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An Examination of the Relationships among Organizational Support, Self-Efficacy Beliefs, and Engagement in Data-Driven Decision-Making

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An Examination of the Relationships among Organizational Support, Self-Efficacy Beliefs, and Engagement in Data-Driven Decision-Making

by

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ABSTRACT

A culture of accountability in K-12 education has created demand for teachers and administrators to closely examine student performance on assessments. A number of schools have embraced data-driven decision-making as an approach to meeting this need. Data-driven decision-making refers to the systematic process of collecting, analyzing, interpreting, and making instructional decisions based on data (Schildkamp & Kuiper, 2009; Mandinach, 2012). Generally, educators analyze data collected on assessments at the classroom level and on benchmark or interim assessments at the school-wide level. However, teachers generally feel unprepared to engage in data-driven decision-making. Few studies have examined the psychological aspect of engagement in data-driven decision-making. This study adds to existing research concerning self-efficacy beliefs for data-driven decision-making (SEBD^{3}M) as it relates to organizational support and engagement in data-driven decision-making.

One goal of the study was to determine the relationship between SEBD^{3}M and engagement in data-driven decision-making. The second goal of the study was to determine significant differences among teachers at the elementary, middle, and high school levels of education. The final goal of the study was to determine the extent to which self-efficacy beliefs and culture mediate the relationship between organizational support and engagement in data-driven decision-making.

A quantitative study was conducted using the survey research method. Participation was solicited from teachers ($n = 232$) and administrators ($n = 44$) in a public school district in central Mississippi who completed questionnaires in an online format. Results of the *SEM* analysis supported a fully mediated model for understanding the relationships among organizational support, SEBD^{3}M, culture, and engagement in data-driven decision-making. There were no differences in SEBD^{3}M among elementary, middle, and high school teachers included in the study. Recommendations for improvements in the areas of teacher in-service training, administrative training, and implementation of data-driven decision-making in school districts were made based on the results of the study. Implications for future research concerning a potential link between organizational support and engagement in data-driven decision-making as well as professional development platforms for teachers was discussed.

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DEDICATION

I would like to dedicate this dissertation to my family who has supported and encouraged me while on this journey to the Ph.D. I would especially like to thank my parents, James and Gloria Pollard. Your unyielding support and unwavering love has sustained me throughout my educational and professional careers.

To my brother, Dr. James Daryl Pollard, your example of faithful dedication and commitment in all you do has been motivating to me to pursue everything I want in life wholeheartedly. Your committed dedication to your family, your faith, and your purpose have meant more to me than you will ever know. To my sister-in-law, Quemekki Pollard, thank you for your positive support and concern you have shown for me during this process.

To my nephews, James Reece Pollard and Aaron Andrew Pollard, may you always know that there is nothing that is impossible for you in life. Dream big and fly high, boys. I love you.

Finally, I would like to dedicate the completion of the dissertation and the Ph.D. to the memories of my late grandparents: Mr. Percy Porter Pollard, Sr., Mrs. Wilma Pollard, Mr. Wilson B. Crosby, Sr., and Mrs. Annie Laura Crosby. Thank you for encouraging me through your words and your examples of service, giving, and sacrifice. Our laughs and memories will never be forgotten.

"Commit to the Lord whatever you do, and your plans will succeed."

-Proverbs 16:3

TABLE OF CONTENTS

LIST OF TABLES

LIST OF ILLUSTRATIONS

LIST OF ABBREVIATIONS

SEBD³M	Self-efficacy Beliefs for Data-Driven Decision-Making
EFA	Exploratory Factor Analysis
SEM	Structural Equation Modeling

CHAPTER I – Introduction

Data-driven decision-making has been part of the national discourse concerning school accountability for the past decade (Dunn, Airola, & Lo, 2013; Datnow & Hubbard, 2015). Since school reform movements of the 1980s, data have been used to measure student achievement, particularly through standardized assessments. In recent years, student performance on standardized assessments have served as an indicator of how effective schools are in educating students (Lange, Range, & Welsh, 2012). Student achievement on these assessments is directly linked to school accountability by way of the No Child Left Behind Act (2001). The passage of the law mandating higher levels of proficiency than was previously expected of students provides the backdrop for the current emphasis on and widespread data use in schools. The 2001 law called for stronger accountability standards for schools which prompted an increased focus on the improvement of instructional practices through data-driven decision-making (Lange, Range, & Welsh, 2012; Murray, 2012; Murray, 2014; Jacobs, Gregory, Hoppey, & Hoppey, 2009).

Data-driven decision-making involves the process of collecting, analyzing, and interpreting data to guide instructional decision-making (Schildkamp & Kuiper, 2009; Mandinach, 2012). Data-driven decision-making is often tied to school improvement due to its focus on accountability measures such as standardized assessments, benchmark assessments, and interim assessments (Murray, 2014; Datnow & Hubbard, 2016). Various researchers define data-driven decision-making similarly in that it is a cyclical process involving making instructional decisions based on data. Sometimes referred to as data-informed decision-making, the process relies on the collection of multiple forms of data in schools including student achievement data.

The process of using data for instructional purposes has become vital for school administrators at the school-wide level, and commensurately, data-driven decision-making has become an integral part of the accountability process for classroom teachers who are subject to accountability at an individual level. Prior research has indicated that many teachers make efforts to respond to the need for data through changes in classroom procedures, but very few respond to the data in ways that influence the instructional pedagogy in their classrooms (Marsh, Bertrand, & Huguet, 2015). Research further documents that many if not most teachers lack the ability to engage in effective data analysis and interpretation that has the potential to lead to meaningful change in teaching and learning processes in the classroom (Huguet, Marsh, & Farrell, 2014; Marsh, Bertrand, & Huguet, 2015; Datnow & Hubbard, 2015).

Datnow & Hubbard (2015) opine that there is a need to develop new skills that allow teachers to use the numerous data sources available to them more effectively. Additional literature supports this notion that they generally lack the ability to use the information gained from the assessments to bring about changes in instructional delivery (U.S. Department of Education, 2010; Mandinach, 2012; Gullo, 2013; Murray, 2014; Datnow & Hubbard, 2015; Marsh, Bertrand, & Huguet, 2015; DuFour, 2015). While deficits in teachers' abilities to engage in data-driven decision-making generally exist among teachers, some researchers have examined educators' internal beliefs about data-driven decision-making and how they influence practice (Dunn, Airola, Lo, & Garrison, 2013; Datnow & Hubbard, 2016). Fewer studies in the literature focus on factors related to self-efficacy beliefs for engaging in data-driven decision-making practices among educators (Jimerson, 2014).

Self-efficacy beliefs for data-driven making (SEBD^{3}M) refers to an educator's beliefs about their ability to engage in the process of data-driven decision-making (Dunn, Airola, Lo, & Garrison, 2013). Prior research on educator self-efficacy beliefs documents the long-term effects of self-efficacy beliefs on teaching. In a 2016 longitudinal study of German teachers, teacher self-efficacy beliefs were found to be a long-term predictor of instructional quality (Kunsting, Nueber, & Lipowsky, 2016). Given its importance to the quality of classroom instruction, a study focusing on the factors related to SEBD^{3}M could be instrumental in strengthening educators' individual and collective beliefs in themselves to effectively use data and improve the overall quality of teaching and learning in the classroom.

Studies concerning educator SEBD^{3}M have examined the relationship between SEBD^{3}M and anxiety for data-driven decision-making (Schildkamp & Kuiper, 2010). Dunn, Airola, Lo, and Garrison (2013), conducted a survey of teachers in K-12 education and reported that efficacy plays a role in data-driven decision-making. The general finding of their survey of K-12 teachers was that a lack of efficacy was related to a struggle with data among teachers (Dunn, Airola, Lo, & Garrison, 2013).

Prior research demonstrates that multiple factors influence teacher beliefs about their abilities to deal with data (Dunn, Airola, Lo, & Garrison, 2013; Farley-Ripple & Buttram, 2015). These factors may be categorized into three areas: organizational factors, social interaction with colleagues surrounding data, and personal beliefs concerning data. From the organizational standpoint, the literature focuses on the influence of school leadership. Educator engagement in data-driven decision-making comes from intentional structures and supports in schools with a focus on data use for school improvement. School leaders' beliefs about data "set the stage" for data use in a school (Datnow & Hubbard, 2016). A number of studies have focused on the process of data-driven decision-making from the school leadership perspective of creating the conditions necessary for data cultures in schools (Halverson, Grigg, Prichett, & Thomas, 2007; Noyce, Perda, & Trayer, 2012; Lange, Range, & Welsh, 2012; Murray, 2014; Datnow & Hubbard, 2015).

Organizational factors positively affecting data use come from school leaders who embrace data-driven decision-making. School leaders who focus on the intentional creation of data cultures in schools are responsible for providing the structured time for the data-driven decision-making process to unfold in schools (Huguet, Marsh, & Farrell, 2014). Typically, the time allowed for focusing on data is collaborative (Lange, Range, & Welsh, 2012; Mandinach & Gummer, 2015). It has been recommended that the process of using data for instructional purposes be intentionally created by the school leadership to encourage instructional improvement (Noyce, Perda, & Trayer, 2012; Lange, Range, & Welsh, 2012). Most studies on the topic of data use in schools note the fact that school leadership plays a vital role in the process by providing the structure and support needed to facilitate data use (Lange, Range, & Welsh, 2012; Jacobs, Gregory, Hoppey, & Hoppey, 2009). The increased focus on school accountability in the twenty-first century has led school leaders to emphasize a closer examination of what is being learned in the classroom (Jacobs, Gregory, Hoppey, & Hoppey, 2009).

Interaction with colleagues in a collaborative setting is also related to data-driven decision-making. Collaboration with peers is a recurring them in the literature surrounding data use when it comes to teachers (Huguet, Marsh, & Farrell, 2014; Vanlommel, Vanhoof, & Petegem, 2016). Collaboration with other teachers has generally been noted as fundamental to data use processes in schools (Love, 2004; Murray, 2014, Mandinanch, Parton, Gummer, & Anderson, 2015). Multiple studies support the idea that dialogue about data involves a structured and collaborative platform in schools (Datnow & Hubbard, 2015; Marsh, Bertrand, & Huguet, 2015; Mandinanch, Parton, Gummer & Anderson, 2015). The consistency of the collaborative theme across studies lends itself to the examination of the relationship between organizational factors and SEBD^{3}M.

Teacher and administrator personal beliefs concerning data-driven decision-making have been examined in recent years. Multiple researchers have determined that personal beliefs about data play a vital role in teachers' and school leaders' data-driven decision-making practices (Schildkap & Kuiper, 2010; Dunn, Airola, Lo, & Garrision, 2012; Datnow & Hubbard, 2016) In a 2008 study, *Investigating Teachers Perceptions of the Data-Driven Decision-making Process at a Georgia Elementary School*, Sikes posits that teachers are an integral part of the school reform process and the impact of any reform is only as effective as the meaning that participants attach to the reform. It follows that the meaning educators attach to data guides their engagement in data-driven decision-making practices. Proposed mental models for understanding educator data use are present in the literature. The models are used to demonstrate hypothesized relationships among variables related to educators' data use in schools. Most models are developed for a conceptual understanding of data-driven decision-making, however, a study that explores the relationships among the organizational, cultural, and personal aspects of data use with educator self-efficacy beliefs is yet to be conducted.

Since student achievement data are frequently connected to school and teacher accountability, administrators and teachers use these data for a variety of purposes within a school with the goal of improving student learning outcomes. Teachers are expected to use data to help assess the need for remediation for students who are struggling academically and enrichment for students who have obtained mastery of skills (Dunn, Airola, & Lo, 2013). Teachers frequently have negative opinions, however, concerning the use of data in student achievement (Marsh, Bertrand, & Huguet, 2015). The accountability pressure that educators face is consistently documented in the literature (Dunn, Airola, & Lo, 2013; Marsh & Farrell, 2015). Multiple research studies document that teachers' opinions concerning student achievement data are that the information is for administrators and not for them (Schildkamp & Kuiper, 2010; Datnow & Hubbard, 2015). Since teachers' performance evaluations are often connected to school performance, teachers often harbor a negative opinion with regard to the data used to measure overall school performance. Despite these reservations, teachers are expected to analyze the data available to them and make instructional changes based on these data. Most teacher preparation programs do not include coursework on data analysis, yet teachers are expected to engage in the process so they will have a grasp of "student growth" for accountability purposes.

In addition to opinions about how data are used, teacher beliefs concerning data use are related to engaging in data-driven decision-making for instructional improvement

(Datnow & Hubbard, 2015). These beliefs are often shaped by the beliefs and values of the school as an organization. The literature on data use in schools points toward the organizational context as a factor related to teachers' views of data use (Coburn & Turner, 2011; Datnow & Hubbard, 2015). The organizational context for a school drives the importance of data to stakeholders within the organization. The norms, routines, expectations, and leadership at work within an organization guides teachers' beliefs concerning the importance of data (Coburn & Turner, 2011).

The literature notes that various forms of assessment data are available to educators, however, teachers reported infrequent engagement in data analysis processes (Datnow & Hubbard, 2015). There is a discrepancy between the frequency of data-driven decision-making reported by teachers and the instructional changes that are actually taking place in the classroom (Datnow & Hubbard, 2015). Understanding this discrepancy requires examining the underlying, internal aspects of data-driven decision-making that ultimately guide the actions of educators.

There is a need for additional research on what Jimerson (2014) refers to as the "precursors" to data use in schools (Dunn, Airola, Lo, & Garrison, 2013). According to the literature, efforts to remedy deficits among teachers concerning data use should be collaborative, job-embedded, and take place in small groups (Young, 2006; Halverson, Grigg, & Prichett, 2007; Dunn, Airola, & Lo, 2013; Marsh, Bertrand, & Huguet, 2015). Any effort to address these precursors should be coupled with a focus on educators' thought processes in becoming more confident data-driven decision makers (Dunn, Airola, & Lo, 2013). A focus on understanding how educator self-efficacy beliefs is shaped by organizational, peer, and personal factors will aide in addressing the need. A closer look at similarities and differences in self-efficacy beliefs for data-driven decision-making among educators at the elementary, middle, and high school levels may help school leaders determine ways to strengthen the self-efficacies of educators as they appeal to the specific needs of the various grade levels in K-12 education.

Theoretical Framework

A framework for understanding how organizational and social factors impact educators is helpful in shaping a study focused on educator self-efficacy beliefs for data-driven decision-making. Organizational learning theory provides a useful framework for understanding how organizational factors relate to educator self-efficacy beliefs for data-driven decision-making. The roots of organizational learning theory began in the early 1970s, and Argyris is often cited for his early work on organizational learning (Kirwan, 2013). The theory is multifaceted with various strands that focus on organizational learning including systems, reflection, and organizational culture. For the present study, a systematic approach to organizational learning will provide the foundation for exploring the organizational factors as they relate to educator self-efficacy beliefs.

Peter Senge (1990) views organizational learning as the collective processes that influence individuals within an organization within a “systems” perspective. From a systems standpoint, Senge posits five disciplines of organizational learning. The five disciplines of organizational learning are: team learning, shared visions, shared mental models, personal mastery, and systems thinking which are vital to the sustainability of an organization, according to Senge (1990). The collaboration, inquiry, and shared beliefs of educators that are trademarks of schools with existing data cultures are also trademarks of organizational learning theory (Collinson, Cook, & Conley, 2006).

Since educators' use of data typically occurs within a social context, shared vision, mental models, and team learning provide a solid foundation for understanding self-efficacy beliefs for data-driven decision-making. Several studies have indicated that peer collaboration is a key component of data use in schools (Hoover & Abrams, 2013; Farley-Ripple & Buttram, 2014; Vanlommel, Vanhoof, & Petegem, 2016). The literature implies that teacher involvement in data use is a social experience involving interactions that relate to data-driven decision-making.

Problem Statement

Research has indicated that many teachers have negative opinions toward the use of data, (Marsh, Bertrand, & Huguet, 2015). In addition, many teachers lack the capacity for using data for instructional change (Dunn, Airola, & Lo, 2013; Datnow & Hubbard, 2015). Furthermore, prior research has shown discrepancies between teachers' reported instructional changes as a result of data analysis and the actual, documented changes that take place in the classroom. Many teachers reported instructional changes after analyzing assessment data, however, most teachers also reported that they rarely conducted data analysis (Datnow & Hubbard, 2015). There is a need to understand the ways in which self-efficacy beliefs either encourages or hinders data analysis among teachers in a school both individually and collectively.

A number of studies have focused on the conditions that foster data-driven decision-making from a school leadership perspective. One year-long study conducted by Halverson, Grigg, Prichett, and Thomas (2007) focused on the conditions school leaders create to facilitate data analysis for improving classroom instructional practices. The researchers found similarities among the four schools included in the study. Each school engaged in data acquisition, data collection, data storage, data reporting, and data reflection, however the ways each school approached these processes varied considerably.

