Service (PST) Data

In order to test the hypothesis that types of semester-long DDDM-related coursework of pre-service and in-service teachers will be significant predictors of DDDM self-efficacy and/or DDDM anxiety in teachers, multiple regression analyses were conducted. Separate regressions were done on the four self-efficacy dimensions and the anxiety factor in each of the imputed PSTs and ISTs (10 separate regression analyses).

Table 6 summarizes results from the analyses of PST data. Across the models, the predictors explained from 4 to 13% of the variance. All ANOVAs for the self-efficacy dimensions and the anxiety factor were significant, as shown in Table 6. Of all the predictors, only five significantly predicted DDDM self-efficacy or anxiety in pre-service teachers: age ($\beta = -.11$, $p < .05$, for data analysis and interpretation), sex ($\beta = -.39$, $p < .05$, for data analysis and interpretation; $\beta = .41$, $p < .05$, for DDDM anxiety), multiple intended school level ($\beta = -.39$, $p < .05$, for DDDM anxiety), DDDM course or courses ($\beta = .59$, $p < .001$, for data identification and access; $\beta = .33$, $p < .01$, for data technology use; $\beta = .64$, $p < .001$, for data analysis and interpretation; $\beta = .40$, $p < .001$, for application of data to instruction), and statistics course or courses ($\beta = -.35$, $p < .001$, for DDDM anxiety).

Table 6

Summary of Multiple Regression Analysis Results for Pre-Service (PST) Dataset

Variable	Access β	Technology β	Analysis β	Instruction β	Anxiety β
Age	-0.07	-0.01	-0.11*	-0.07	-0.06
Sex					
Female	-0.20	-0.12	-0.39*	-0.23	0.41*
Race					
White	-0.13	-0.08	-0.02	0.02	0.17
Ethnicity					
Hispanic	0.01	-0.19	0.00	0.01	-0.08
Intended Subject					
Math/Science	-0.12	0.39	0.07	-0.21	-0.24
Intended Level					
Middle	0.12	-0.07	0.16	-0.03	-0.31
High	-0.02	-0.14	-0.15	-0.20	0.19
Multiple	0.14	-0.02	0.23	0.28	-0.39*
Course					
Assessment	-0.08	0.00	-0.03	0.14	0.04
DDDM	0.59***	0.33**	0.64***	0.40***	-0.16
RTI	0.02	0.09	0.02	-0.05	0.01
Teacher Inquiry	0.18	0.16	0.17	0.15	-0.07
Research	-0.01	-0.01	-0.05	-0.01	0.25
Statistics	0.11	0.06	0.09	0.05	-0.35***
Model					
R^2	0.13	0.07	0.16	0.09	0.10
Adjusted R^2	0.10	0.04	0.13	0.05	0.07
ANOVA					
F (14, 397)	4.30***	2.11*	5.39***	2.69**	3.26***

Note. *p < .05. **p < .01. ***p < .001. Coefficient correlations are pooled results. Model and ANOVA values are from Imputation 1 for each regression.

Multiple Regression Analysis Results for In-Service (IST) Data

Table 7 summarizes results from the multiple regression analyses of IST data. Across the models, the predictors explained from three to seven percent of the variance. All ANOVAs for the self-efficacy dimensions and the anxiety factor were significant for Imputation 1 (Imputations 2, 4, and 5 did not contain significant effects for access; Imputations 2, 4, and 5 had a different *p* value of .05 for the effect of DDDM self-efficacy for technology). Of all the predictors, six significantly predicted DDDM self-efficacy or anxiety in in-service teachers: sex (β = -.29, p < .05, for data identification and access; β = -.34, p < .05, for data analysis and interpretation; β = .45, p < .01, for DDDM anxiety), middle-school level taught (β = -.27, p < .05, for data technology use), high-school level taught (β = -.43, p < .01, for data identification and access; β = -.58, p < .001, for data technology use), multiple school levels taught (β = -.48, p < .01, for data technology use; β = .39, p < .05, for DDDM anxiety), DDDM course or courses (β = .26, p < .05, analysis; β = .32, p < .05, for application of data to instruction), and teacher inquiry course or courses (β = -.32, p < .05, for DDDM anxiety).