In addition, researchers and practitioners have made suggestions from their experiences noting the conditions that school leaders must create to facilitate data-driven decision-making for school improvement. Few empirically-based studies have focused on factors related to the internal view educators have about themselves when it comes to data-driven decision-making (Dunn, Airola, & Lo, 2013; Datnow & Hubbard, 2015). Moreover, Dunn, Airola, and Lo (2013) note that there is very little research that deals with the change process that unfolds when teachers engage in data-driven decision-making. Studies that focus on the change process narrowly focus on one school or a handful of teachers without examining the change process that takes place internally for educators who are analyzing and interpreting data.

There is a need to understand educators' opinions concerning their SEBD^{3}M. The study will examine the relationships among organizational, cultural, and personal factors as they relate to SEBD^{3}M. Many factors relate to how teachers use data including their beliefs about the usefulness of data and their ideas about how assessment data is used in the school (Datnow & Hubbard, 2015). Little (2012) argues a need for "zooming in" to closely examine teachers' data use at the classroom level. The present study will examine the SEBD^{3}M of teachers at the classroom level and administrators at the grade and school-wide levels.

Purpose

Educator self-efficacy beliefs has been previously studied in K-12 education with a focus on teaching math, teaching science, and classroom management, among other areas of interest. The purpose of the present study is to contribute to existing research literature related to data-driven decision-making. A study that examines the connections among organizational support, SEBD^{3}M, and engagement in data-driven decision-making has yet to be conducted. The study will be conducted to determine the ways in which SEBD^{3}M is associated with organizational and individual factors within a school setting.

The literature indicates that teachers' beliefs about data vary and are shaped by external sources of influence. Discussions with other educators concerning student achievement data, for example, may shape teachers data-driven decision-making practices at the classroom level. The same is true for administrators at the school and district levels who lead the process of data gathering and analysis in schools. In a recent study concerning teacher motivation for data use, Vanlommel, Vanhoof, & Petegem (2016) noted the need for additional research that focuses on how individual and organizational conditions may affect teachers' data use. The purpose of the present study is to contribute to the research literature by determining the extent to which organizational support and culture are related to SEBD^{3}M for educators. The study will used to further determine differences in reported SEBD^{3}M at the elementary, middle, and high school levels.

The study will add to a small number of studies in the literature that focus on the educator self-efficacy beliefs and data-driven decision-making simultaneously. Prior research has focused on self-efficacy beliefs for other areas within education including classroom management and instructional quality, to name a few. However, there have been very few studies focus on self-efficacy beliefs and data-driven decision-making as it relates to organizational support and culture as spheres of influences within this process. Findings from the study could potentially establish relationships concerning self-efficacy beliefs in the data-driven decision-making body of research.

Justification

Teachers and administrators are subject to accountability in schools. The context of accountability has put teachers and administrators in a position to closely examine data for school improvement. A potential benefit to participants in the present study is the opportunity to reflect on data-driven decision-making practices as they relate to classroom instruction. This reflection could potentially influence teachers' future data use practices by reflecting on their current levels of data-driven decision-making practices at the classroom level. The results of the study could have practical implications for these participants moving forward in their practices as teachers.

The larger population from which the sample is drawn could benefit from the findings of the study. As educators' opinions concerning their SEBD^{3}M are determined, the findings of the study could propel improvements in existing school policies and procedures surrounding data use. The results could also provide guidance for schools that are just beginning to create data cultures in their schools. Other schools that are more developed in data use practices could use the information gained from the study to address existing concerns from educators regarding the structures, supports, and routines concerning data-driven decision-making.

The results of the study are potentially valuable to school and district administrators. For school administrators, the present study also has the potential to influence administrative decisions concerning their approach to data use in schools. As school administrators become more aware of the increasing need for using data for school improvement, they are likely to search for the most effective means to encourage data use for instructional change among teachers. A close examination of educators' data-driven decision-making practices could potentially influence organizational and individual self-efficacies for data use in the future.

At the district level, administrators could use the information gained in this study to encourage the use of specific supports and structures that lend themselves to the SEBD^{3}M of educators in the building. Leaders at the district level are responsible for guiding the direction and pacing of the curriculum in schools. As these leaders work together with school leaders on data use, attention should be given to preparing teachers to engage in data-driven decision-making practices that ultimately lead to improved student outcomes at the classroom level.

Additional structured time for educator collaboration about data may be needed to increase educator self-efficacy beliefs as data-driven decision makers for teacher and school accountability purposes. Teachers have access to multiple data points, but there is an overall lack in ability to use this information for instructional change. The present study could further develop the discourse surrounding effective practices for improving SEBD^{3}M of educators in schools.

Finally, the results of the study have implications for the future of teacher preparation coursework in colleges and universities. The literature supports a need for improvement in this area for teachers given that many teachers report feeling they lack the capacity for performing data analysis and using the data to change classroom instructional practices, which ultimately connects to student achievement outcomes. Perhaps the study could shed light on this issue and encourage university faculty and administrators to re-examine existing course curricula to ensure that preparation for teaching includes coursework in data-driven decision-making behaviors.

Research Questions

Educator opinions concerning self-efficacy beliefs for data-driven decision-making will be the focus of the present study. Teachers and administrators will give opinions on existing organizational support for data-driven decision-making in their schools. The first research question is: What is the relationship between educator SEBD^{3}M and engagement in data-driven decision-making? The second research question is: Are there significant differences in SEBD^{3}M for educators at the elementary, middle, and high school levels? Finally, to what extent do SEBD^{3}M and culture mediate the relationship between organizational support for data use and engagement in data-driven decision-making?

Methodology

The survey method will be used to collect data from elementary, middle, and high school teachers and administrators about organizational support and SEBD^{3}M. The questionnaires will be made available to participants in online and paper-based formats for completion. Permission from the Institutional Review Board at The University of Southern Mississippi and school district-level leadership will be obtained prior to soliciting participation in the study.

CHAPTER II – LITERATURE REVIEW

Data-Driven Decision-Making

In the field of education, data-driven decision-making has come to refer to a multifaceted process involving the collection, analysis, and interpretation of data (Mandinach & Gummer, 2015). The process is cyclical and ideally ends with the use of the information gained from the data to guide instructional practices in the classroom. Mandinach (2012) described data-driven decision-making as a process of engagement with data to make decisions concerning policy and practice in schools. Data-driven decision-making as a research field of interest relatively new, however, the literature notes that teachers have been engaged in some of form of data-driven decision-making for several decades (Mandinach, 2012). Although the process in years past was typically informal and less systematic, teachers and administrators collected data through observation and questioning students (Mandinach 2012). Educators have been making decisions about academic instruction through intuition for years, yet data-driven decision-making in education as a research field of interest has emerged in recent years. Increasing accountability demands over time have demanded that instructional decisions be based on data rather than intuition or observation of learning.

Mandinach (2012) provides a succinct definition of the research area of interest. Mandinach states, “Data-driven decision-making (DDDM) pertains to the systematic collection, analysis, examination, and interpretation of data to inform practice and policy in educational settings” (p.71). Others have used various labels to refer to this process such as data-based decision-making, data-informed decision-making, data literacy, and data use (Coburn & Turner, 2011; Mandinach 2012; Anthanases, Bennett, &

Wahleithner, 2013). Each of the terms used to describe the process implies that data are used to guide decisions about teaching and learning at the classroom, school, district, and state levels. Each term mentioned above similarly describes the process as including the collection, analysis, and interpretation of data.

Schildkamp & Kuiper (2010) define data-driven decision-making as systematically analyzing data sources and applying the outcomes of the data sources to instructional improvements in the school. Gullo (2013) draws a definition similar to Schildkamp & Kuiper (2010) when he parallels data-driven decision-making with standards-based accountability. Standards-based accountability provides a foundation for the use of data for school improvement. Gullo (2013) equates the increased focus on using data to make educational decisions with the passage of *No Child Left Behind Act* (2001). The most recent federal legislation broadly impacting K-12 education, the *Every Student Succeeds Act* (2015), continues to promote schools improving the quality of education students receive in American schools.

The research literature on data-driven decision-making includes several common themes. Most research studies have described data-driven decision-making as a systematic process. Schools that embrace data-driven decision-making have systems and procedures in place for educators to focus on data (Schildkamp & Kuiper, 2010). A systematic approach to data involves intentional decisions from educators who operate in a culture that encourages data use. Some intentional and systematic supports cited in the literature include the prioritization of scheduled time for data and platforms for conversations about data including professional learning communities (Wells & Feun, 2012; DuFour, 2015) data teams, and data coaches (Farley-Ripple & Buttram, 2014;

Marsh & Farrell, 2015; Coburn & Turner, 2011). School leaders select and implement these systems based on planning and human resources available to them in their schools and districts (Halverson, Grigg, Pritchet, & Thomas, 2007).

Another theme that is consistently noted in the literature is the increase of data in schools in recent years. According to Datnow & Hubbard (2016), the amount of data available to educators has proliferated. The proliferation of data has occurred in response to the increased focused on school accountability. Sources of data in K-12 education include: formative and summative classroom assessments, benchmark assessments, and observations, to name a few. With advancements in assessments using technology, data reports are being generated at a much faster rate than years past (U.S. Department of Education, 2008). Many platforms for data collection are technological and produce score reports from computer-based assessment programs that teachers may use for analysis and interpretation (Mandinach 2012). These advancements have allowed for student achievement data to be readily available for analysis by teachers and administrators.

Data access using technology is a theme that has recurred in multiple studies that focus on data-driven decision-making. The research acknowledges that educators must have skills in data access to obtain reports for analysis and interpretation. Technological advancements have made the collection of data a much more efficient process than in previous years by gathering data in a central location and generating reports more quickly based on the data collected (U.S. Department of Education, 2008). With technological advancements in data collection (Wayman, 2015) educators now have access to multiple sources of student achievement data. Research emphasizes that educators are "inundated" with student achievement data (Marsh, Betrand, & Huguet, 2015). As such, data collection has become more prevalent in schools, and teachers and administrators have responded to the data in various ways depending on culture and expectations surrounding data in the schools.

An example of one computer-based system is the Grow Network used in New York City's public school system (Brunner et al, 2005). Students take assessments online and the system creates reports for various audiences including administrators, teachers, and parents. The emergence of computer-based systems has gained popularity in recent years with districts that have the financial means to purchase these systems for use in their districts.

A final theme from the research literature on the topic of data-driven decision-making is a lack of capacity for data use among teachers. Multiple studies note that generally, teachers have access to data in schools but lack data analysis skills to use data to inform instructional decision-making (Huguet, Marsh, & Farrell, 2014; Marsh, Bertrand, & Huguet, 2015; Datnow & Hubbard, 2015). There is consensus in the literature is that the data-driven decision-making process is a cyclical one and requires structure and support in order to be considered an effective process in schools (Marsh, Bertand, & Huguet, 2015; Lange, Range, & Welsh 2012; Mandinach 2012).

Additional keys to data-driven instruction include: assessment, analysis, and systems (Bambrick-Santoyo, 2012). Bambrick-Santoyo (2012) states that teachers and administrators examine assessments as the "roadmap to rigor" (p.25). An analysis of data collected from the assessments is necessary to understand where students' weaknesses are when it comes to academic standards of proficiency. Action refers to the plans, decisions, and steps educators will take to address these areas of weaknesses. "Systems" refers to the process of establishing routines and procedures so that the process of data-driven decision-making is a continuous one.

The systemic process involves data collection which is commonly acknowledged as the initial step in data-driven decision-making. Research on data-driven decision-making notes that the process is cyclical and repetitive with data collection as the first step (Dunn, Airola, Lo, & Garrison, 2013). Informal data collection has taken place in education for years. In the past, teachers collected data based on observation, graded assignments, and intuition, to name a few (Jimerson & Wayman, 2015). Over time, the data collection process has become increasingly structured and systematic. Technological advancements have made the collection of data a much more efficient process by gathering data in a central location and generating reports more quickly based on the data collected (U.S. Department of Education, 2008).

Brunner et. al (2005) conducted a two-year exploratory study of teacher experiences with a computer-based and print-based system called the Grow Network. During the years the study was conducted, the Grow Network was being used in New York City's public school system. Students take assessments online and the system creates reports for various audiences including administrators, teachers, and parents. The emergence of computer-based systems has gained popularity in recent years with districts that have the financial means to purchase these systems for use in their districts.

Once data have been collected, analysis is the next step in the data-driven decision-making process. Research indicates that teachers, in general, lack the capacity to analyze standardized assessment data (Dunn, Airola, & Lo, 2013; Datnow & Hubbard, 2016). Data analysis is often missing in teacher preparation programs (U.S. Department of Education, 2008), yet teachers and administrators engage in this behavior when it comes to the evaluation of teaching and learning. Developing teachers' abilities to engage in data-driven decision-making is often the responsibility of school administrators (Levin & Datnow, 2012; Jimerson, 2014).

After data have been collected and analyzed, teachers and administrators glean meaning from the analysis. Interpretation is an instrumental part of the process because the way data are interpreted ultimately guides the decisions that are made about teaching and learning. This stage of the data-driven decision-making process involves the data user drawing information from the data that informs instructional decisions. According to Paul Bambrick-Santoyo (2012), "action" is one of the keys to data-driven instruction. The actions involved in data-driven instruction are educators' responses to their interpretations of the data. The implementation of new ideas to address areas of concern from student achievement data serves as a response following data analysis.

The literature on data-driven decision-making presents pictorial depictions of the process. Most frameworks visually depict the process as a cyclical and continuous undertaking with the recurring steps of data collection, analysis, interpretation, and action. Mandinach (2012) presents a conceptual framework for understanding data-driven decision-making. See Figure 1 for a visual depiction of the data-driven decision-making process.

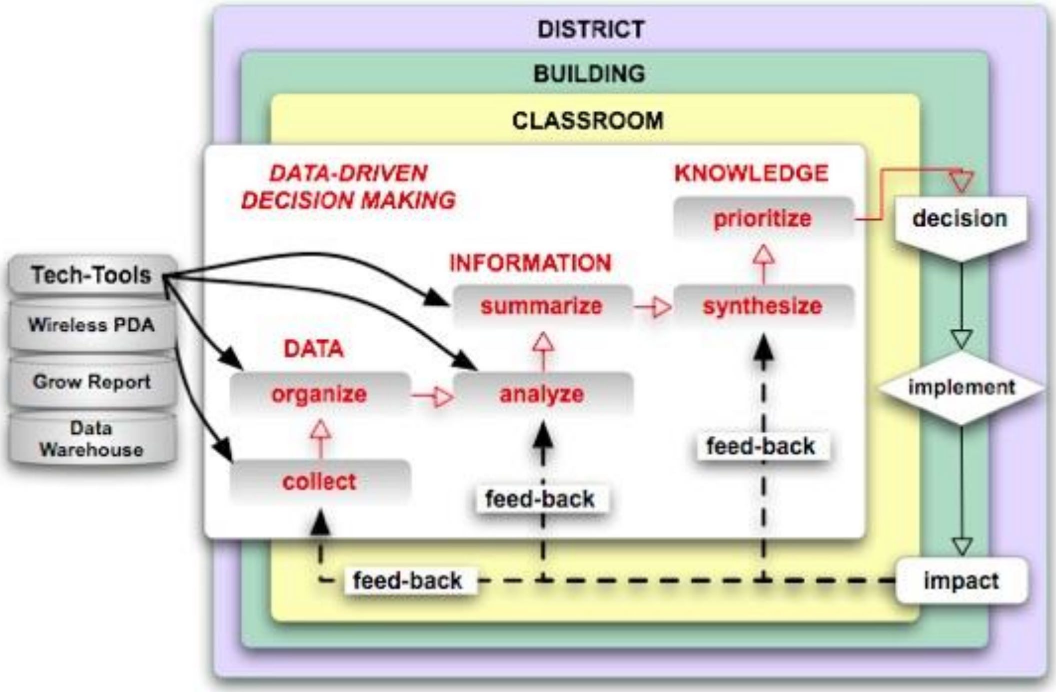


FIGURE 1 Conceptual framework for data-driven decision-making. Reprinted with permission from *A Conceptual Framework for Data-Driven Decision-making* by E. B. Mandinach, M. Honey, D. Light, and C. Brunner. Copyright 2008 by Teachers College Press.

The framework includes data collection, information gained through analysis and interpretation, and knowledge through feedback and impact of the data. As indicated in Figure 1, these processes are thought to occur at the classroom, building, and school levels. While a scant amount of studies explore self-efficacy beliefs for data-driven decision-making, a study exploring the relationships among organizational supports, self-efficacy beliefs, and engagement in data-driven decision-making is yet to be conducted.