Table 7

Summary of Multiple Regression Analysis Results for In-Service (IST) Dataset

Variable	Access β	Technology β	Analysis β	Instruction β	Anxiety β
Age	0.08	-0.03	-0.10	-0.08	0.08
Experience	-0.04	-0.02	0.09	0.11	-0.11
Sex					
Female	-0.29*	-0.22	-0.34*	-0.02	0.45**
Race					
White	0.10	-0.07	0.09	0.08	0.28
Ethnicity					
Hispanic	0.14	0.09	0.07	0.10	0.50
Subject Taught					
Math/Science	0.13	0.20	0.22	0.16	-0.12
Level Taught					
Middle	-0.26	-0.27*	-0.11	-0.01	-0.08
High	-0.43**	-0.58***	-0.29	-0.27	0.20
Multiple	-0.01	-0.48**	-0.12	-0.08	0.39*
Course					
Assessment	-0.02	0.16	0.17	0.15	-0.12
DDDM	0.18	0.12	0.26*	0.32*	-0.08
RTI	0.07	-0.04	0.05	0.10	0.15
Teacher Inquiry	0.26	0.11	0.10	0.09	-0.32*
Research	0.03	0.27	0.26	0.18	-0.11
Statistics	-0.17	-0.16	-0.14	-0.05	-0.19
Model					
R^2	0.07	0.08	0.09	0.09	0.11
Adjusted R^2	0.03	0.05	0.06	0.05	0.07
ANOVA					
F (15, 356)	1.71*	2.18 **	2.46 **	2.29 **	2.95***

Note. *p < .05. **p < .01. ***p < .001. Coefficient correlations are pooled results. Model and ANOVA values are from Imputation 1 for each regression.

Summary of Primary Independent Variable Findings

One objective of the study was to examine the relationship between the type of DDDM-related courses taken by pre-service and in-service teachers and their DDDM self-efficacy. One of the six courses was consistently positive and significant in both the PST and IST data with small to medium effect sizes for the relationships. Having taken at least one course in DDDM was associated with higher DDDM self-efficacy in six of eight DDDM self-efficacy dependent variables. In the PST data, pre-service teachers who had taken a course in DDDM had higher DDDM self-efficacy for technology by 0.33 *SD*s ($p < .01$), for access by 0.59 *SD*s ($p < .001$; medium effect), for analysis by 0.64 *SD*s ($p < .001$; medium effect), and self-efficacy for instruction by 0.40 *SD*s ($p < .001$). In the IST data, in-service teachers with a course in DDDM had significantly higher DDDM self-efficacy for analysis by 0.26 *SD*s ($p < .05$) and for instruction by 0.32 *SD*s ($p < .05$).

Another objective of the study was to examine the relationship between the type of DDDM-related courses taken by pre-service and in-service teachers and their DDDM anxiety. There were two significant effects of DDDM-related courses on DDDM anxiety. Both effects were positive with small effect sizes. In the PST data, having taken at least one course in statistics was associated with lower DDDM anxiety by 0.35 *SD*s ($p < .001$). In the IST data, having taken at least one course in teacher inquiry was associated with DDDM anxiety scores that were 0.32 *SD*s lower ($p < .05$).

Summary of Covariate Findings

Demographic independent variables were important covariates in the models. In the PST dataset, an increase of one standard deviation (*SD*) in age was associated with a 0.11 *SD* decrease in DDDM self-efficacy for analysis and interpretation. While a small effect, this indicates that an increase in age of pre-service teachers is associated with a decrease in DDDM self-efficacy for analysis and interpretation.

Sex was a significant predictor in both the PST and IST data regression analyses. While the effect sizes were small, females showed lower DDDM self-efficacy than males in both the PST and IST data by 0.39 and 0.34 *SD*s respectively, and less DDDM self-efficacy for access in the IST data by 0.29 *SD*s. In addition, in both the PST and IST data analyses, females had more DDDM anxiety than males by 0.41 and 0.45 *SD*s, correspondingly.

School level was also significant in both the PST and IST data regression analyses, though more so in the IST data. For DDDM self-efficacy for technology, middle-, high-, and multiple-level teachers all had less self-efficacy for technology than elementary teachers by 0.27, 0.58, and 0.48 *SD*s, respectively. The effect of being a high school teacher was moderate in size. High school teachers also showed lower DDDM self-efficacy for access than elementary teachers by 0.43 *SD*s. Additionally, in both the PST and IST data, pre-service and in-service teachers for multiple levels showed significantly different DDDM anxiety than elementary teachers, while pre-service teachers intending to teach at multiple levels had lower DDDM anxiety than elementary teachers by 0.39 *SD*s, and in-service teachers teaching at multiple levels had higher DDDM anxiety by 0.39 *SD*s. Both effects were small in size.

CHAPTER 5

DISCUSSION

With continued and expanded policies emphasizing accountability in education, educators are increasingly expected to use additional varieties and quantities of educational data to increase student achievement (ESSA, 2015; Mandinach, 2012). Research supports that data-driven decision making (DDDM) can be effective for teachers in processing data (Dunn, 2013a; Reeves, 2017a); however, with a lack of data literacy and self-efficacy in DDDM and anxiety towards the process, DDDM continues to be a struggle for teachers to use effectively (Mandinach & Gummer, 2016; Wayman & Jimerson, 2014). In theory, DDDM-related coursework learning opportunities should provide teachers increased mastery experiences and, in turn, greater self-efficacy for DDDM and lower anxiety of the practice (Bandura, 1977; Dunn et al., 2013b; Marsh et al., 2006; Reeves & Chiang, 2018). The field should have a better understanding of the scope and nature of DDDM-related coursework and its relationship with DDDM self-efficacy and DDDM anxiety.