Purposes of Data-Driven Decision-making in Schools

The data-driven decision-making process is used for multiple purposes by various stakeholders in schools (Mandinach, 2012). Administrators, teachers, and parents make various decisions based on information gleaned from student achievement data

(Mandinach, 2012). One purpose of data-driven decision-making for classroom teachers and administrators is to inform instructional decisions about teaching and learning at the classroom level (Schildkamp & Kuiper, 2010). Administrators can identify grade level or classroom level concerns with regard to proficiency while a classroom teacher can use the same student achievement data to examine strengths and weaknesses at the classroom level and for individual students. Administration may shift resources or attention to the areas from improvement identified in the data-driven decision-making process (Schildkamp & Kuiper, 2010). The classroom teacher may adjust the pacing or order of teaching specific skills where students demonstrate deficiencies. The literature notes that teachers who respond to data generally use re-teaching and re-grouping of students to address the areas of deficiency for their students (Hoover & Abrams, 2013).

Datnow & Hubbard (2016) mention that an additional purpose for data-driven decision-making is the use of data for school improvement planning. School administrators may use student achievement data to determine instructional goals for the school year, for example. Monitoring the progress of students toward these instructional goals using student achievement data is part of the data-driven decision-making process. Monitoring progress of students toward mastery on standards often happens on a weekly and quarterly basis in many schools. Teachers are monitoring student progress on a weekly basis through the use of classroom assessments while teachers, administrators, and districts monitor schools' progress on standards through interim assessments.

The U.S. Department of Education conducted a research study (2007) involving a nationally representative sample of K-12 teachers. The survey method was used to gather data on teachers' use of student data to improve instruction. The findings of the study emphasized the expectations and practices surrounding data use as pivotal in improving existing programs and practices in schools (U.S. Department of Education, 2007). The findings also support the idea of regular progress monitoring, which is linked to school improvement for accountability purposes (Jimerson, 2014).

A 2006 case study including teachers and administrators in a New York school district examined patterns in practice surrounding data. Breiter & Light (2006) found that administrators use data for identifying areas of need, targeting resources, planning, supporting conversations, and professional development. The data helped administrators determines areas of need and shift resources to address the need. Examining differences in subgroups was useful in the selection of resources that would appeal to the subgroups demonstrating a deficiency in a particular area of learning. In the area of planning, the data helped administrators set priorities for the school (Breiter & Light, 2006). Curriculum and instructional planning as well as instructional program selection are guided by the student achievement data administrators review, analyze, and interpret.

In addition to teacher and administrators using data to inform decision-making, district leaders, parents and community members involved with teaching and learning processes in schools make different decisions based on their perspectives. Parents use student achievement data to monitor their child's progress in school. Student achievement data may help parents decide to enroll their children in private tutoring during after school hours, for example. The attentiveness of the general public to school rankings and accountability is documented in the literature. Stakeholders attribute success to schools with the highest rankings according to State accountability scores for schools and districts.

Schildkamp & Kuiper (2010) conducted a qualitative study of six schools in the Netherlands that were considered "best practice schools for upper secondary education" when the study was conducted. Interviews were conducted with teachers and school leaders concerning data use. Administrators included in the study used student achievement data for evaluative purposes such as evaluating individual, team, and grade level performance on accountability standards (Schildkamp & Kuiper, 2010). The information the administrator gains from examining results on standardized assessments and classroom grades help to determine strengths and weaknesses on grade level and individual levels in a subject area. Administrators use student achievement data for evaluative purposes (Schildkamp & Kuiper, 2010). Examples include goal-setting and personnel decisions as well as professional development needs for teachers (Schildkamp & Kuiper, 2010).

One of the primary purposes of data-driven decision-making in schools is to determine students' instructional needs (Reeves & Honig, 2015). Student achievement data can be useful in determining which students have obtained mastery and which students need remediation. Young (2006) conducted a study focused on teachers' collaborative data use. Young (2006) reported that information gained from data have helped determine grouping of students and interventions. Grouping students according to mastery and remediation has been discovered to be helpful in targeting the specific needs of students to improve their learning. This process described by Young (2006) mirrors the concept of "monitoring student progress" that Reeves & Honig (2015) note when they describe the shift from the less formal processes of data-driven decisions making to the more systematic processes of recent years.

Schildkamp & Kuiper (2010) note studies have indicated teachers use assessment data to reflect on their teaching effectiveness. Teacher reflection and inquiry surrounding data often happens during structured time for collaboration (Datnow & Hubbard, 2016). Schilkamp & Kuiper (2010) suggest that using data to provide students with feedback encourages self-directed learning among students. Student reflection on the information from student achievement data takes place at the classroom level. A number of studies have noted the sense of ownership derived from students examining their own performance at the classroom level (Breiter & Light, 2006; Young, 2006; Schildkamp & Kuiper, 2010).

In Schildkamp & Kuiper's (2010) study, K-12 teachers reportedly used data for altering assessments and reported changes in instructional strategies less frequently. However, some teachers engaged in limited data use In a study on the teacher self-efficacy beliefs and anxiety concerning data-driven decision-making, Dunn, Airola, Lo & Garrison (2013) surveyed teachers with varying levels of data-related professional development. The researchers note that teachers do in fact use student achievement data to determine if students need remediation or enrichment (Dunn, et. al., 2013) The authors found that participants in their study use these data sources to guide decisions about selection of materials for remediation or enrichment and concerning the instructional approach to the content. Participants in the study reportedly reviewed student achievement data to determine proficiency or mastery on individual and classroom levels. With this information from the data-driven decision-making process, the teacher may adjust pacing of lessons, reteach content, and create ability groups for future instruction in the classroom (Dunn, et. al. 2013).

The literature suggest that many teachers engage in instructional decision-making on a daily basis, but little is known concerning the extent to which they engage in data-driven decision-making behaviors including analysis and interpretation (Hoover & Abrams, 2013). The challenges associated with the analysis and interpretation of data are more likely to be overcome by a teacher with a strong sense of self-efficacy beliefs (Dunn et. al., 2013). A study conducted through the U.S. Department of Education found that teacher confidence in analysis and interpretation was related to their likelihood of engaging in data-driven decision-making at the classroom level (U.S. Department of Education, 2008).

Self-efficacy beliefs for data-driven decision-making may be hindered by the overall lack of skill and unpreparedness among educators in data-driven decision-making (Datnow & Hubbard, 2016). According to the findings of the U.S. Department of Education's (2007) empirical study *Teachers' Use of Student Data Systems to Improve Instruction*, support for educators' use of data systems comes from the schools rather than formal coursework or training in teacher preparation programs. According to the literature, teachers must be trained on how to engage in the data-driven decision-making process (Datnow & Hubbard, 2015). Without this training, teacher confidence in their abilities to use data will decrease (Datnow & Hubbard, 2015).

There are universities that are recognizing the need for training on data use in teacher preparation programs and making efforts to include data-driven decision-making as part of the clinical experiences of their students. In a study of pre-service teachers, Hoagland, Birkenfield, & Bluiett (2014) introduced the implementation of a data model through data teams and data meetings during the teaching internship for teacher candidates at Samford University. The model challenged teacher candidates to be actively engaged with data through analysis, collaboration, and sharing of the data with peers and school leaders. Student participation as daily leaders for data-rich conversations was used to meet the standards set forth by the teacher preparation program and determine to what extent candidates were impacting student achievement through data.

Accountability & Data-Driven Decision-making

The increased accountability pressure from No Child Left Behind (2001) and the call for increased rigor in America's classrooms has created a demand for the close scrutiny of student achievement on standardized assessments (Mandinach, 2012). Data-driven decision-making has increased in its popularity and use as an educational reform in response to increasing accountability demands (Datnow & Hubbard, 2015). The *No Child Left Behind Act* (2001) set the stage for the widespread use of data to inform decision-making.

Prior to the enactment of No Child Left Behind (2001), the 1983 publication of *A Nation at Risk* sparked a nationwide effort to increase rigor in teaching and learning in American schools. The National Commission on Excellence in Education stated that the nation was losing ground in the areas of innovations in science and technology. The argument was based on the idea that America lagged behind in educational attainments. Russia's launch of Sputnik called attention to the condition of American education in its schools. Reform movements in education since the landmark publication have sought to improve teaching and learning processes in the schools.

Educational reforms continue to be made under federal laws and mandates. The most recent legislation, *Every Student Succeeds Act (ESSA)*, was signed into law by President Barack Obama in December 2015. The educational legislation reauthorizes the *Elementary and Secondary Education Act* of 1965. The focus of the law is equal education opportunity for all students. School accountability through school rankings at the State level places pressures on schools to produce results that demonstrate progress toward college and career readiness standards (U.S. Department of Education, 2015).

The adoption of Common Core State Standards by a majority of States in recent years has been a point of controversy in the K-12 educational arena. Forty-two states made the decision to adopt the standards which include what students should know and be able to do in English Language Arts and Mathematics at the end of each grade level (Common Core State Standards Initiative, 2017). The Common Core Standards arguably created more rigorous standards for States to meet than did previous State standards. Schools that have the goal of meeting increasing accountability demands of State curriculum standards often engage in systematic processes for improvement. These intentional process reshape the ways teachers and administrators think about teaching and learning in the classroom. In response, many districts have adopted data-driven decision-making processes in schools to focus on monitoring student progress and improving student achievement.

Sources of Student Achievement Data in Schools

Data have saturated schools in recent years (Datnow & Hubbard, 2016). Some district leaders that have chosen to adopt data-driven instructional policies have made the collection of data a consistent expectation for school leaders and educators in their districts. According to the research literature on data-driven decision-making, teachers are inundated with multiple forms of data including benchmark data, behavioral data, demographic data, and student achievement data, to name a few (Mandinach, 2012). Teachers report a heavy reliance on benchmark assessment data because they have been required to administer these assessments to their students (Datnow & Hubbard, 2015). Benchmark assessments are typically given at a minimum of three times a year. Using data from these assessments, teachers and administrators are able to adjust instruction based on areas for improvement.

Teachers and administrators typically focus on student achievement data because of its direct link to teacher accountability and school accountability (Jimerson, 2014). State standardized assessments are given at a pre-determined time of the year according to individual state guidelines. Most “high-stakes” standardized assessments are given at the end of the school year. Some educators have expressed frustration at the amount of time between the administration of these assessments and receiving the results (Jimerson, 2014). Student achievement on these standardized assessments factors into school and district accountability rankings, which are shared with the general public in compliance with federal *ESSA* mandates for States. Accountability demands have sparked the continuous cycle of data-driven decision-making. Accessing and collecting data is one part of the process, but interpretation and use of the results of benchmark and standardized assessments to inform instructional practices involves a different set of skills and understandings about data.

It is repeatedly stated in the literature that teachers have access to a wide array of assessments, and they administer these assessments frequently (Datnow & Hubbard, 2015). Datnow & Hubbard (2015) note that understanding how instructional practices are informed using this data is unclear. In order for teachers to engage in data-driven decision-making practices, they need the knowledge and skills required to analyze, interpret, and use data at more complex levels (Datnow & Hubbard, 2015). Oftentimes, the focus of data-driven decision-making is on students who need remediation based on the results of assessments. Teachers report re-grouping students, changing the pace of instruction, or differentiating instruction based on data (Datnow & Hubbard, 2015; Hoover & Abrams, 2013).

With technological advancements in data collection (Wayman, 2015) educators now have access to multiple sources of student achievement data. Research emphasizes that educators are "inundated" with student achievement data (Marsh, Betrand, & Huguet, 2015). As such, data collection has become more prevalent in schools, and teachers and administrators have responded to the data in various ways depending on culture and expectations surrounding data in the schools.

Data have proliferated in schools in recent years making it possible for educators to analyze, interpret, and use data to improve teaching and learning processes in schools. Formative assessments are used daily in classrooms. Students are given classroom level quizzes and respond to questioning from teachers during the lesson as ways of formatively assessing student learning. Students are also given summative assessments in the form of tests at the end of a week of instruction or at the end of a teaching unit. Teachers use summative assessments to determine mastery of the standards for their grade level and subject area.

The literature on data-driven decision-making among teachers primarily focuses on how teachers use benchmark data to inform instructional practices in the classroom. However, benchmark data is not the only source of data available to teachers. The data that teachers encounter consists for benchmark, interim, and informal assessment data as well as other forms of data (Datnow & Hubbard, 2015). Traditionally, teachers have heavily relied on benchmark data to inform instructional practices, but the increased pressure in school accountability has led teachers to using multiple sources of data to inform instruction (Datnow & Hubbard, 2015).

Datnow & Hubbard (2015) note the prevalence of interim benchmark assessments in schools. These assessments are typically administered at least three times a year within a school district. Teachers and administrators use the information from benchmark assessments to monitor student progress toward the standards. Datnow & Hubbard (2015) mention that teachers are frequently using a wide variety of assessments, but they are not engaging in analysis of the data from those assessments as frequently. According to the literature, teachers rarely report translating the data into meaningful information for instructional changes in the classroom.

Perspectives Concerning Data in Schools

The Role of the Public in Data Use. School accountability involves expectations from multiple stakeholders including district and school-based administrators as well as the general public. Educators face daily decisions that impact student progress toward proficiency in meeting the demands of State and local policies. Existing pressure from the implementation of these state and local educational policies that demand schools improve student achievement pervade educators' daily experiences. Jacobs, Gregory, Hoppey, & Hoppey (2009) reinforce this idea when they mention that high stakes accountability has made data "more visible". The researchers also note a sense of "urgency" surrounding data (Jacobs et al., 2009). The demands of stakeholders in the community and the general public add to the pressure because of the link between student achievement and school rankings. Arguably, the general public's opinion concerning a school's effectiveness is either informed or shaped by school rankings based on student achievement data.

The *No Child Left Behind Act* (2001) mandates the public dissemination of data to the public but allows States to decide the format used for reporting. In a study of school accountability reporting formats, Jacobsen, Snyder, and Saultz (2014) found that the format of dissemination of data concerning schools has an impact on public views' concerning school effectiveness. Higher rankings have the tendency to garner a more positive view of the school than lower rankings (Jacobsen, Snyder, & Saultz, 2014). With the increased focus of communities and the general public on high stakes accountability for schools, data-driven decision-making has also increased in popularity and use across the country (Datnow & Hubbard, 2015).

Proponents of data use in schools posit that schools that use data-driven decision-making have seen positive results (Bambrick-Santoyo, 2012). Prior research touts benefits of data-driven decision-making for various stakeholders including students and parents. When data is used effectively, achievement gaps may be narrowed and instructional goals for the school may be defined. Some teachers have expressed an excitement surrounding work with data (Jimerson, 2014). In contrast, educators with an opposing view toward the use of data in schools express frustration with data in schools.

In a study concerning mental models for data use among teachers and school leaders, many teachers expressed a frustration with their experiences with data (Jimerson, 2014). Teachers included in the study made comments about the utility of data and the additional responsibility of "more paperwork" in data analysis and interpretation (Jimerson, 2014).

The Role of Administrators in Data Use. The literature repeatedly demonstrates the role of school leadership in data-driven decision-making (Levin & Datnow, 2012). Multiple studies corroborate the idea that district administrators and school-based administrators impact the data use culture in schools (Levin & Datnow, 2012). Administrators in schools that embrace data-driven decision-making create goals for the school, provide structures, build capacity for data use, and establish a trusting and collaborative environment that encourages data use (Levin & Datnow, 2012).

Administrators focus on decisions including goal-setting, personnel decisions, and professional development needs for teachers and staff members. Administrators often link data to teacher accountability by searching the data for evidence of growth over a period of time. Data show pedagogical practices that work well and areas that need improvement in the school's instructional program (Gullo, 2013). Paul Bambrick-Santoyo (2012) promotes the use of data as a roadmap to instructional rigor. Bambrick-Santoyo notes that in the past decade, school leaders who have embraced data-driven decision-making have seen results through increase scores on standardized assessments. Administrators who believe data-driven decision-making as a practice provides guidance to staff members and build their capacities to engage in data-driven decision-making.

Coburn & Turner (2011) provided a framework for understanding data use and data-based interventions. They argue that the organizational contexts in which data are situated largely influence the process of data use and the interventions used to improve the data-driven decision-making process. Teacher efficacy and capacity for data-driven decision-making might be affected by school leaders' approaches to data use in schools. Any structure or support an administrator puts in place concerning teachers and data use should be job-embedded and small group, according to the literature (Lange, Range, & Welsh, 2012).

Supports and structures that encourage data use among teachers indicate a shift in the way that teachers are trained to be effective practitioners in schools today. One publication by the Institute of Education Sciences focuses on how organizations on the ability of educators to engage in data-driven decision-making. The ways in which teachers use data are largely influenced by organizational beliefs concerning data, school leadership, and structures for discussions about data. A data-driven decision-making culture is shaped by the beliefs and vision for data use in schools. The vision concerning data may come from the school administrator with a focus on improving student achievement data.

Multiple studies have acknowledged the role of the principal in schools that engage in data-driven decision-making (Wohlstetter, Datnow, & Park, 2008; Levin & Datnow, 2012; Farrell, 2015). One qualitative study (Levin & Datnow, 2012) focused on the role of the principal in data-driven decision-making provides an in-depth view of how the principals' actions shaped data-driven decision-making behaviors in teachers. Levin & Datnow (2012) conducted a case study of an urban school that demonstrated a strong implementation of data-driven decision-making. Schools included in the study served diverse student populations and have a demonstrated record of improving student achievement. The findings of the study revealed that a principal in a school with strong implementation of data-driven decision-making engages in goal setting based on the needs of the students, provides the structure for data-driven decision-making, builds human and social capital, and creating a climate of trust and collaboration surrounding data use (Levin & Datnow, 2012).

Effective principals model data use and work together with teachers to examine what the data demonstrates about student learning (Levin & Datnow, 2012). On the other hand, a principal may hinder data use. If a principal does not possess skills in data literacy, he or she hinder data use in staff members. Levin & Datnow (2012) note that a principal's "lack of engagement in data-driven decision-making could be a barrier to the process at the school-wide level (p.180). Levin & Datnow (2012) also found that teachers wanted consistency and guidance from the principal for discussions of data and assessment in meetings.

Teacher Perspectives Concerning Data. The literature acknowledges that schools are typically inundated with data from various data sources (Marsh, Bertrand, & Huguet 2015). While the data collected on students has proliferated in recent years, teachers' knowledge of using the information for instructional changes in the classroom have remained stagnant (Marsh, Bertrand, & Huguet 2015). However, teachers who are engaged in data-driven decision-making practices report the decisions that data influence in their daily practices. Breiter and Light's (2006) study reported 'areas of instructional practice' identified by teachers who engage in data-driven decision-making. Teachers use data for targeting instruction through changes made to lesson plans and lesson pacing based on weaknesses observed in the data. According to the findings of the study, teachers were able to differentiate instruction with the additional information given about students' individual strengths and weaknesses. Finally, teachers reported using data to reflect on their own teaching practices and encouraging students to engage in self-directed learning. Self-directed learning has emerged as another area in which teachers use data to have their students take ownership of the learning (Breiter & Light, 2006).

Jimerson (2014) conducted a mixed methods study of teachers, school leaders, and central office administrators concerning the development of mental models for data use. Jimerson (2014) discovered that a lack of skills in the area of data-driven decision-making as well as negative feelings toward the use of assessment data for accountability purposes was common among teachers included in the study (Jimerson, 2014). This finding coincides with additional findings that mention teachers feeling that data-driven decision-making is a bureaucratic process. Teachers feel that the data is for administrators and not for their own use. They also felt less ownership of the data and see it as less valuable in informing their practice (Datnow & Hubbard, 2015). However, teachers generally understand its purpose in monitoring student learning and mastery of content.

Self-efficacy beliefs for Data-Driven Decision-making

Accountability demands to increase the number of students demonstrating proficiency on state and district level assessments have led to teachers and school leaders using data to inform instructional decisions. Conditions outside of educators' control often shape the data-driven decision-making process. Few studies have examined psychological concepts such as self-efficacy beliefs as they relate to external supports and conditions for data-driven decision-making. According to the literature, there are people, structures, systems, and supports that may facilitate or impede the data-driven decision-making process for educators (Schildkamp & Kuiper, 2010). Examining the interplay of these factors as they relate to educator self-efficacy beliefs would provide insight into the impact of these factors on educators' self-efficacy beliefs for data-driven decision-making.

A focus on self-efficacy beliefs for data-driven decision-making could potentially align with Bandura's idea about self-efficacy beliefs and its connection with human agency. Bandura (1997) notes that people who demonstrate self-efficacy beliefs for a behavior are more likely to take advantage of structures and make changes whereas individuals with lower self-efficacy beliefs are discouraged and less apt to make changes. In order to fully understand a behavior, such as data-driven decision-making, an integrated approach involving social influences and self-efficacy beliefs must be adopted (Bandura, 1997). Examining psychological or social factors in isolation does not provide a full perspective of how self-efficacy beliefs is related to action (Bandura, 1997). A study of self-efficacy beliefs as it relates to data-driven decision-making would improve understanding about what happens with educators when internal beliefs and opinions meet external systems and supports.

Self-efficacy beliefs refers to a person's belief in his or her ability to "…produce desired results by their own actions" (Bandura, 1997, p.3). In *Self Efficacy: The Exercise of Control*, Bandura further defines self-efficacy beliefs as "…beliefs in one's capabilities to organize and execute the courses of action required to produce given attainments" (Bandura, 1997, p.3). Educators may possess self-efficacy beliefs for various aspects of their position in education including disciplining students in the classroom or explaining mathematical concepts to students (Skaalvik & Skaalvik, 2014). However, a study that examines educator self-efficacy beliefs for data-driven decision-making as it relates to organizational and peer influence is yet to be conducted.

The concept of self-efficacy beliefs has been studied in multiple fields including the examination of creative self-efficacy beliefs in a business setting (Bei & Yidan, 2016) and academic self-efficacy beliefs among business students (Elias, 2008). Self-efficacy beliefs has also been examined in various populations including prospective teachers (Saka, Bayram & Kabapinar, 2016) and practicing teachers (Dunn, Airola, Lo, & Garrison, 2013). With regard to teachers, self-efficacy beliefs has been studied as it relates to teacher engagement and job satisfaction in K-12 education (Skaalvik & Skaalvik, 2014). Skaalvik & Skaalvik (2014) found that teacher autonomy and self-efficacy beliefs among teachers are predictors of engagement and job satisfaction. Bandura (1997) notes that people who demonstrate self-efficacy beliefs for a behavior are more likely to take advantage of structures and make changes whereas individuals with lower self-efficacies are discouraged and less apt to make changes. In order to fully understand a behavior, such as data-driven decision-making, an integrated approach involving social influences and self-processes must be adopted (Bandura, 1997). Examining psychological or social factors in isolation does not provide a full perspective of how self-efficacy beliefs is related to action (Bandura, 1997).

Bandura (1997) explains that there are multiple sources of self-efficacy beliefs for individuals. The sources include enactive mastery experiences, vicarious experiences, verbal persuasion and social influences, and physiological and affective states. Enactive mastery experiences are the authentic experiences of success and failure in a behavior.

Successes provide a boost to self-efficacy beliefs while failures suppress self-efficacy beliefs. Pre-existing knowledge structures also play a role in self-efficacy beliefs. Individuals face tasks with a pre-existing sense of self and perspective of the world around them. These structures determine the interpretation of the task and approach to the task (Bandura, 1997).

Vicarious experiences are also sources of information for self-efficacy beliefs. These experiences often involve modeling attainment of a certain goal measured in comparison to others in a similar position, which may provide a sense of self-efficacy beliefs. For most activities, a measure to determine adequacy in a given activity does not exist. Therefore, individuals often appraise their self-efficacy beliefs through comparisons to peer in similar position or standing. Outperforming peers on a given activity raises self-efficacy beliefs while underperforming when compared to a peer lowers self-efficacy beliefs (Bandura, 1997).

Another source of information for self-efficacy beliefs is verbal persuasion. When an individual receives a verbal expression of confidence from another in his or her ability to complete a task, this experience contributes to his or her self-efficacy beliefs. When struggling with a task or activity, a verbal expression of confidence in an individual's ability may provide a boost to the individual develop determination and overcome obstacles to complete the task to the best of his or her ability.

Physiological and affective states also provide information for individuals' self-efficacies. Bandura (1997) mentions that people read their physiological reactions to stressful or challenging situations. Mood states may also affect feelings about personal self-efficacy beliefs. Recollection of past failures and successes may be conjured by a positive or negative mood state. A positive mood state may be tied to past accomplishments while a negative mood state may be associated with past failures. Either mood state has an effect on self-efficacy beliefs for a given task. The integration of the four sources of information, make a contribution to an individual's self-efficacy beliefs. Bandura (1997) posits that there a multiple benefits to a strong sense of self-efficacy beliefs. Research studies with a focus on teacher self-efficacy beliefs (Skaalvik & Skaalvik, 2014; Kunsting, Neuber, & Lipowsky, 2016) support Bandura's ideas concerning the benefits of self-efficacy beliefs.

Kunsting, et al. (2016) conducted a longitudinal study in Germany that focused on teacher self-efficacy beliefs as a long-term predictor of their mastery goal orientation and instructional quality in the classroom. The researchers began the study with a focus on self-efficacy beliefs of teachers defining the concept as a trait that encompasses a teacher's beliefs about his or her ability to handle a specific task or situation (Kunsting et al., 2016). Kunsting et al. (2016) focused the study on three dimensions of instructional quality: supportive classroom climate, classroom management, and cognitive activation. The researchers explain teacher self-efficacy beliefs as "…the degree to which teachers believe that they will cope successfully with tasks, situations, or conditions in the teaching profession" (Kunsting, Neuber, & Lipowsky, 2016, p.300). The construct of self-efficacy beliefs was measured in 2001, 2008, and 2011 in a longitudinal study. The researchers note that one aim of the study was to examine the stability of teacher self-efficacy beliefs over time. The researchers also wanted to examine self-efficacy beliefs as a long-term predictor of instructional quality. Indicators of instructional quality were described for the study. A supportive classroom environment includes constructive feedback to students and individual support for students in areas of strength and weaknesses. Effective classroom management involved clear expectations and the management of behavior so learning can take place. The researchers describe cognitive activation as having students engaged in stimulating and challenging tasks. When students are cognitively stimulated in the classroom, they reflect on their own learning, provide support for their own reasoning, and generate thoughtful ideas. According to Kunsting et al. (2016), these behaviors related to cognitive activation in the classroom have been positively related to student achievement. Mastery goal orientation for teachers was also a key indicator of instructional quality in the research study. The researchers describe mastery goal orientation as the setting of a goal and moving toward learning and developing skills to reach the goal. Teachers' beliefs about their abilities to master goals could be linked to the frequency and extent to which they set mastery goals for themselves. As self-efficacy beliefs has been found to predict instructional quality, it follows that instructional quality is related to school accountability. The research study (Kunsting, et al. 2016) included teachers in Germany who completed teacher education degree programs from six German colleges of education. The participants completed a self-assessment in 2001, 2008, and 2011. The researchers found that teacher self-efficacy beliefs remains stable over time. Self-efficacy beliefs was determined to be a predictor of all three dimensions of instructional quality from data gathered using self-report measures completed by the teachers. The longitudinal study sets the stage for a study examining self-efficacy beliefs and data-driven decision-making.

Bandura (1997) provided support for the idea of mastery goal orientation when he opined that self-efficacy beliefs plays a role in human action. In the article "Social

Cognitive Theory: An Agentic Perspective", Bandura states that "Efficacy beliefs are the foundation of human agency" (p.10). Motivation to continue with a course of action hinges on an individual's ability to view themselves as capable of achieving the desired results (Bandura, 2001). Data-driven decision-making is expected of teachers and administrators in districts with a focus on data-driven instruction. Therefore, teacher and administrator efficacies for the collection, analysis, and interpretation of data could vary based on a number of external factors.

Organizational factors may impact educator self-efficacy beliefs for data-driven decision-making. The literature notes that there is variation in the way that teachers engage in data-driven decision-making, and there are several factors that potentially influence this process for teachers. These include school leadership (Levin & Datnow, 2015), organizational culture concerning data, and teacher beliefs concerning data. These external and internal factors potentially shape the way teachers use data to inform instructional changes in the classroom.

In a recent study of teacher self-efficacy beliefs on the related concerns of collaboration and refocusing, researchers found that self-efficacy beliefs does influence these factors among teachers (Dunn, Airola, Lo, & Garrison, 2013). The study focused on three components of efficacy for data-driven decision-making: efficacy for data access and collection, efficacy for data tool and technology use, and anxiety for data-driven decision-making. For the purposes of the study, collaboration concerns for teachers meant navigating the process of analyzing data together and refocusing concerns meant innovation in instructional strategies in response to discoveries as a result of teacher collaboration (Dunn et al. 2013).

Dunn et al.'s (2013) study on data-driven decision-making efficacy and data-driven decision-making anxiety supports Bandura's idea about efficacy being the foundation of action in individuals. In the quantitative study, participants included a sample of 1,728 K-12 teachers from a northwestern state who participated in various levels of job-embedded professional development related to data use. Participants responded to items focused on data-driven decision-making self-efficacy beliefs and data-driven decision-making anxiety. The development of an instrument used to measure both constructs simultaneously was the aim of the researchers work with this sample. The purpose of the study was to add to the body of knowledge concerning the change process that occurs with teacher engagement in data-driven decision-making.

Individuals' beliefs about their abilities to perform a task affect thought patterns, emotions, and ultimately behavior (Dunn, et al., 2013). Moreover, their thoughts about how well they will perform the task affect thought patterns and behaviors. Mental images of past success and failures with a given task affect a stronger or weaker sense of self-efficacy beliefs in educators. As teachers and administrators in schools with a focus on data engage in data-driven decision-making, efficacies may or may not adjust or remain stagnant over time. Tshchannen-Moran and Hoy (2001) conducted a review of measures focused on the construct, teacher self-efficacy beliefs. They note that self -efficacy affects teacher efforts, goals, and aspirations (Tschannen-Moran & Hoy, 2001).

The relationship between self-efficacy beliefs and decision-making has been examined in prior research studies focused on career decision-making among high school students (Chiesa, Massei, & Gugliemi, 2016) and college graduates (Boyoung, Rhee, Gyuyoung, Joonyoung, & Lee, 2016). However, a study examining the relationships among external supports, self-efficacy beliefs and data-driven decision-making is yet to be discovered. The present study seeks to fill a gap in the literature on educator self-efficacy beliefs for data-driven decision-making.

Organizational Learning Theory

Organizational learning theory provides a framework for understanding self-efficacy beliefs for data-driven decision-making. The early work of behavioral psychologist Chris Argyris in the 1970s laid the groundwork for organizational learning theory. Argyris (1978) explains the framework for understanding organizational learning in *Organizational Learning: A Theory of Action Perspective*. Argyris notes that organizations are continuously engaged in the behaviors of deciding and taking action (Argyris, 1978). According to Argyris, organizational learning occurs based on individual learning of members of the organization. Individual learning coupled with collaborative inquiry provide the basis for organizational learning (Argyris, 1978). Organizational learning may be examined through multiple lenses including reflection and organizational culture. For the purposes of this study, organizational learning with a focus on systems will provide a basis for understanding self-efficacy beliefs for data-driven decision-making.

Organizational learning involves individuals acting as learning agents making decisions and responding to internal and external influences. The response to these influences are engrained in what Argyris refers to as the images and mental maps of the members of the organization. Through reflection and collaborative inquiry images and maps of individuals and the organization may change over time. The initial work of

Argyris aligns with the later work of Peter Senge, author of *The Fifth Discipline: The Art & Practice of The Learning Organization*.

In the seminal work focused on organizational learning, Senge (1990) introduces the concept of a learning organization using a systems perspective. Senge refers to a learning organization as "…the organization that discover[s] how to tap people's commitment and capacity to learn at all levels in an organization" (p.4). According to Senge (1990), the organizations that will experience success and be globally competitive will experience learning through their work. Senge views participants in the learning organization as learners. According to Senge (1990), successful organizations understand that learning does not happen in isolation with the organization's leader who disseminates knowledge to members of the organization. In a learning organization, learning drives all members in developing their capacity to perform tasks. The systems, structure, and routines of the organization foster learning and development in the individuals that make up the organization.

Senge (1990) presents systems thinking as the first "discipline" of a learning organization. Senge (1990) notes that systems thinking is focused on the idea that a system of tools and processes are in place to examine patterns within the organization and make changes accordingly. Systems thinking focuses on a holistic view of the interrelations and connections within the organization rather than individual processes. Senge (1990) argues that systems thinking is needed now more than ever before due to the increasing production of information, interdependency and change occurring in the world. Senge (1990) cites examples from the business world when focuses on key elements of a learning organization. Senge describes systems thinking as a way of seeing wholes and examining the interrelationships between entities within an organization. Senge recognizes that there are patterns of change that exist within an organization. Systems thinking requires a shift in mindset of an organization. Members of an organization view themselves as active participants in their own learning experiences. For the second discipline of learning organizations, Senge focuses on mental models. Mental models refer to shared assumptions or beliefs present in the organization that influence individuals' words and actions while operating in their roles within the learning organization. Individuals may or may not be aware of mental models and the way they ultimately impact their behavior (Senge, 1990). Fauske & Raybould (2005) parallel this idea when they discussed mental models in a study focused on organizational learning and instructional technology. Fauske & Raybould mention the cognitive and behavioral parts of mental models. The approach to solving problems and addressing issues are formulated based on "existing schema" (Fauske & Raybould, 2005, p.24). Members of the organization share the collective schema of shared experiences with data in a school that focuses on data-driven decision-making. Senge refers to an example of a scenario involving two individuals experiencing the same event. These two individuals may view the same event differently due to their existing mental models. Mental models may cause these individuals to focus on different details of the same matter. The mental models educators may have surrounding data could be positive or negative depending on their experiences. Past experiences with data that are negative may discourage educators from future engagement in data-driven decision-making. Positive experiences with data could serve as catalysts for continued engagement in the data-driven decision-making process. School leaders who desire to increase engagement in data-driven decision-making craft the intended uses and purposes of data to suit the needs of staff and students. A misuse of data can lead to unintended responses. Schilkamp & Kuiper (2010) give the example of schools focusing only on data that leads to easy adjustments in instruction versus data that points to the need for long-term improvements in the curriculum.