In order to investigate this relationship this study examined the relationships among pre-service and in-service teacher participation in DDDM-related courses and their DDDM self-efficacy and anxiety. The research questions included an analysis of the extent to which pre-service and in-service teachers have taken DDDM-related courses, the relationship between the type of DDDM-related courses taken by pre-service and in-service teachers and their DDDM self-efficacy, and the relationship between the type of DDDM-related courses taken by pre-service and in-service teachers and their DDDM anxiety.

In order to conduct the analyses for the present study, data were originally gathered from five separate, unduplicated data sources. Three data sources were previously published and two were not. The data were merged into one full dataset and then separated into two separate datasets (PST dataset and IST dataset) based on whether the respondent was a pre-service teacher (PST dataset) or an in-service teacher (IST dataset) in the original data sources. After data management, cleaning, and imputation of missing data, descriptive statistics and multiple regression analyses were conducted on each of the two final datasets (PST and IST) to investigate the research questions from the present study.

The first research question pertained to the extent to which teachers have taken DDDM-related coursework. At over 80% in both datasets, evidence from the study showed that most teachers had taken at least one assessment course. This finding is aligned with other literature that shows that most teachers have taken assessment courses and that many DDDM learning opportunities and interventions are embedded in assessment coursework (Dunlap & Piro, 2016; Mandinach et al., 2015; Reeves, 2017a; Reeves & Chiang, 2017; Reeves et al., 2016). This finding is not surprising after recognizing the considerable emphasis in education on assessment and measuring student achievement.

In addition, teachers in this study took other DDDM-related courses at a higher extent than the literature previously indicated. Pre-service teachers in this study had taken a course in four of the six types of DDDM-related course categories (assessment, RTI, teacher inquiry, research) at rates higher than 50% and in-service teachers in this study had taken a course in the six types of courses at rates higher than 50%.

In-service teachers may have higher percentages of teachers taking related courses than those of pre-service teachers because many have acquired additional degrees and have had an opportunity to take more classes in DDDM-related topics. Even with this explanation, both pre-service and in-service teachers in this study had higher percentages of teachers taking related courses than were expected from the literature. While not specifically looking at the number of courses taken by students in these same specific classes, previously investigated course programs showed a much stronger emphasis on assessment literacy as opposed to other related areas of DDDM than the present study found (Greenberg & Walsh, 2012; Mandinach et al., 2015). This may be due to a more randomized and larger sample in Mandinach et al. (2015) or because these previous studies used data from teacher preparation syllabi versus data collected from the teachers themselves. Teacher education programs may also be responding to current policies with curricular updates more readily in Illinois. It may also be related to the understanding participants in the present study had to what constitutes a semester-length course in each topic. These findings do suggest that DDDM content has worked its way into teacher education to some degree in terms of formal coursework. More research needs to be done on DDDM-related course-taking patterns of teachers on the frequency and quality of available courses. This additional study can help to determine if progress is being made in offering courses that can provide teachers with the information and experiences necessary to both increase their DDDM self-efficacy and their effective use of the process in practice.

For the second research question, the present study investigated the relationship between DDDM-related coursework and the DDDM self-efficacy of both pre-service and in-service teachers. Due to the increased mastery experiences provided by DDDM-related coursework in assessment, DDDM, RTI, teacher inquiry, research, and statistics, it was hypothesized that teachers with additional coursework in these topics would have significantly higher self-efficacy than those would did not (Bandura, 1977). While the present study examined relationships between these six different types of DDDM-related coursework, only one type of course consistently and repeatedly had significant relationships with factors of self-efficacy for DDDM. A specific, stand-alone course in DDDM showed significant relationships with two areas of DDDM self-efficacy in in-service teachers and with all four areas in pre-service teachers, with small to medium effect sizes per conventional guidelines (Cohen, 1988). These findings suggest that effects on DDDM self-efficacy are linked with taking full, semester-long courses in DDDM specifically, rather than in *related* courses that “embed,” “tack on,” or “include” DDDM-related topics or interventions. Because self-efficacy beliefs arguably influence one’s effectiveness in performing a particular behavior, these findings may be potentially substantial in understanding what kinds of learning opportunities may influence a teacher’s ability to confidently use each area of DDDM and to ultimately increase student achievement (Bandura, 1997).

Unfortunately, the present study’s evidence on the distribution of course-taking patterns for taking a stand-alone, specific course in DDDM shows that the course-taking frequency for them among teachers is among the lowest when compared to other DDDM-related courses.

Fewer pre-service teachers have taken a stand-alone DDDM course than all but one other DDDM-related course (statistics) and fewer in-service teachers have taken at least one course in DDDM than any other DDDM-related coursework. These findings are aligned with current literature that shows that teacher education programs are inadequately covering DDDM skills including analytics and instructional decision making (Greenberg & Walsh, 2012). Many institutions may be addressing DDDM in the context of other courses, such as those *related* courses examined in the study or as interventions or “add-ons” to other program courses. Findings from the present study suggest that this may not be enough and that, importantly, an increase in the availability of stand-alone courses in DDDM specifically may do more to provide additional teachers with increased self-efficacy for using DDDM effectively.