The third discipline of a learning organization, according to Senge (1990) is shared vision. A shared vision refers to the common goals and values that propel the daily activities of the learning organization. Senge (1990) argues that companies or organizations have not been successful without a shared vision of their futures. The concept of a shared vision lends itself to the next discipline Senge puts forth for learning organizations—team learning. This is a collaborative form of learning that involves dialogues and approaching issues from a teamwork standpoint. The process of growing and discovering happens collaboratively within a learning organization. The learning that takes place may impact the decision-making process and ultimately the actions of the individuals who are part of the organization (Senge, 1990). The fifth or final discipline of a learning organization according to Senge (1990) is personal mastery. Senge (1990) explains personal mastery as realizing the results that matter to an individual within an organization. Personal mastery is described as a continual state of learning toward individual proficiency at a skill or goal of the organization. Senge implies that striving toward personal mastery must be encouraged. Arguably, Senge (1990) believes that most organizations do not encourage personal mastery in its individuals which ultimately leads to "untapped resources" within the organization (p.7).

The five disciplines of the learning organization share common threads of organizational or collective thinking, collaborative team learning, and personal mastery. The organizational, collaborative, and individual themes presented among these disciplines provide multiple approaches to examining self-efficacy beliefs for data-driven decision-making. The interdependence of the five disciplines on each other provides a foundation for determining connections between these elements and educator self-efficacy beliefs for data-driven decision-making.

The literature cites organizational beliefs, structures, support, and routines as factors that impact the data-driven decision-making process (Wohlstetter, Datnow, & Park, 2008; Levin & Datnow, 2012). These factors parallel the elements identified by Senge that focus on the tenets of organizational learning theory. School leaders are responsible for conditions related to data-driven decision-making among teachers. Lange, Range, & Welsh expound on the conditions needed to facilitate effective data use among teachers. They note that school leaders must provide professional development opportunities for teachers to becoming data-driven decision makers. In a data-driven culture, educators are provided the support and systems that facilitate data-driven decision-making (Noyce, Perda, & Traver, 2000).

According to Datnow & Hubbard (2015), there is a need to focus on the interactions among teachers concerning data-driven decision-making and their responses to these interactions. Administrators addressed the need for data-related professional learning using various platforms for discussions about data including data chats, data walls, data coaches, and professional learning communities. Very few studies have examined the process that unfolds during data-driven decision-making and how this process is shaped by contextual factors (Farrell, 2015). Farrell (2015) conducted a research study that focused on designing systems to encourage data use. The study compared school districts and charter management organizations. The findings of the study demonstrated that regardless of school type, leaders and teachers faced accountability pressures, and data use was shaped largely by organizational factors (Farell, 2015).

The literature consistently emphasizes collaboration which aligns with Senge's "team learning" concept involved in organizational learning. Schildkamp & Kuiper (2010) parallel this idea when they note that data use is a "team effort" (p.486). Teachers work together to review data and make plans about actions to take based on the data in a collaborative environment. Additional benefits to collaboration concerning data include: improvement of teaching practices within the school and increased connections between teachers (Schildkamp & Kuiper, 2010). The benefit of teachers working together to collect, analyze, and interpret data has been found with teachers implementing response-to-intervention models in their schools (Jacobs, Gregory, Hoppey, & Hoppey, 2009). Jacobs et. al. (2009) conducted a qualitative study that included semi-structured interviews of teachers who shared their experiences on how contextual influences shape how they think about data. Teachers included in the study sample were from schools that demonstrated varied levels of "readiness for data use and data support". The schools were classified as demonstrating low, medium, or high levels of readiness.

Teachers included in the study expressed a need for using data to differentiate instruction for students in the response-to-intervention process. The findings of the study also provided evidence for differences in teachers' data use based on experience and professional knowledge. Teachers in this study reported using data differently based on experiences with professional learning concerning data use. In this case, two teachers in the same school with the same supports for data used responded differently to the data in instructional decision-making. The researchers note the need to take current research a step further by examining the conditions in which the ways teacher think about data shifts during the data-driven decision-making process. The findings of the study are suggestive of implications for administrators who provide resources and support for data use to teachers.

Coburn & Turner (2011) note that using data to drive instructional practices requires that educators are actively engaged with data. The recommendation is that the active engagement with data occur during the school day. The notion of "job-embedded" professional development surrounding data use has been introduced in previous research (Lange, Range, & Welsh, 2012). In Jimerson & Wayman's 2015 research study on needs and supports of teachers engaged in professional learning using data, teachers noted that summer professional development on data use was not beneficial to them. The use of "sporadic" professional development sessions did not provide the sustained and continuous support teachers needed when engaging in data-driven decision-making. A situation in which teachers engage with data in a collaborative setting with other teachers in the same grade level or subject area was considered to likely be more beneficial to teachers whose opinions were expressed in the study (Jimerson & Wayman, 2015). These teachers' perspectives on data use are suggestive that data-related professional development in a collaborative setting may be conducive to optimal data-driven decision-making in schools.

A closely related theme that consistently emerges in the literature on data-driven decision-making is that small group experiences with data are beneficial. The aforementioned study alludes to this point. One teacher interviewed in Jimerson & Wayman's (2015) study specifically mentioned that professional development with a large number of teachers in one room with a computer hardly benefited her development in data-driven decision-making. The importance of collaboration in the data-driven decision-making process is well established in the research literature (Hoover & Abrams, 2013; Farrell, 2015) Sharing effective instructional strategies among teachers is one way data use helps educators to be more effective (Hoover & Abrams, Farrell, 2015; Vanlommel, Vanloof, & Petegem, 2016). A research study that explores how peer data use is related to educator self-efficacy beliefs would be useful because collaborative inquiry is prevalent in the literature. In schools that embrace data-driven decision-making, colleagues often engage in conversations about data. A study that examines the way self-efficacy beliefs, organizational and collaborative support, and engagement in data-driven decision-making connect is yet to be discovered in the literature. In addition, prior research suggests there is a need for studies that examine contextual factors affecting data use for instructional decision-making (Farrell, 2015).

The existing body of research on the topic of data-driven decision-making in K-12 education has consistently documented that teachers lack the skills to engage in data-driven decision-making practices. The scant amount of research on school administrators, who are often responsible for creating the conditions for effective data use in schools, provides little insight into their internal processes when it comes to data use in schools. A study that focuses on the self-efficacies of teachers and administrators for engagement in data-driven decision-making behaviors might be beneficial in helping educators get the most out of their experiences with data in schools.

Low self-efficacies among educators could potentially hinder the data-driven decision-making process in schools. While the need for technological, pedagogical, and statistical skills for engagement in data-driven decision-making has been acknowledged in the literature (Dunn Airola, & Lo, 2013), studies that examine the psychological aspect of data-driven decision-making are few in number. A close examination of the organizational and peer structures and supports existing in schools as they relate to educator self-efficacy beliefs would provide insight into educators' psychological relationship to data-driven decision-making. Exploring the relationships among self-efficacy beliefs, organizational and peer support, and engagement in data-driven decision-making will provide direction for ensuring that teachers and administrators have meaningful experiences with data that elevates their practices.

Dunn, Airola, Lo & Garrison (2013) note the need for additional research on the change process for teachers adopting data-driven decision-making practices. Change processes unfold from a changing mindset. It might be productive if the body of literature includes the interaction of psychological processes with organizational factors and peer factors for a complete view of data-driven decision-making in schools. Previous studies have examined organizational factors or self-efficacy beliefs for data-driven decision-making in isolation. The purpose of this study is to add to the body of literature by determining the ways in which self-efficacy beliefs for data-driven decision-making is related to organizational support, peer support, and engagement in data-driven decision-making behavior.

The exploration of beliefs that educators have about their abilities to use data could potentially influence the way administrators approach data use in schools. The present study fills a gap in the research literature by appraising educators' internal views of self-efficacy beliefs for data-driven decision-making. An additional aim of the study is to determine differences in self-efficacies of educators at the elementary, middle, and high school levels of education. Finally, the study aims to determine the extent to which organizational and peer contexts may influence educators' self-efficacy beliefs for data-driven decision-making.

Data-driven decision-making as an educational reform movement has become more prevalent in schools in recent years than in years past. Increased attention to data-driven decision may be attributed to increased accountability demands that school districts and school leaders face. The amount of data available to educators in schools has also increased. While the amount of data have proliferated in recent years, the topic of data-driven decision-making in schools has been a relatively new field of research in education. Few research studies on the topic of data use in schools focus on the psychological aspect of data-driven decision-making among data users. The present study seeks to fill in the gap in the research literature by focusing on self-efficacy beliefs for data-driven decision-making among teachers and school leaders. The study will examine the interplay of organizational support, self-efficacy beliefs, and engagement in data-driven decision-making.

Self-efficacy beliefs has been previously linked to instructional quality in prior research. The present study seeks to examine the relationships among organizational support, self-efficacy beliefs and data-driven decision-making. Results of the study will be used to determine existing differences among self-efficacy beliefs for data-driven decision-making among elementary, middle, and high school teachers. Finally, a goal of the present study is to examine the extent to which self-efficacy beliefs mediates the relationships between organizational support and engagement in data-driven decision-making.

CHAPTER III – METHODOLOGY

Research Questions

The study examined the interplay of organizational support, self-efficacy beliefs, and engagement in data-driven decision-making. Self-efficacy beliefs for data-driven decision making (SEBD^{3}M) was the focus of the present study. Participants responded to items related to four areas of interest: self-efficacy beliefs, organizational support, collaborative support, and engagement in data-driven decision-making. Teachers and administrators gave opinions on existing organizational and collaborative support for engagement in data-driven decision-making in their schools. Participants shared opinions concerning personal self-efficacy beliefs for data-driven decision-making as they relate to their past and present experiences as a classroom teacher or school leader. They responded to items related to their engagement in data-driven decision-making. The following research questions were addressed:

1. What is the relationship between educator self-efficacy beliefs and engagement in data-driven decision-making?
2. Are there significant differences in educator self-efficacy beliefs for using data to inform instructional decisions at the elementary, middle, and high school levels?
3. To what extent do self-efficacy beliefs for data-driven decision-making and culture mediate the relationship between organizational support and engagement in data driven decision-making?

Participants

Potential participants were employed as teachers or administrators in grades K-12 in a school district in central Mississippi. The A-rated school district serves approximately 13,000 students at 23 school sites. Mississippi Department of Education ethnic data on the student population for the 2016-2017 school year indicated that 51.46% of students were Caucasian-American, 39.09% were African-American, and less than 5% each were classified in the following categories: Asian, Hispanic, Native American, Multi-Racial, and Pacific Islander.

District Profile

Voluntary participants in the study included elementary, middle, and high school teachers from one school district. The study also included elementary, middle, and high school building-level and district-level administrators from the school district. Participation was solicited from all school sites in the district via email on the district listserv. The email containing solicitation for participation contained a link to informed consent information prior to completion of the questionnaires. The informed consent information explained that participation in the study was completely voluntary. Individual responses remained anonymous and confidential through all phases of the research study. The results of the study may be shared with faculty through a presentation and may be published in research publications and presented at local and national research conferences. By clicking on the statement of agreement regarding informed consent, voluntary participants gave consent to participation in the study.

Research Design

Procedure

The survey methodology was employed and conducted in both online and paper-based formats. Permission to conduct the study was obtained through submission to the Institutional Review Board at The University of Southern Mississippi. The researcher gained permission from the superintendent of education to solicit participation in a school district in central Mississippi as part of the IRB submission process. Once permission to conduct the study in the school district was granted and IRB approval was obtained, the researcher solicited participation from teachers and administrators via email. Informed consent was included in the link to the questionnaire through the Qualtrics website. The links to the teacher questionnaire and administrator questionnaire were contained in the email soliciting participation in the study. Participants clicked on the link and the initial question contained informed consent. Participants clicked a statement indicating they agreed to informed consent prior to responding to items concerning SEBD^{3}M. For the purposes of this study, administrators included principals, assistant principals, literacy specialists, and district office administrators. Teachers included participants who teacher a grade level or subject area in grades Pre-K through 12.

Data was collected using Qualtrics, a survey hosting site used to store data collected from participants in the study. The data collected from Qualtrics was transferred to SPSS. SPSS was used to analyze the data. A summary of the results of the survey were made available to participants, school district leaders, and in addition to being used in this dissertation, the results of the study may form the basis for research publications and/or research conference presentations in the future.

Instrumentation

Teacher instrument. The instrument for teachers contained 28 items focused on self-efficacy beliefs for data-driven decision-making, organizational support for data use, collaborative support for data use, and engagement in data-driven decision-making. The questionnaire contained multiple response scales. The first section contained a response scale of 1-9 with 1 being "None at All" and 9 being "A Great Deal". The second and third sections of the questionnaire contained response scales with Likert items on a scale of 1 to 5 with 1 being "Strongly Disagree" and 5 being "Strongly Agree". On the fourth section of the questionnaire, the items concerning engagement in data-driven decision-making contained responses indicating frequency with 1 being "Never" and 5 being "Always". Demographic information was collected as part of the questionnaire for identifying trends in the data collected during the study. The questionnaire for teachers was available in online and paper-based formats.

A portion of the items contained in the teacher instrument were originally created for the 3D-MEA Inventory created by Dunn, Airola, Lo, and Garrison (2013). The instrument was previously used for their study focused on measuring the constructs of data-driven decision-making efficacy and anxiety. With permission from the researchers, selected items were modified and used as part of the teacher and administrative questionnaires for the present study. The first section of questions measured teachers' and administrators' beliefs in their ability to engage and use data. The items contained in the second section of the instrument were used to focus on organizational aspects of data use that included the expectations and priorities of school leaders. The third section of the instrument contained items related to collaborative support for data use. The final section of the instrument contained items that gauge educators' self-reported levels of engagement in data-driven decision-making. The following pages provide a detailed explanation of each section of items contained on the teacher measure for this study.

Self-efficacy beliefs for data-driven decision-making. The first section of the questionnaire for teachers included items concerning self-efficacy beliefs for data-driven decision-making behaviors. In items 1-6 of the teacher questionnaire, participants were directed to share their beliefs about their abilities to access, understand, and interpret reports from interim assessments. Participants were directed to share their beliefs about their abilities to determine instructional needs for their students using interim assessment data. Items 1-6 required teachers to select one response from the response scale that ranges from 1-9 with 1 being "None At All" and 9 being "A Great Deal". Table 3.1 includes the items contained in the first section of the teacher questionnaire.

Table 3.1

Items from Teacher Questionnaire

Self-Efficacy Beliefs for Data-Driven Decision-Making
1. How confident are you in your ability to access interim assessment results for your students?
2. How confident are you in your ability to comprehend interim assessment reports?
3. How confident are you in your ability to interpret subtest or strand scores to determine student strengths and weaknesses in a content area?
4. How confident are you in your ability to use data to identify gaps in student mastery of curricular concepts?
5. How confident are you in your ability to use data to group students with similar learning needs for instruction?
6. How confident are you in your ability to use data to guide your selection of targeted interventions for gaps in student understanding?

Organizational support for data use. The second section of the teacher questionnaire included items related to organizational support for data use. Items 7-12 were related to existing expectations for data use in their experiences as teachers. For these items, participants selected one response from the Likert response concerning existing expectations for data use in their experiences as teachers. The items also prompted participants to reflect on opportunities to engage in data-driven decision-making as well as existing structures and routines surrounding data-driven decision-making in their schools. The response scale for this section of the instrument contained Likert responses with 1 being “Strongly Disagree” and 5 being “Strongly Agree”. Table 3.2 includes items related to organizational support for data use from the teacher questionnaire.

Table 3.2

Items from Teacher Questionnaire

Organizational Support for Data Use
7. There is an expectation in my school that I analyze interim assessment data.
8. There is an expectation in my school that I use interim assessment data to inform my instructional decisions in the classroom.
9. There is a culture of trust among my grade level or department when it comes to discussions about the results of interim assessment data.
10. I take advantage of opportunities to meet with my colleagues to discuss the results of interim assessment data.
11. Discussions about interim assessment data occur in a small group setting in my school.
12. I have received training on how to analyze and interpret my interim assessment data.

Collaborative support for data use. The third section of the teacher questionnaire included items related to collaborative support for data use. These items prompted participants to reflect on collaboration with fellow teachers surrounding data use in their current teacher experiences. For items 13-17, participants indicated their levels of agreement concerning collaboration with colleagues using interim assessment data in their schools. The response scale for this section of the instrument contained

Likert responses with 1 being "Strongly Disagree" and 5 being "Strongly Agree". Table 3.3 includes the items included in section three of the teacher questionnaire.

Table 3.3

Items from Teacher Questionnaire

Collaborative Support for Data Use
13. I analyze interim assessment data with my fellow teachers in my department.
14. I interpret interim assessment data with my fellow teachers in my department.
15. My fellow teachers share ideas about how they are using interim assessment data in their individual classrooms.
16. My fellow teachers generally have a positive outlook on interim assessment data collection in our school.
17. My fellow teachers generally support the idea of using interim assessment data to inform instructional decision-making.

Engagement in data-driven decision-making. The fourth section of the teacher questionnaire included items that prompted participants to reflect on engagement in data-driven decision-making. Item responses in this section of the questionnaire were related to the frequency with which participants engage in activities related to data-driven decision-making. Self-reported responses concerning frequencies of engagement in data-driven decision-making behaviors were solicited in items 18-22. The response scale for this section of the instrument ranged from "Never" to "Always". Table 3.4 below includes items related to engagement in data-driven decision-making.

Table 3.4

Items from Teacher Questionnaire

Engagement in Data-Driven Decision-making
18. I use interim assessment data to provide targeted feedback to my students about their performance.
19. I analyze interim assessment data to group my students based on strengths and weaknesses.
20. I analyze interim assessment data to remediate standards that my class did not master.

Table 3.4 Continued

21. I analyze interim assessment data to enrich standards that my students have already mastered.
22. I make changes in instructional pacing based on student performance on interim assessments.

Demographic information. The final section of the teacher questionnaire included items concerning demographic data. Items contained in the demographic section of the instrument included: gender, ethnicity, years of teaching experience, grade level, and Title I status. Appendix B includes items related to demographic data of teachers in the study.

Administrator instrument. The instrument for administrators contained 28 items focused on self-efficacy beliefs for data-driven decision-making, organizational support for data use, collaborative support for data use, and engagement in data-driven decision-making. The questionnaire contained multiple response scales. The first section contained a response scale of 1-9 with 1 being "None at All" and 9 being "A Great Deal". The second and third sections of the questionnaire contained response scales with Likert items on a scale of 1 to 5 with 1 being "Strongly Disagree" and 5 being "Strongly Agree". On the fourth section of the questionnaire, the items concerning engagement in data-driven decision-making contained responses indicating frequency with 1 being "Never" and 5 being "Always". Demographic information was collected as part of the questionnaire for identifying trends in the data collected during the study. The questionnaire for administrators was available in online and paper-based formats.

Items for the administrative questionnaires were developed by the researcher. A portion of the items contained on the administrative scale instrument were originally created for the 3D-MEA Inventory. The instrument was used for data collection in a previous study conducted by Dunn, Airola, Lo, and Garrision (2013). With permission from the researchers and some modifications to the items, a portion of the items were used for developing the administrator questionnaire. Questionnaire items focused on $SEBD^3M$ gauged administrators' opinions about what they individually believe they can do with data. The items contained in the second section of the instrument were used to focus on organizational aspects of data use. Collaborative support for data use was the focus of the third section of the administrative questionnaire. The final section of the instrument contained items that gauged administrators' self-reported levels of engagement in data-driven decision-making. The following section provides a detailed explanation of each section of items contained on the administrative questionnaire for this study.

Self-efficacy beliefs for data-driven decision-making. The first section of the questionnaire for administrators included items concerning self-efficacy beliefs for data-driven decision-making behaviors. For items 1-6 of the administrative questionnaire, participants were directed to share their beliefs about their abilities to access, understand, and interpret reports from interim assessments. Participants were also directed to share their beliefs about their abilities to determine instructional needs for their schools using interim assessment data. Items 1-6 required administrators to select one response from the response scale that ranges from 1-9 with 1 being "None At All" and 9 being "A Great Deal". Table 3.5 includes the items contained in the first section of the questionnaire for administrators.

Table 3.5

Table 3.5 Continued

Items from Administrator Questionnaire

Self-efficacy beliefs for Data-Driven Decision-making
1. How confident are you in your ability to access interim assessment results for your school?
2. How confident are you in your ability to understand interim assessment reports for your school?
3. How confident are you in your ability to interpret subtest or strand scores to determine overall strengths and weaknesses in a given subject area at your school?
4. How confident are you in your ability to use data to identify gaps in student understanding of curricular concepts for each subject area?
5. How confident are you in your ability to use data to set academic goals for your school?
6. How confident are you in your ability to use data to guide your selection of instructional resources and materials for targeted interventions to address gaps in student understanding?

Organizational support for data use. The second section of the administrator questionnaire included items related to organizational support for data use. Items 7-12 prompted participants to reflect on existing expectations for data use in their experiences as administrators in their school district. The items also prompted participants to reflect on opportunities to engage in data-driven decision-making as well as structures and routines surrounding data-driven decision-making in their schools. The response scale for this section of the instrument contained Likert responses with 1 being “Strongly Disagree” and 5 being “Strongly Agree”. Table 3.6 includes items related to organizational support for data use from the administrator questionnaire.

Table 3.6

Items from Administrator Questionnaire

Organizational Support for Data Use
7. I expect teachers in my school to interpret interim assessment data.
8. I expect teachers in my school to use interim assessment data to inform instructional decisions in their classrooms.

Table 3.6 Continued

9. I emphasize the importance of data to inform instructional decisions to my teachers and staff.
10. There is a culture of trust among grade levels when it comes to discussions about the results of interim assessment data.
11. I provide teachers with opportunities to discuss the results of interim assessment data with their colleagues.
12. Discussions about interim assessment data occur in a small group setting in my school.
13. I have received training on how to analyze and interpret interim assessment data.

Collaborative support for data use. The third section of the administrator questionnaire included items related to collaborative support for data use. These items prompted participants to reflect on collaboration with fellow administrators surrounding data use in their current roles as school leaders. For items 14-17, participants indicated their levels of agreement concerning collaboration with colleagues using interim assessment data in their schools. The response scale for this section of the instrument contained Likert responses with 1 being "Strongly Disagree" and 5 being "Strongly Agree". Table 3.7 includes the items included in section three of the administrator questionnaire.

Table 3.7

Items from Administrator Questionnaire

Collaborative Support for Data Use
14. My fellow administrators generally have a positive outlook on interim assessment data collection in our schools.
15. My fellow administrators generally support the idea of using interim assessment data to inform instructional decision-making.
16. I analyze the results of interim assessment data with other school leaders in my school.
17. I interpret the results of interim assessment data with other school leaders in my school.

Engagement in data-driven decision-making. The fourth section of the administrator questionnaire included items that ask participants to reflect on engagement in data-driven decision-making. Item responses in this section of the questionnaire were related to the frequency with which participants engage in activities related to data-driven decision-making. Self-reported responses concerning frequencies of engagement in data-driven decision-making behaviors were solicited in items 18-22. The response scale for this section of the instrument ranged from "Never" to "Always". Table 3.8 below includes items related to engagement in data-driven decision-making for administrators.

Table 3.8

Items from Administrator Questionnaire

Engagement in Data-Driven Decision-making
18. I use interim assessment data to provide targeted feedback to my teachers about their performance.
19. I analyze interim assessment data to identify school-wide strengths and weaknesses.
20. I analyze interim assessment data to make decisions related to personnel.
21. I analyze interim assessment data to determine professional development activities for teachers at my school.
22. I use interim assessment data to recognize student growth in proficiency levels.

Demographic information. The final section of the administrator questionnaire included items concerning demographic data. Items contained in the demographic section of the instrument included: gender, ethnicity, years of teaching experience, grade level, and Title I status. Appendix C includes items related to demographic data of administrators in the study.

Data Collection

Prior to data collection, a pilot study was conducted to assess the reliability and validity of the instruments. The types of validity that both questionnaires were assessed for include face validity and content validity. Internal consistency reliability was checked using a statistical method, *Cronbach's alpha*, in SPSS. The instruments were emailed to participants who agreed to participation in the pilot study. The instruments contained items from previously developed instruments and items created by the researcher. The pilot study was conducted with voluntary participation from teachers and administrators outside of the school district containing the participant sample this study. Items on the teacher and administrator instruments were revised based on feedback from the pilot study participants.

During a two-week window, November 30, 2017 through December 8, 2017, questionnaires were available through Qualtrics, the survey hosting site, for voluntary participants to complete the survey. Participation was solicited via email on the district listserv. The researcher solicited participation from teachers and administrators using an email containing information concerning informed consent and a link to complete the online version of the questionnaire. One link included the teacher instrument, and the other link included the administrator instrument. By clicking on the link to the teacher or administrator questionnaire, voluntary participants were redirected to informed consent and the questionnaire items. Paper-based versions of the questionnaires were also available upon request as an option for teachers and administrators in the district.

Data Analysis

Prior to conducting the data analysis, the data was cleaned beginning with a visual inspection of the data for missing values. The multiple imputation method was used to address missing data through the software program, Statistical Package for Social Sciences (SPSS) (IBM Corp., 2016). An *MCAR* analysis was conducted on the teacher sample to determine if data were missing completely at random. The results of Little's *MCAR* test were $X^2 = 150.902$, $DF = 148$, $p = .418$. A non-significant result during the *MCAR* analysis provided evidence that the data points were missing completely at random. The multiple imputation method was used to deal with missing data points in SPSS. After imputing missing values, data was transferred to AMOS for *SEM* Analysis.

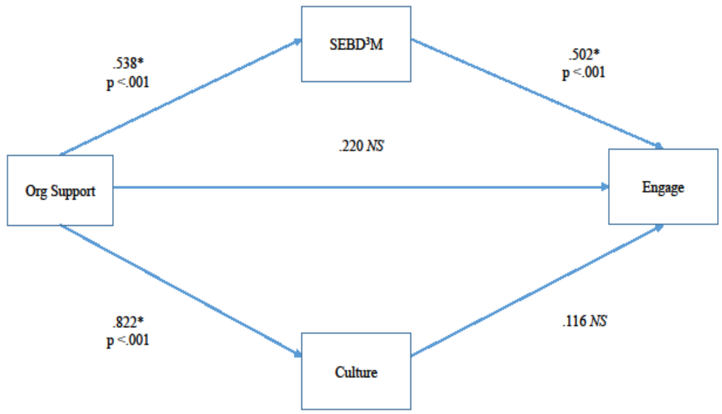
An overview of the data collected including tables containing summaries of the demographic data information and averages for each item on the teacher and administrator questionnaires were generated. The researcher also generated histograms for each item of the teacher and administrator questionnaires. The researcher visually inspected the histograms for any patterns, trends, or outliers in the data.

Data collected in the survey were analyzed using SPSS (IBM Corp., 2016). Multiple analyses were run using SPSS (IBM Corp., 2016) for the preliminary analysis of the data. Demographic data and an item analysis were conducted during the preliminary analysis of data to determine patterns or trends in the data. To address each of the research questions in the study, a Structural Equation Model (SEM) was used. The *SEM* analysis was conducted through the software program, MPlus (Muthén & Muthén, 1998-2017).

Structural Equation Modeling was used to determine how well the proposed fit the observed data collected from participants in the study. *SEM* is a technique that is suitable for use with large sample size of teachers that may be obtained during the study. This technique allowed the researcher to examine the fit *a priori*. An *Exploratory Factor Analysis* (*EFA*) was conducted to determine the factor structure for the model prior to testing the structural model.

The present structural equation model was developed to examine the latent variable—self efficacy. The model was used to test the effects of predictors on self-efficacy beliefs and culture as mediators. The relationships among organizational support, the mediators, and the dependent variable of engagement in data-driven decision-making were examined. The mediators and predictors included in the model emerged during a literature review of existing research on the topic of SEBD^{3}M. The theoretical model was developed based on themes that emerged during the literature review on the topic. It was predicted that there was a direct relationship between organizational support and SEBD3M, and a direct relationship between SEBD3M and engagement in data-driven decision-making. It was predicted that there was a direct relationship between organizational support and culture. It was predicted that there was a direct relationship between culture and engagement. The *SEM* model is pictured below in Figure 2.

Figure 2. *SEM* Model with Mediation



In the *SEM* model above, averages of scores on the items related to each variable were used to represent the latent variable. SEBD^{3}M was a mediator for organizational support and engagement in data-driven decision-making. Items contained in two sections of the instrument, organizational support for data-driven decision-making and collaborative support for data-driven decision-making, included items concerning expectations and beliefs from organizational and collaborative standpoints. These items related to beliefs and expectations are collectively represented in the model as culture, which was a mediator for organizational support and engagement in data-driven decision-making. “Collaborative support” was initially included in the model, however, this variable was removed from the model during the *EFA* due to a lack of items remaining after item elimination to capture the construct “collaborative support” on the teacher instrument.

Structural equation modeling allowed the researcher to test the hypotheses concerning predictive relationships among variables in the data. After data were collected, the original model was compared to the data collected in the study. The *SEM* analysis was conducted using MPlus software (Muthén & Muthén, 1998-2017). The proposed model was compared to the data to determine the fit or match between the hypothesized model and the observed data. Fit was determine using the *Comparative Fit Index* (*CFI*) and *Tucker Lewis Index (TLI)* as indicators. Values that were closer to 1 for the *CFI* and *TLI* indicated a better "fit" of the model to the data. The *Root Mean Square Error of Approximation* (*RMSEA*) was an indicator that was analyzed to determine the fit of the model. *RMSEA* values that were equal to or between 0.08-0.10 indicate a good "fit" of the model to the data. To test the mediation of the model, the bootstrapping method was used. Bootstrapping was a nonparametric procedure that allowed the researcher to test mediation in the absence of a normal distribution of data (Preacher and Hayes, 2008). After determining the "fit" of the data to the model, the proposed model was retained for discussion of implications of the model.

CHAPTER IV– RESULTS

Participants

A convenience sampling method was used to solicit participation from teachers and administrators for the study. The sample included teachers and administrators from one district in central Mississippi. The district is made up of 23 school sites ranging from Pre-K through 12th grade. All participants completed the questionnaires online through the survey hosting site, Qualtrics. The teacher questionnaire was completed by 232 participants, and the administrator questionnaire was completed by 44 participants. The response rate for teacher participants in the study was 22%, and the response rate for administrator participants in the study was 53%.

There were two samples for the study. The sample of teachers included in the study consisted of 23 male participants and 182 female participants. The ethnic makeup of the sample of teachers included: 13.8% African-Americans, 69.8% Caucasian Americans, 1.7% Hispanic Americans, and 3% identifying as Other. Additional demographic information gathered during the study included years of teaching experience, grade level taught, and Title I status. See Table 4.1 below for demographic information of teacher participants who participated in the study.

Table 4.1

Demographic Information for Teacher Sample

Demographic Information	Frequency	Percent
Gender		
Male	23	9.9
Female	182	78.4
Other	0	0
Missing	27	11.6
Total	232	100

Table 4.1 Continued

Demographic Information for Teacher Sample

Ethnicity		
African-American	32	13.8
Caucasian American	162	69.8
Hispanic American	4	1.7
Other	7	3.0
Missing	27	11.6
Total	232	100
Years of Teaching Experience		
0-2 years	11	4.7
3-5 years	26	11.2
6-10 years	48	20.7
11-15 years	48	20.7
16 years and above	74	31.9
Missing	25	10.8
Total	232	100
Grade Level		
Elementary	100	43.1
Middle	58	25.0
High School	49	21.1
Missing	25	10.8
Total	232	100
Title I Status		
Title I	55	23.7
Non-Title I	150	64.7
Missing	27	11.6
Total	232	100

The sample of administrators in the study consisted of 12 male participants and 26 female participants. The ethnic makeup of the sample of administrators included 30% African-Americans and 56% Caucasian Americans. Six participants did not identify an ethnicity in the study. Additional demographic information gathered during the study included years of administrative experience, grade level taught, and Title I status.

Demographic information participants in administrative sample are included in Table 4.2 below.