The present study investigated the relationships between DDDM self-efficacy and other DDDM-related coursework other than stand-alone courses in DDDM. While researchers have found that learning opportunities like coursework and focused interventions can increase data literacy skills that are necessary for effective DDDM, significant relationships between *related* courses and increased DDDM self-efficacy were not found in the evidence from the present study for any courses except those specifically in DDDM (Dunlap & Piro, 2016; Dunn, Airola, & Garrison, 2013; Marsh et al., 2010; Reeves & Chiang, 2017; Reeves & Honig, 2015). These relationships in teachers may not be present because teachers have not had opportunities in RTI, teacher inquiry, research, or statistics courses to apply the related data-literacy skills they have learned to DDDM. The absence of significant relationships with these DDDM-related courses and DDDM self-efficacy in teachers is potentially important because, while it indicates stand-alone courses in DDDM may be most beneficial, it may also indicate that more work needs to be done to develop curriculums that focus on applying data-literacy skills in *related* courses for DDDM. In theory, those increased chances for mastery experiences can then arguably affect teacher DDDM self-efficacy and then positive student outcomes (Bandura, 1997).

The third research question for the present study involved an investigation into the relationships between DDDM-related course taking and DDDM anxiety, a construct that describes the apprehension teachers feel about using DDDM (Dunn et al., 2013a). Being that DDDM anxiety is a reverse indicator of efficacy and routinely present in teachers challenged to use DDDM in practice, less anxiety was expected in teachers who had taken DDDM-related courses due to the expected increase in DDDM skills and experiences (Dunn et al., 2013a).

In Mandinach and Gummer's (2016) inquiry cycle framework for data literacy in teachers, an important factor in transforming data into information is understanding statistics. Being probably the most math-related course of the DDDM-related courses examined in the present study, previous literature shows evidence that teachers with additional coursework in math have higher student achievement, and this was thought to possibly have something to do with increased self-efficacy for math (Wayne & Youngs, 2003). Results from the present study did not show significant relationships between taking statistics and a teacher's DDDM self-efficacy but did find a significant relationship between taking statistics and less DDDM anxiety in pre-service teachers. Because of the math components rooted in DDDM, math anxiety and DDDM anxiety may be somewhat related constructs. Previous research has found that math anxiety can be a major factor in teachers' performance and attitudes about math and suggests that to reduce this anxiety, teachers should learn specific content knowledge to perform a mathematical task effectively (Novak & Tassell, 2017). It would be reasonable to speculate that courses in statistics and the content knowledge learned within may contribute to the relationship found between statistics courses and lower DDDM anxiety.

Unfortunately, less than half of pre-service teachers in the present study's sample had taken at least one course in statistics. More research into how DDDM anxiety and math anxiety could be related, and also into other math course distributions within teacher education programs, could give more understanding to the correlations found in the present study.

While statistics courses were taken less frequently, over 70% of in-service teachers in the present study's sample had taken at least one course in teacher inquiry/teacher research/action research. Theories behind teacher inquiry explicate the idea that teacher research can help teachers "construct alternative ways of observing and understanding students' work" and that learning to teach does not end with the conclusion of pre-service coursework but is a continuing process throughout a teaching career (Cochran-Smith & Lytle, 1999). The relationship found between in-service teachers who had taken a course in teacher inquiry and significantly less anxiety may be explained by the principles of teacher inquiry imparted in those courses. When faced with DDDM reforms in their teaching practice, teachers with inquiry-based skills may look at DDDM as a continuing-education learning experience, another tool for the their toolkits, and part of the process of professional growth and may look at it less as a new initiative to cause worry and tension. Investigating the link between teacher inquiry and less DDDM anxiety may present exciting opportunities in the future for professional development.

In order to investigate the present study's research questions, additional ancillary variables were examined for correlations with the dependent variables of DDDM self-efficacy and DDDM anxiety and significant relationships were found with the age, sex, and school level intended or taught of teachers. In regard to age, as age increased for pre-service teachers, they showed lower DDDM self-efficacy for analysis, interpretation, and application of data. Research has found that teacher self-efficacy in pre-service teachers increases through student teaching and decreases in the first few years of teaching (Hoy & Spero, 2015), whereas Veldman et al. (2017) found that age was not a significant factor. While the present study found age was significant for one area of DDDM self-efficacy, it was not found to be significant for any others. Because of the inconsistency of significance findings on the relationships between age and constructs of self-efficacy, additional research is necessary to explore the correlations.

The present study also showed evidence that there were several significant relationships between areas of DDDM self-efficacy and DDDM anxiety and the sex of participants. Specifically, females showed lower DDDM self-efficacy for analysis, interpretation, and application of data for both pre-service and in-service teachers and also showed lower DDDM self-efficacy for identifying and accessing data than their male counterparts. These findings are aligned with previous literature that has found that when compared with males, females have lower general self-efficacy, lower self-efficacy for some teaching self-efficacy constructs, and less confidence and more anxiety associated with technology and computer use (Gesc, 1989; He & Freeman, 2009; Klassen & Chiu, 2010). Almost 80% of teachers in the United States are female and self-efficacy beliefs and anxiety can play significant roles in the application of effective processes like DDDM in teacher practice, so it is important to continue researching the factors that contribute to increasing their self-efficacy.

The intended school level pre-service teachers planned to teach in the future and the school level currently taught by in-service teachers also showed significant correlations with areas of DDDM self-efficacy and/or DDDM anxiety. In-service elementary teachers showed substantially more DDDM self-efficacy for identifying and accessing data than high school teachers and for data technology than middle, high, and multiple level teachers. This finding is in line with previous research that showed teachers in elementary schools are more likely to use data for instructional decision making than teachers at the middle- and high-school levels (Reeves, 2017b). Additionally, researchers have found that teaching in elementary school is associated with higher teacher self-efficacy and self-efficacy for engaging students and classroom management (Klassen & Chiu, 2010; Wolters & Daugherty, 2007). Interestingly, the evidence showed that pre-service teachers who intended to teach at the elementary level had significantly more DDDM anxiety than those who planned to teach at multiple levels, and actual in-service elementary teachers showed less DDDM anxiety than teachers of multiple levels. In the absence of previous literature on relationships between school level and teacher DDDM anxiety, future research should investigate differences in anxiety levels present in teachers at different grade levels.

Implications, Limitations, Future Research

This research study is valuable to the literature on teacher self-efficacy and data-driven decision making. Teacher efficacy can determine the academic progress of their students (Bandura, 1993). Increasing teacher self-efficacy influences teacher behavior and that behavior can potentially benefit student outcomes. Research on teacher efficacy is lacking in its ability to describe what kinds of coursework, training, and/or professional development experiences can contribute to a change process in the efficacy of teachers in response to new initiatives and best practices (Tschannen-Moran & Hoy, 2001). Based on data and conclusions from this and other intervention studies, new professional development opportunities based on effective ways to promote teacher efficacy can be continued, modified, and developed.

As the field of education continues to be inundated with multiple forms of assessment and data, the pressure for teachers and schools to use data to make instructional decisions expands, and the expectation for educators to be proficient in data literacy grows. Accumulated knowledge about how teachers develop efficacy with these skills will become increasingly essential to school districts and researchers alike. Conclusions from this study may contribute to the knowledge and understanding of how learning experiences can promote teacher efficacy with DDDM. This knowledge can be used by institutional program developers to inform what courses to offer. As the literature builds, additional understandings can be used in conjunction by stakeholders and lawmakers in deciding which courses should be required for licensing and included in state policy.

Results from this study suggest that the majority of both pre-service and in-service teachers are taking DDDM-related courses and that these courses are associated with higher DDDM self-efficacy and lower DDDM anxiety in teachers. The evidence also shows that semester-long, stand-alone DDDM courses are most linked to higher DDDM self-efficacy but are one of the least DDDM-related courses taken by both pre-service and in-service teachers. Both initial and continuing teacher education programs and initiatives can use this information to evaluate the presence of (and possibility increase the availability of) DDDM courses in their programs. As programs continue to build in courses on DDDM, researchers should dive deeper into the nature and learning experiences within specific DDDM courses that may be the most linked to higher self-efficacy in order to replicate the relationship in the future. It is important that future studies discover the elements of these courses that may be the most effective in establishing teachers with strong self-efficacy in DDDM.

Evidence from this study also suggests that DDDM-related courses are associated with lower DDDM anxiety in teachers. Specifically, statistics courses in pre-service teachers and teacher inquiry/teacher research/action research courses in in-service teachers showed significant links with less DDDM anxiety. As with specific courses in DDDM, evaluating the presence and availability within their teacher education programs for these courses is an essential step in creating programs that are the most effective in lowering DDDM anxiety among teachers. To replicate the connection, it is also necessary that forthcoming studies carefully analyze the aspects of inquiry and statistics courses that are associated with less DDDM anxiety.

Other conclusions from the present study may also have substantial relevance for stakeholders and future research. In this study, the age and sex of participants and the school level within which they teach or intend to teach were associated with significant differences in DDDM self-efficacy and/or DDDM anxiety. These connections present interesting opportunities for exploration and the expansion of professional development targeted for teachers with these demographic characteristics. It is important for stakeholders to explore current programs, professional development experiences, and/or DDDM reform initiatives for implicit bias and/or ineffective strategies so they can be improved.

Despite the relatively large sample size and use of various control variables, follow-up research should address the key methodological limitations present in this study. To begin with, the original datasets contained data that were collected with non-probability sampling approaches and most of the data came from teachers in Illinois. These have limited the generalizability of some of the present study's findings to all U.S. pre- and in-service teachers, so future work should be conducted with more diverse groups of teachers in a variety of contexts.