Table 4.2

Demographic Information for Administrator Sample

Demographic Information	Frequency	Percent
Gender		
Male	12	27
Female	26	59
Other	0	0
Missing	6	14
Total	44	100
Ethnicity		
African-American	13	30
Caucasian American	25	56
Hispanic American	0	0
Asian American	0	0
Missing	6	14
Total	44	100
Years of Administrative Experience		
0-2 years	6	14
3-5 years	9	20
6-10 years	11	25
11-15 years	5	11
16 years and above	7	16
Missing	6	14
Total	44	100
Grade Level		
Elementary	21	48
Middle	7	16
High School	9	20
Missing	7	16
Total	44	100
Title I Status		
Title I	12	27
Non-Title I	26	59
Missing	6	14
Total	44	100

Instruments

Two instruments were developed and used for this study. See Appendix B for the teacher instrument. See Appendix C for the administrator instrument. Both instruments included five sections: self-efficacy beliefs for data-driven decision-making, organizational support for data use, collaborative support for data use, engagement in data-driven decision-making, and demographic information. The first section, self-efficacy beliefs for data-driven decision-making, included six items focused on self-efficacy beliefs for data-driven decision-making (SEBD^{3}M) with a 9-point confidence scale. The second section, organizational support for data use, included six items concerning structures, systems, and routines for data use. The second section of both instruments used a Likert response scale of agreement.

The third section of the instrument, collaborative support for data use, included items that focused on the collaborative aspect of SEBD^{3}M. A Likert response scale of agreement was also used for the third section of the instruments. The fourth section of the instrument contained items that focused on engagement in data-driven decision-making. The response scale for the fourth section included a five-point frequency scale ranging from “Never” to “Always”. Categories included in the demographic section of each instrument were: gender, ethnicity, years of teaching or administrative experience, grade level, and Title I status.

Pilot Study and Reliability Analysis

A pilot study was conducted to determine reliability of the instruments and determine the factors to be included on the final instrument. Feedback provided from participants in the pilot study helped improve the format of the instrument. The sample used for the pilot study consisted of 19 teachers and 10 administrators from various school districts across the state. The teachers and administrators who participated in the pilot study were from districts that were excluded from the sample included in the research study.

A visual inspection of the data from the pilot study involving the teacher sample revealed missing data points. A Missing Completely At Random (*MCAR*) analysis was conducted to determine if data were missing completely at random. The results of Little's *MCAR* test were $x^2 = 43.628$, $df = 50$, $p = .725$. This non-significant result for the *MCAR* analysis provided evidence to support the idea that the data points were missing completely at random. The multiple imputation method was used to deal with missing data points in SPSS. After imputing missing values, internal consistency reliability of the questionnaire items was determined by analyzing the *Cronbach alpha coefficients*. The *Cronbach's alpha coefficient* for the first section related to SEBD^{3}M for teachers was .890. The *Cronbach's alpha coefficient* for items in the second and third sections of the teacher instrument, organizational support and collaborative support, was .934 for items 8-18. For the final section related to engagement in data-driven decision-making for teachers, the *Cronbach's alpha coefficient* was .934.

A visual inspection of the data in the pilot study involving the administrator sample revealed missing data points for one participant. The multiple imputation method was used to deal with missing data points in SPSS. After imputing missing values, internal consistency reliability of the administrator questionnaire items was determined by analyzing the *Cronbach alpha coefficients*. The *Cronbach's alpha coefficient* for items 2-7 related to SEBD^{3}M was .946. The *Cronbach's alpha coefficient* for items related to organizational support and collaborative support was .914 for items 8-18. For items 19-23 related to engagement in data-driven decision-making, the *Cronbach's alpha coefficient* was .907.

An internal consistency reliability analysis was conducted on the teacher instrument used in the survey. The *Cronbach's alpha coefficient* for the entire teacher instrument was .922. The results of the EFA revealed that there were three factors present on the teacher instrument. A visual inspection of the scree plot provided additional evidence to support the presence of three factors on the teacher instrument. Bartlett's Test of Sphericity was statistically significant with $p < .001$. Item correlations ranged from .774 to -.575. A summary of the means and standard deviations for the first section of the instrument related to SEBD^{3}M are included in table 4.3 below.

Table 4.3

Means and Standard Deviations for Teacher Instrument Items Related to SEBD^{3}M

Items	M	SD
6. Confidence in ability to use data to group students for instruction	7.08	1.626
5. Confidence in ability to identify gaps in student mastery	6.77	1.717
7. Confidence in ability to guide selection of targeted interventions	6.70	1.723
3. Confidence in ability to comprehend results	6.66	1.856
2. Confidence in accessing results	6.63	1.924
4. Confidence in ability to interpret subtest or strand scores	6.61	1.759

The highest mean in the section related to SEBD^{3}M was item 6—"confidence in ability to use data to group students for instruction" (M = 7.08, SD = 1.626. The lowest mean for items related to SEBD^{3}M for the teacher sample in the study was for the item focused on interpretation of score reports (M = 6.61, SD = 1.759). For the second and third sections of the teacher instrument, a Likert response scale was used. The items in the two sections that contained Likert response scales focused on organizational support and collaborative support. Notably, the highest means in these two sections related to existing expectations that teachers analyze data on item 8 and use data to inform instructional decisions on item 9, respectively (M = 4.25, SD = .855, M = 4.25, SD = .900). Items related to existing expectations concerning data use are included in the proposed model as "culture". The lowest mean was on item 17, "My fellow teachers generally have a positive outlook on interim assessment data collection in our school" (M = 3.52, SD = .941). See Table 4.4 below for a summary of the means and standard deviations items related to organizational support and collaborative support.

Table 4.4

Means and Standard Deviations for Teacher Instrument Items Related to Organizational Support and Collaborative Support

Items	M	SD
8. Expectation in my school that I analyze data	4.25	.855
9. Expectation in my school that I use data to inform instructional decisions	4.25	.900

Table 4.4 Continued

10. Culture of trust among my grade level/department when it comes to data	4.08	.966
11. I take advantage of meeting with colleagues to discuss results	3.92	.968
18. My fellow teachers generally support using data to inform decisions	3.72	.821
15. I interpret interim assessment data with colleagues	3.71	1.085
14. I analyze interim assessment data with colleagues	3.70	1.111
13. I have received training on how to analyze and interpret my data	3.64	1.152
16. My fellow teachers share ideas about how they are using data	3.59	1.123
17. My fellow teachers generally have a positive outlook on data collection	3.52	.941

The final section of the teacher questionnaire was related to engagement in data-driven decision-making. For items, 19-23, participants responded to items concerning the frequency with which they engage in data-driven decision-making behaviors. Item 21, "I analyze interim assessment data to remediate standards that my class did not master", had the highest mean among teacher participants (M = 3.76, SD = .995). A summary of the means and standard deviations for these items is in Table 4.5 below.

Table 4.5

Means and Standard Deviation for Teacher Instrument Items Related to Engagement in Data-Driven Decision-making

Table 4.5 Continued

Items	M	SD
19. Use interim assessment data to provide targeted feedback	3.42	.993
20. Analyze interim assessment data to group students	3.53	.986
21. Analyze interim assessment data to remediate standards	3.76	.995
22. Analyze interim assessment data to enrich standards	3.42	.995
23. Make changes in pacing based on student performance	3.74	1.020

Exploratory Factor Analysis

An *Exploratory Factor Analysis* (*EFA*) was conducted on the teacher sample in the study using SPSS. Prior to conducting the *EFA*, an *MCAR* analysis on the teacher sample revealed that the data were missing completely at random. The multiple imputation method was used to deal with missing data in the teacher sample prior to conducting the *EFA*. An *EFA* was used to determine the factor structure of the instrument. Principal axis factoring with a direct oblimin rotation was used for the analysis.

The *EFA* was initially conducted using 22 items of the teacher instrument. An analysis of the factor loadings on each item revealed double loadings for four items. The criteria for double loadings included items that loaded at .4 or higher on more than one factor. The four items were excluded from the analysis in an attempt to achieve a simple structure. The following items were excluded from the analysis due to double loadings: "How confident are you in your ability to comprehend interim assessment reports?";

“There is a culture of trust among my grade level or department when it comes to discussions about the results of interim assessment data.”; “My fellow teachers generally have a positive outlook on interim assessment data collection in our school.”; “My fellow teachers generally support the idea of using interim assessment data to inform instructional decision-making.” One of these items was removed from the SEBD^{3}M section of the teacher instrument. One item was removed from the organizational support section of the teacher instrument. The remaining 2 items were removed from the collaborative support section of the teacher instrument.

The 18 remaining items were used to determine the potential factors on the instrument. In the first section related to SEBD^{3}M, there were 5 items remaining after the *EFA*. In the second section, organizational support, there were 5 items remaining after the EFA. In the third section, collaborative support, there were 3 items remaining after 2 items were eliminated from the section. All 5 items in the final section, engagement in data-driven decision-making, were retained for further analysis.

Based on a review of the literature and previously developed instruments related to data-driven decision-making, it appeared the three factors of the instrument could be related to self-efficacy beliefs, organizational support, and engagement. The first factor consisted of the items related to individual self-efficacy beliefs concerning data use. A second factor related to engagement in data driven behaviors such as analyzing, remediating, and adjusting the pace of instruction in the classroom. The third component extracted during the analysis collectively referred to elements of organization support. These items related to scheduling, routines, and processes related to data-driven decision-making. The principal axis factoring matrix with factor loadings is included in Table 4.6 depicted below.

Table 4.6

Factor Loadings for Exploratory Factor Analysis with Direct Oblimin Rotation—Teacher Instrument

Items	SEBD^{3}M	Organizational Support	Engagement
2. Confidence in accessing results	**.530**		
4. Confidence in ability to interpret subtest or strand scores	**.734**		
5. Confidence in ability to identify gaps in student mastery	**.806**		
6. Confidence in ability to use data to group students for instruction	**.841**		
7. Confidence in ability to guide selection of targeted interventions	**.947**		
8. Expectation in my school that I analyze data		**.502**	
9. Expectation in my school that I use data to inform instructional decisions		**.584**	

Table 4.6 Continued

11. I take advantage of meeting with colleagues to discuss results		**.756**	
12. Discussions about results take place in a small group setting in my school		**.792**	
13. I have received training on how to analyze and interpret my data	**.466**	**.413**	
14. I analyze interim assessment data with colleagues		**.875**	
15. I interpret interim assessment data with colleagues		**.876**	
16. My fellow teachers share ideas about how they are using data		**.780**	
19. Use interim assessment data to provide targeted feedback			**-.617**
20. Analyze interim assessment data to group students			**-.707**
21. Analyze interim assessment data to remediate standards			**-.823**
22. Analyze interim assessment data to enrich standards			**-.857**
23. Make changes in pacing based on student			**-.814**

performance

Note. Values <.4 were suppressed during the analysis. Factor loadings for each item are in boldface.

Evidence from the scree plot and Eigenvalues greater than 1.0 generated during the analysis supported the presence of three factors on the teacher instrument. Collaborative support was removed from the proposed model due to a lack of items to capture the construct for analysis. The three factors appeared to be related to self-efficacy beliefs concerning data-driven decision-making, organizational support for data-driven decision-making, and engagement in data-driven decision-making, respectively. A summary of the alpha coefficients for each factor are included in Table 4.7 below.

Table 4.7

Alpha Coefficients for Factors on Teacher Instrument

Factor	Cronbach's alpha Coefficient
SEBD^{3}M	α = .906
Organizational Support	α = .844
Engagement	α = .910

The table above includes Cronbach's alpha coefficients for each of the factors on the instrument. A factor score correlation matrix was generated during the analysis to determine correlations among the factors. There were moderate correlations among

SEBD^{3}M, organizational support, and engagement. The factor score correlation matrix is summarized in Table 4.8 below.

Table 4.8

Factor Score Correlation Matrix for Teacher Instrument

Factor	SEBD^{3}M	Organizational Support	Engagement
SEBD^{3}M	1.000	.452	-.577
Organizational Support	.452	1.000	-.484
Engagement	-.577	-.484	1.000

Reliability Analysis of Administrator Instrument

An internal consistency reliability analysis was conducted on the administrator instrument used in the survey. The *Cronbach's alpha coefficient* for the entire administrator instrument was .878. A summary of the means and standard deviations for the first section of the administrator instrument related to SEBD^{3}M are included in table 4.7 below.

Table 4.7

Means and Standard Deviation for Administrator Instrument Items Related to SEBD^{3}M

Items	M	SD

Table 4.7 Continued

Confidence in accessing results	8.14	1.241
Confidence in ability to comprehend results	7.93	1.135
Confidence in ability to interpret subtest or strand scores	7.83	1.181
Confidence in ability to identify gaps in student mastery	7.52	1.330
Confidence in ability to use data set academic goals for school	7.83	1.267
Confidence in ability to guide selection of instructional resources	7.55	1.329

The highest mean in the section related to SEBD^{3}M was item 2—"confidence in ability to comprehend results" (M = 8.14, SD = 1.241). The lowest mean for items related to SEBD^{3}M for the administrator sample in the study was for the item focused on identifying gaps in student mastery (M = 7.52, SD = 1.330). For the second and third sections of the administrator instrument, a Likert response scale was used. The items in the two sections focused on organizational support and collaborative support. Notably, the highest mean in these two sections related to administrators' expectations for teachers to use interim assessment data to inform instructional decisions on item 9 (M = 4.77, SD = .423). The lowest mean for administrators in these sections of the instrument related to support was on item 11, "There is a culture of trust among grade levels/departments when it comes to discussions about the results of interim assessment data" (M = 4.03, SD = .873). See Table 4.8 below for a summary of the means and standard deviations items related to organizational support and collaborative support for administrators.

Table 4.8

Means and Standard Deviation for Administrator Instrument Items Related to Organizational Support and Collaborative Support

Items	M	SD
I expect teachers to analyze interim assessment data	4.75	.439
I expect teachers to use interim assessment data to inform decisions	4.77	.423
I emphasize the importance of using data to teachers and staff	4.73	.452
There is a culture of trust among grade levels/depts. when it comes to data	4.03	.873
I provide teachers with opportunities to discuss results with colleagues	4.52	.679
Discussions about interim assessment data occur in a small group setting	4.52	.679
I have received training on analyzing and interpreting data	4.20	.939
My fellow administrators generally have a positive outlook on data collection	4.13	.615
My fellow administrators generally support using data to inform decisions	4.28	.605
I analyze the results of interim assessment data with other school leaders	4.21	.833
I interpret the results of interim assessment data with other school leaders	4.26	.785

The final section of the administrator questionnaire was related to engagement in data-driven decision-making. For the items in the final section of the instrument, participants responded to items concerning the frequency with which they engage in data-driven decision-making behaviors. Item 20, “I analyze interim assessment data identify school-wide strengths and weaknesses", had the highest mean among administrator participants (M = 4.54, SD = .600). The item, "I analyze interim assessment data to make decisions related to personnel" had the lowest mean (M = 3.89, SD = .764). A summary of the means and standard deviations for these items is in Table 4.9 below.

Table 4.9

Means and Standard Deviation for Administrator Instrument Items Related to Engagement in Data-Driven Decision-Making

Items	M	SD
Use interim assessment data to provide targeted feedback to teachers	4.23	.706
Analyze interim assessment data to identify strengths and weaknesses	4.54	.600
Analyze interim assessment data to make decisions related to personnel	3.89	.764
Use interim assessment data to determine professional development	4.32	.702
Use interim assessment data to recognize student growth in proficiency	4.51	.601

Validity

The instruments were assessed for content validity and construct validity. The content of the instrument relates to the variables of interest in the study as they are presented in research literature related to SEBD^{3}M. A portion of the questionnaire items were derived from existing instruments that have previously been determined to be reliable and valid. Additional questionnaire items were developed by the researcher based on an extensive review of the research literature on the topic.

Pearson r Correlation for Administrator Sample

To address the first aim of the study using the administrator sample, a Pearson r correlation matrix was generated. Correlations were examined for relationships between SEBD^{3}M and engagement in data-driven decision-making for administrators in the sample. The results of the analysis revealed a moderate correlation between SEBD^{3}M and engagement in data-driven decision-making (r =.595) that was statistically significant (p <.001). The correlation matrix is pictured below in Table 4.10.