Secondly, while using a multiple imputation method for handling missing values allowed the study to preserve sample size and statistical power, some differences in the significance of the overall ANOVA models were found due to the stochastic nature of the values produced in each imputed dataset. In the multiple regression results from the IST data that SPSS was unable to pool, there were inconsistent findings across multiply imputed datasets for DDDM self-efficacy for access and for DDDM self-efficacy for technology. While all other ANOVAs for the self-efficacy dimensions and the anxiety factor were significant in all five imputed IST datasets, due to the inconsistencies in the findings, it is necessary to interpret these particular results with caution. Future work should attempt to replicate these findings in additional contexts to add strength and generalizability to the results.

Third, while a relative strength of the study was its contribution to the literature highlighting the relationships between specific types of DDDM coursework and DDDM self-efficacy and anxiety, in terms of the Course Taking variable, a validity issue should be addressed in future work. Course-taking estimates in the results were seemingly high when compared to the literature and researcher knowledge of teacher education in the state, which may be due to individual participant interpretations of the course-variable survey questions. In the future, defining the domain represented by each course cluster may be beneficial for participants to refer to when responding. Additionally, future work may benefit from other modes of estimating course-taking patterns and distributions such as examining syllabi or course catalogs.

Additionally, though merging several datasets and then separating them into two specific sets with one for pre-service teacher participants and a separate one for in-service teacher participants afforded the beneficial opportunities for working with larger sample sizes, limitations in the original collection of data may have presented bias in the results and mitigated some of the observed relationships. Specifically, in the pre-service data, it was not possible to completely account for exactly how much of their program participants had completed at the time of data collection. This may have introduced some downward bias in the results for the first research question, and due to this restriction of range, there may be some attenuation to the relationships found for Research Questions 2 and 3. Additionally, whether pre-service participants were undergraduates or graduates was also undeterminable and therefore impossible to disaggregate findings by program level. Both limitations to the study present unique opportunities to remedy and investigate in future research.

Furthermore, the final regression models contain considerable amounts of unexplained variance, even with the inclusion of several possible predictors of DDDM self-efficacy and DDDM anxiety in teachers. This evidence shows that while the predictors in this study are potentially significant in their relationship with DDDM self-efficacy factors, further exploration of other more substantial variables in the future could build on the results found in the present study. Other variables that may be substantial could include the data culture held by school/schools within which a teacher is employed, types of educational degrees held, frequency and types of professional development experiences, association with school support staff well trained in DDDM, and a teacher's actual skill level in applying factors of DDDM. Future study should consider these and other variables while exploring factors that may contribute to or be associated with DDDM self-efficacy and/or DDDM anxiety.

REFERENCES

Bandura, A. (1977). Self-efficacy: toward a unifying theory of behavioral change. *Psychological Review*, *84*(2), 191.

Bandura, A. (1993). Perceived self-efficacy in cognitive development and functioning. *Educational Psychologist*, *28*(2), 117-148.

Bandura, A. (1997). Self-efficacy: The exercise of control. New York: Freeman.

Caprara, G. V., Barbaranelli, C., Steca, P., & Malone, P. S. (2006). Teachers' self-efficacy beliefs as determinants of job satisfaction and students' academic achievement: A study at the school level. *Journal of School Psychology*, *44*(6), 473-490.

Carlson, D., Borman, G. D., & Robinson, M. (2011). A multistate district-level cluster randomized trial of the impact of data-driven reform on reading and mathematics achievement. *Educational Evaluation and Policy Analysis*, *33*(3), 378-398.

Chen, G., Gully, S., & Eden, D. (2001). Validation of a new general self-efficacy scale. *Organizational Research Methods*, *4*, 62-83.

Cochran-Smith, M., & Lytle, S. L. (1999). The teacher research movement: A decade later. *Educational Researcher*, *28*(7), 15-25.

Cohen, J. (1988). The effect size index: d. *Statistical power analysis for the behavioral sciences*, *2*, 284-288.

Dunlap, K., & Piro, J. S. (2016). Diving into data: Developing the capacity for data literacy in teacher education. *Cogent Education*, *3*(1), 1132526.

Dunn, K. E., Airola, D. T., & Garrison, M. (2013). Concerns, knowledge, and efficacy: An application of the teacher change model to data driven decision-making professional development. *Creative Education*, *4*(10), 673.

Dunn, K. E., Airola, D. T., Lo, W. J., & Garrison, M. (2013a). Becoming data driven: The influence of teachers’ sense of efficacy on concerns related to data-driven decision making. *The Journal of Experimental Education*, *81*(2), 222-241

Dunn, K. E., Airola, D. T., Lo, W. J., & Garrison, M. (2013b). 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.

Every Student Succeeds Act of 2015, P. L. 114-95, S.1177, 114th Cong. (2015)

Gallagher, L., Means, B., & Padilla, C. (2008). *Teachers' use of student data systems to improve instruction: 2005 to 2007.* Washington, D.C.: US Department of Education, Office of Planning, Evaluation and Policy Development.

Gecas, V. (1989). The social psychology of self-efficacy. *Annual review of sociology*, *15*(1), 291-316.

Ghaith, G., & Yaghi, H. (1997). Relationships among experience, teacher efficacy, and attitudes toward the implementation of instructional innovation. *Teaching and Teacher Education*, *13*(4), 451-458.

Goddard, R. D., Hoy, W. K., & Hoy, A. W. (2000). Collective teacher efficacy: Its meaning, measure, and impact on student achievement. *American Educational Research Journal*, *37*(2), 479-507.

Goldring, R., Gray, L., & Bitterman, A. (2013). *Characteristics of public and private elementary and secondary school teachers in the United States: Results from the 2011-12 schools and staffing survey.* NCES 2013-314. National Center for Education Statistics.

Green, J. L., Schmitt-Wilson, S., & Versland, T. M. (2016). Teachers and data literacy: A blueprint for professional development to foster data driven decision making. *Journal of Continuing Education and Professional Development*, *3*(1), 14-32.

Greenberg, J., & Walsh, K. (2012). *What teacher preparation programs teach about K-12 assessment: A review.* Washington, DC: National Council on Teacher Quality.

Guo, Y., Justice, L. M., Sawyer, B., & Tompkins, V. (2011). Exploring factors related to preschool teachers' self-efficacy. *Teaching and Teacher Education*, *27*(5), 961-968.

Guskey, T. R. (1988). Teacher efficacy, self-concept, and attitudes toward the implementation of instructional innovation. *Teaching and Teacher Education*, *4*(1), 63-69.

He, J., & Freeman, L. (2009). Are men more technology-oriented than women? The role of gender on the development of general computer self-efficacy of college students. *AMCIS 2009 Proceedings*, 672.

Henson, R. K. (2001). Teacher self-efficacy: Substantive implications and measurement dilemmas. Keynote address presented at the meeting of the Educational Research Exchange, College Station, TX, USA

Hoy, A. W., & Spero, R. B. (2015). Changes in teacher efficacy during the early years of teaching: A comparison of four measures. *Teaching and Teacher Education*, *21*(4), 343-356.

Hughes, G. D. (2012). Teacher retention: Teacher characteristics, school characteristics, organizational characteristics, and teacher efficacy. *The Journal of Educational Research*, *105*(4), 245-255.

Individuals with Disabilities Education Improvement Act, H.R. 1350, 108th Congress (2004).

Keuning, T., Van Geel, M., Visscher, A., Fox, J. P., & Moolenaar, N. M. (2016). The transformation of schools' social networks during a data-based decision making reform. *Teachers College Record*, *118*(9), 1-33.

King, J. (2016). *The state of racial diversity in the educator workforce.* Washington, D.C.: US Department of Education.

Klassen, R. M., & Chiu, M. M. (2010). Effects on teachers' self-efficacy and job satisfaction: Teacher gender, years of experience, and job stress. *Journal of Educational Psychology*, *102*(3), 741.

Little, R. J. (1988). A test of missing completely at random for multivariate data with missing values. *Journal of the American Statistical Association*, *83*(404), 1198-1202.

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

Mandinach, E., Friedman, J. M., & Gummer, E. (2015). How can schools of education help to build educators' capacity to use data? A systemic view of the issue. *Teachers College Record*, *117*(4), n4.

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.

Marsh, J. A., Pane, J. F., & Hamilton, L. S. (2006). *Making sense of data-driven decision making in education.* : Evidence from recent RAND research (OP-170). Santa Monica, CA: RAND Corporation.

Marsh, J. A., Sloan McCombs, J., & Martorell, F. (2010). How instructional coaches support data-driven decision making: Policy implementation and effects in Florida middle schools. *Educational Policy*, *24*(6), 872-907.

Marzano, R. J. (2010). When practice makes perfect…sense. Art & science of teaching. *Educational Leadership*, *68*(3), 81–83.

Means, B., Chen, E., DeBarger, A., & Padilla, C. (2011). *Teachers' Ability to Use Data to Inform Instruction: Challenges and Supports.* US Department of Education Office of Planning, Evaluation and Policy Development.

Means, B., Padilla, C., DeBarger, A., & Bakia, M. (2009). *Implementing data-informed decision making in schools: Teacher access, supports and use.* US Department of Education.

Means, B., Padilla, C., & Gallagher, L. (2010). *Use of education data at the local level: From accountability to instructional improvement.* US Department of Education.

No Child Left Behind Act of 2001, P.L. 107-110, 20 U.S.C. § 6319 (2002).

Novak, E., & Tassell, J. L. (2017). Studying preservice teacher math anxiety and mathematics performance in geometry, word, and non-word problem solving. *Learning and Individual Differences*, *54*, 20-29.

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.

Piro, J. S., Dunlap, K., & Shutt, T. (2014). A collaborative Data Chat: Teaching summative assessment data use in pre-service teacher education. *Cogent Education*, *1*(1), 968409.

Prenger, R., & Schildkamp, K. (2018). Data-based decision making for teacher and student learning: a psychological perspective on the role of the teacher. *Educational Psychology*, 1-19.

Reeves, T. D. (2017a). Pre-service teachers' data use opportunities during student teaching. *Teaching and Teacher Education*, *63*, 263-273.

Reeves, T. (2017b). School Level and Other Differences in Illinois Teachers’ Use of Data to Inform Instruction. *Mid-Western Educational Researcher*, *29*(4), 332-354.

Reeves, T. D., & Chiang, J. L. (2017). Building pre-service teacher capacity to use external assessment data: An intervention study. *The Teacher Educator*, *52*(2), 155-172.

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.

Reeves, T. D., & Honig, S. L. (2015). A classroom data literacy intervention for pre-service teachers. *Teaching and Teacher Education*, *50*, 90-101.

Reeves, T. D., Summers, K. H., & Grove, E. (2016). Examining the landscape of teacher learning for data use: The case of Illinois. *Cogent Education*, *3*(1), 1211476.

Reeves, T. D., Wei, D., Scheel, K. & Hamilton, V. (2018, October). *In-service teachers' use of non-academic data for decision-making purposes*. Paper presented at the meeting of the Mid-Western Educational Research Association, Cincinnati, OH.

Rubin, D. B. (1996). Multiple imputation after 18+ years. *Journal of the American statistical Association*, *91*(434), 473-489.

Schwarzer, R., & Hallum, S. (2008). Perceived teacher self-efficacy as a predictor of job stress and burnout: Mediation analyses. *Applied Psychology*, *57,* 152-171.

Skaalvik, E. M., & Skaalvik, S. (2007). Dimensions of teacher self-efficacy and relations with strain factors, perceived collective teacher efficacy, and teacher burnout. *Journal of Educational Psychology*, *99*(3), 611.

Sleeter, C. E. (2017). Critical race theory and the whiteness of teacher education. *Urban Education*, *52*(2), 155-169.

Snyder, T. D., de Brey, C., & Dillow, S. A. (2016). *Digest of education statistics 2015*. NCES 2016-014. National Center for Education Statistics.

Staman, L., Visscher, A. J., & Luyten, H. (2014). The effects of professional development on the attitudes, knowledge and skills for data-driven decision making. *Studies in Educational Evaluation*, *42*, 79-90.

Swackhamer, L. E., Koellner, K., Basile, C., & Kimbrough, D. (2009). Increasing the self-efficacy of inservice teachers through content knowledge. *Teacher Education Quarterly*, *36*(2), 63-78.

Tschannen-Moran, M., & Hoy, A. W. (2001). Teacher efficacy: Capturing an elusive construct. *Teaching and Teacher Education*, *17*(7), 783-805.

van der Scheer, E. A., & Visscher, A. J. (2016). Effects of an intensive data-based decision making intervention on teacher efficacy. *Teaching and Teacher Education*, *60*, 34-43.

Van Geel, M., Keuning, T., Visscher, A. J., & Fox, J. P. (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.

Veldman, I., Admiraal, W., Mainhard, T., Wubbels, T., & Van Tartwijk, J. (2017). Measuring teachers' interpersonal self-efficacy: relationship with realized interpersonal aspirations, classroom management efficacy and age. *Social Psychology of Education*, *20*(2), 411-426.

Wayman, J. C. (2005). Involving teachers in data-driven decision making: Using computer data systems to support teacher inquiry and reflection. *Journal of Education for Students Placed at Risk*, *10*(3), 295-308.

Wayman, J. C., & Jimerson, J. B. (2014). Teacher needs for data-related professional learning. *Studies in Educational Evaluation*, *42*, 25-34.

Wayman, J. C., Jimerson, J. B., & Cho, V. (2012). Organizational considerations in establishing the data-informed district. *School Effectiveness and School Improvement*, *23*(2), 159-178.

Wayman, J. C., Midgley, S., & Stringfield, S. (2006). Leadership for data-based decision-making: Collaborative educator teams. *Learner Centered Leadership: Research, Policy, and Practice*, 189-206.

Wayne, A. J., & Youngs, P. (2003). Teacher characteristics and student achievement gains: A review. *Review of Educational Research*, *73*(1), 89-122.

Williams, M. N., Grajales, C. A. G., & Kurkiewicz, D. (2013). Assumptions of multiple regression: Correcting two misconceptions. *Practical Assessment, Research, & Evaluation*, *18*, 1–14.

Wolters, C. A., & Daugherty, S. G. (2007). Goal structures and teachers' sense of efficacy: Their relation and association to teaching experience and academic level. *Journal of Educational Psychology*, *99*(1).