Table 4.10

Correlation Matrix for Administrative Instrument

Pearson r Correlation	SEBD^{3}M	Engagement
SEBD^{3}M	1.000	.595*
Engagement	.595*	1.000

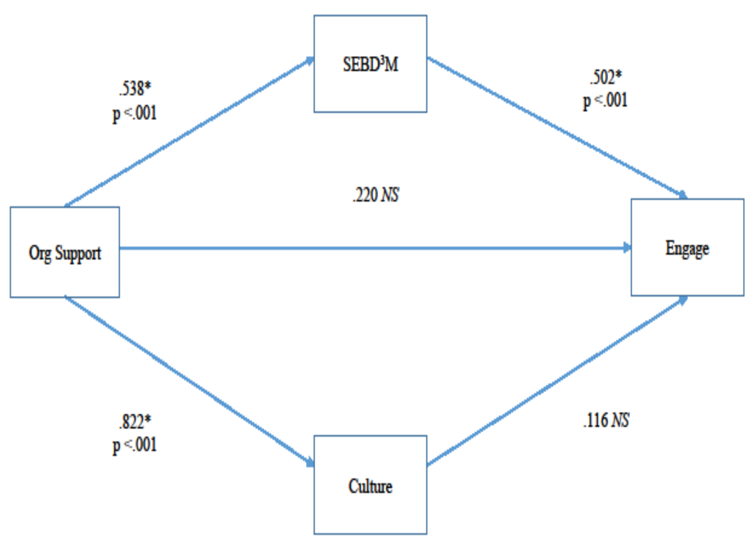
Note. An asterisk* denotes a statistically significant correlation of p <.001.

Results of *SEM* Analysis

An *SEM* analysis was conducted to address the three aims of the study using the teacher sample. The *SEM* analysis was conducted to determine the relationship between SEBD^{3}M and engagement in data-driven decision-making and to determine the extent to which SEBD^{3}M and culture mediate the relationship between organizational support and engagement in data-driven decision-making. The model pictured below was developed to assess the direct and indirect effects of the average scale scores of items related to "organizational support", "SEBD^{3}M", and "culture" on "engagement in data-driven decision-making". Each average scale score in the model was measured by three to five indicators per average scale score. First, it was predicted that "engagement" was predicted by "SEBD^{3}M" and "culture". The second prediction was that "SEBD^{3}M" and "culture" were predicted by organizational support. A diagram of the SEM model with beta coefficients for each path is pictured in figure 3 below.

Figure 3

Diagram of SEM Model with Beta Coefficients



Note: An asterisk* denotes a path with a significance value of p <.001.

Indicators of "organizational support" included opportunities to meet to discuss interim assessment data, small group discussions on data, and training on analyzing and interpreting data. Indicators of "SEBD^{3}M" included participants' confidence levels in accessing, analyzing, interpreting, and using data to inform instructional decisions. Indicators of "culture" included expectations for data use, shared beliefs about data, and support of the idea of using data to inform instructional decision-making. Indicators of "engagement in data-driven decision-making" include using interim assessment data to group students, remediate and enrich instruction, and adjust pacing at the classroom level.

The results of the *SEM* analysis revealed a statistically significant Chi square test χ^2 (3, n = 206) = 10.809, p = .013). There were 3 degrees of freedom in the freely estimated model with a comparative fit index (CFI) of .979 and a Tucker Lewis index (TLI) of .875. The root mean square error of approximation (RMSEA) was .113 with a 90% confidence interval of .46 to .189. The results of the constrained model for the teacher sample revealed a statistically significant Chi square test χ^2 (13, n = 206) = 28.840, p = .007). There were 13 degrees of freedom in the constrained model with a CFI of .958 and a TLI of .941. The RMSEA was .077 with a 90% confidence interval of .039 to .116.

A Chi square difference test was conducted to determine if the fit of the model was significantly worse when compared to the critical value. The Chi square critical value at 3 degrees of freedom is 7.815. The fit of the model did become significantly worse when compared to the critical value. Therefore, the freely estimated model was retained for further analysis and interpretation. Table 4.11 below contains a summary of the freely estimated and constrained *SEM* models with path analysis information for elementary, middle, and high school participant groups.

Table 4.11

Summary of *SEM* Models and Path Analysis Information for Teacher Groups

Model	df	Chi square value	Change in Chi square	CFI	TLI	RMSEA
Freely estimated	3	10.809		.979	.875	.113
Constrained	13	28.840	21.025	.958	.941	.077
b1 e v m	4	14.432	3.623	.972	.875	.113
b1 e v h	4	15.269	4.46	.970	.865	.118
b1 m v h	4	10.908	.099	.982	.917	.092
b2 e v m	4	13.356	2.547	.975	.888	.107
b2 e v h	4	10.815	.006	.982	.918	.092
b2 m v h	4	12.923	2.114	.976	.893	.105
b3 e v m	4	11.092	.283	.981	.915	.093
b3 e v h	4	10.848	.039	.982	.918	.092
b3 m v h	4	10.871	.062	.982	.917	.092
b4 e v m	4	13.445	2.636	.975	.887	.108
b4 e v h	4	11.164	.355	.981	.914	.094
b4 m v h	4	14.067	3.258	.973	.879	.111
b5 e v m	4	19.492	8.683*	.959	.814	.138
b5 e v h	4	12.953	2.144	.976	.892	.105
b5 m v h	4	11.850	1.041	.979	.906	.098

Note. e = elementary, m = middle, and h = high. An asterisk* denotes a statistically significant difference between teacher groups for the specified path.

Results of Invariance Testing

An analysis of each path in the model was conducted to examine differences among groups of teachers in the sample. Comparisons were made among elementary, middle, and high school participants on the five paths in the model. There was a difference in culture as a predictor of engagement in data-driven decision-making when elementary teachers were compared to middle school teachers for the sample in the present study. A summary of the significance values and standardized coefficients for each path is included in table 4.12 below.

Table 4.12

Summary of Standardized Coefficients for Freely Estimated SEM Model

Path	Elem Stand. Coeff.	p value	Middle Stand. Coeff.	p value	High Stand. Coeff.	P value
$SEBD^3M$ ← Org. Support	.538	<.001	.569	<.001	.502	<.001
Culture ← Org. Support	.822	<.001	.413	<.001	.768	<.001
Engagement ← Org. Support	.220	.089	-.122	.304	-.246	.191
Engagement ← $SEBD^3M$	.502	<.001	.436	<.001	.484	<.001

Table 4.12 Continued

Engagement←Culture	.116	.341	.567	<.001	.474	.007

Standardized estimates for the relationships between the latent variables and the observed variables revealed three significant paths in the freely estimated model for all three groups of teachers. The following 3 paths were statistically significant for elementary, middle, and high school teachers in the sample: SEBD^{3}M was predicted by "organizational support", "culture" was predicted by "organizational support", and "engagement" was predicted by SEBD^{3}M. In the model, culture was a predictor of "engagement" for middle and high school teachers but not for elementary teachers.

Mediation Analysis

A mediation analysis with bootstrapping was conducted in MPlus to determine the extent to which SEBD^{3}M and culture mediated the relationship between organizational support and engagement in data-driven decision-making. The results of the mediation analysis supported a fully mediated model. The standardized estimate for the direct effect, not accounting for the mediators, was 0.481. This reflects the relationship between organizational support and engagement excluding the mediators. The standardized estimate for the direct effect, when accounting for the mediators, was 0.220.

The standardized estimate was 0.238 with 95% CIs [0.337, 0.560] for the indirect effect between organizational support and engagement with SEBD^{3}M as the mediator. This indirect effect accounted for approximately 49% of the mediation in the model. The standardized estimate was 0.322 with 95% CIs [0.262, 0.591] for the indirect effect between organizational support and engagement with culture as the mediator. This indirect effect accounted for approximately 67% of the mediation in model.

A mediation analysis with bootstrapping was conducted for each group of teachers at the elementary, middle, and high school levels. For elementary teachers (n = 100) in the present sample the standardized estimate for the total effects in the mediation analysis was 0.582. This reflects the relationship between organizational support and engagement excluding the mediators. The standardized estimate for the total direct effects including the mediators was 0.219. The standardized estimate was 0.269 with 95% CIs [0.317, 0.667] for the indirect effect between organizational support and engagement with $SEBD^3M$ as the mediator. This indirect effect accounted for approximately 46% of the mediation in the model. The standardized estimate was 0.094 with 95% CIs [-0.170, 0.368] for the indirect effect between organizational support and engagement with culture as the mediator. This indirect effect accounted for approximately 16% of the mediation in model.

For middle school teachers (n = 58) in the present sample, the standardized estimate for the total effects in the mediation analysis was 0.475. This reflects the relationship between organizational support and engagement excluding the mediators. The standardized estimate for the total direct effects including the mediators was -0.118. The standardized estimate was .240 with 95% CIs [0.174, 0.608] for the indirect effect between organizational support and engagement with $SEBD^3M$ as the mediator. This indirect effect accounted for approximately 51% of the mediation in the model. The standardized estimate was .227 with 95% CIs [0.454, 1.000] for the indirect effect between organizational support and engagement with culture as the mediator. This indirect effect accounted for approximately 48% of the mediation in model.

For high school teachers (n = 48) in the present sample, the standardized estimate for the total effects in the mediation analysis was 0.349. This reflects the relationship between organizational support and engagement excluding the mediators. The standardized estimate for the total direct effects including the mediators was -0.238. The standardized estimate was .235 with 95% CIs [0.290, 0.694] for the indirect effect between organizational support and engagement with $SEBD^3M$ as the mediator. This indirect effect accounted for approximately 67% of the mediation in the model. The standardized estimate was .352 with 95% CIs [0.105, 0.800] for the indirect effect between organizational support and engagement with culture as the mediator. This indirect effect accounted for approximately 101% of the mediation in model.

CHAPTER V – DISCUSSION

Conclusions

Increased accountability demands have prompted many school leaders to embrace the use of data-driven decision-making in schools to improve student achievement on standardized assessments. A number of school districts have implemented interim assessments throughout the year to monitor student progress toward mastery of academic standards covered on standardized assessments. Expectations to use the results of these assessments to guide instructional decisions in the classroom have led to the need for structures, supports, and routines to facilitate data use among teachers and administrators. The purpose of the present study was to examine the interplay of organizational support, self-efficacy beliefs, and engagement in data-driven decision-making.

The first goal of the research study was to determine the relationship between self-efficacy beliefs for data-driven decision-making (SEBD^{3}M) and engagement in data-driven decision-making for teachers and administrators. The findings concerning SEBD^{3}M as it relates to teachers suggest that SEBD^{3}M and culture jointly made a difference in teacher engagement in data-driven decision-making. For the teachers in this study, SEBD^{3}M was associated with engagement, regardless of grade level. Culture made a difference in engagement for middle and high school teachers but not for elementary teachers. This finding raises new questions about existing data cultures in elementary schools. Are expectations for data use in elementary school settings as explicit as they are in middle and high school settings? An in-depth exploration of expectations at each grade level would be needed to determine the nuances of the expectations for data use. Expectations generally come from organizational leadership at the school and district levels. The shared beliefs of a school as a learning organization comes from collective experiences with data. Perhaps elementary school teachers have minimal experiences with using interim assessment data to guide instructional decisions and are more comfortable with other forms of student assessment data that come from formative and benchmark assessments, for example.

Organizational support predicted SEBD^{3}M and culture. This finding may suggest the potential for a causal link between organizational support and SEBD^{3}M. The results of this study are consistent with the possibility that higher levels of organizational support may cause increased levels of SEBD^{3}M in teachers, and in turn, have the potential to create more effective data cultures in schools. As SEBD^{3}M increases in teachers, they are more apt to use data at the classroom level. Schools that function as learning organizations embrace actions at the individual level as contributing to the knowledge base of the organization as a whole. Additional research using a different research methodology, however, would be needed to establish such a causal relationship should it exist.

For administrators included in the study, their SEBD^{3}M was moderately related to engagement in data-driven decision-making. There was evidence to support a stronger connection between SEBD^{3}M and engagement for teachers when compared to administrators. Strengthening the relationship between SEBD^{3}M and engagement in data-driven decision-making for administrators could be a goal of districts that embrace data-driven decision-making. Additional research would be needed to determine the factors that strengthen SEBD^{3}M among administrators to guide this effort. There may be a need for professional development for practicing administrators concerning data use for instructional decision-making. Prior literature suggests the influence of school leadership in establishing a data culture. Administrators who expect teachers to engage in data-driven decision-making may need training themselves in order to effectively model the process for teachers.

The second goal of the research study was to determine if there were any statistically significant differences in SEBD^{3}M among elementary, middle, and high school teachers. The results indicated that there was no significant difference in the SEBD^{3}M for teachers at the elementary, middle, and high school levels in the present study. This finding may provide insight into the depth of existing beliefs of teachers regardless of what grade level they teach. This finding may indicate that teachers are more similar than they are different across grade levels when it comes to existing SEBD^{3}M. However, other circumstances aside from SEBD^{3}M may make a difference in engagement in data-driven decision-making for elementary school teachers when compared to middle and high school teachers. These circumstances may include but are not limited to: negative past experiences with interim assessment data or a lack of training in analysis and interpretation of interim assessment data.

The final goal of the study was to determine the extent to which SEBD^{3}M and culture mediate the relationship between organizational support and engagement in data-driven decision-making. Overall, the model provided evidence to support the conditions that could maximize data-driven decision-making at the individual and organizational levels. A combination of organizational support, SEBD^{3}M, and culture seem to make a difference in engagement for teachers. One of these elements alone is not adequate to facilitate engagement in data-driven decision-making. For example, culture without organizational support could be an ineffective approach to data use in schools. By the same token, SEBD^{3}M without organizational support would likely not be beneficial to teachers as data users. These conditions collectively facilitate data use among teachers. Further research with a larger administrative sample would be needed to determine if this is also true for school and district level administrators. Cultural elements such as expectations and support for the process of data-driven decision-making, related to actual engagement in data-driven decision-making for teachers. SEBD^{3}M and organizational support combined made a difference in engagement in data-driven decision-making among all teachers included in the study.

In the present study, culture was strongly tied to organizational support for data-driven decision-making. This finding was consistent with the research literature that suggested the importance of school leadership in facilitating data use in schools. The ways that school leaders prioritize time spent on discussions of data, analysis, and expectations for data use were connected. Culture also predicted collaborative support. A culture of expectation for data use and trust with colleagues concerning data discussions impacted the collaboration of teachers surrounding data use.

Additional noteworthy findings during the analysis suggest teachers' opinions concerning SEBD^{3}M were strongest when it came to grouping students for instruction. However, additional evidence from teacher opinions concerning SEBD^{3}M in this study suggested that improvement is needed in training teachers on data analysis and interpretation. Teachers acknowledged the expectations in their schools to use data to inform instructional decisions, however opinions gathered during the survey indicate that they do struggle to have a positive outlook on data collection in schools. Since teachers, in the present sample at least, generally struggled to understand the utility in data collection, the approach a school leader uses to facilitate discussions about data should be safe and non-threatening. Prior research (Park, Daly, & Guerra, 2012) suggests a non-evaluative approach to discussions about data would help improve self-efficacy beliefs among teachers concerning data-driven decision-making.

Administrators included in the study were confident in their ability to access interim assessment results, but they were not as confident in identifying gaps in student mastery. The evidence supports the idea of a need for data analysis and interpretation training for administrators. Generally, administrators expected teachers to use interim assessment data to inform instructional decisions, but the culture of trust surrounding data may not be solidified in their schools.

Implications

A key implication of the research study is that organizational support plays a key role in SEBD^{3}M for teachers. The structures, systems, and supports that encompass the idea of organizational support come from school leadership and district leadership. Scheduling of time to collaborate, providing training through professional development, and providing tools and resources to facilitate data use come are decisions that come from organizational leaders. These decisions made concerning data use affect what teachers do at individual level in the classroom. The research is consistent with prior research that acknowledges the influence of organizational decisions on what is happening on the individual level.

An additional implication of the research is that organizational support influences culture. Organizational leaders set the stage for the culture surrounding data use in schools. The expectations and shared beliefs of members of an organization are derived from modeling and decision-making at the organizational level. It appears, from the findings of the study, however, that having support for data use alone may not be enough to overcome existing beliefs among teachers about data collection in schools.

A third implication was the SEBD^{3}M affected engagement in data-driven decision-making. For teachers in the study, existing beliefs about their abilities to access, comprehend, interpret, and use data for instructional decision-making played a role in culture. The evidence seems to suggest that shared beliefs about data-driven decision-making may be partially derived from what the individual believes about his or her own ability to use data. Organizational decisions about support for data-driven decision also affect SEBD^{3}M. A final implication of the study is that culture was associated with and may have affected engagement in data-driven decision-making. Culture, for the purposes of this study, referred to the collective mindset of teachers and existing expectations for data use. Culture affected how often teachers reportedly engaged in data-driven decision-making behaviors.

Limitations

The purpose of the present study was to examine SEBD^{3}M for teachers and administrators, to determine differences in SEBD^{3}M among elementary, middle, and high school teachers, and to determine the extent of the relationships among organizational support, self-efficacy beliefs, and engagement in data-driven decision-making.

One important limitation of the study relates to the sample. One district was used for the pool of participants. While using one school district allowed the researcher to control for variability in access, resources, and training, one school district is not necessarily representative of others and therefore, caution must be exercised in generalizing the present findings. At minimum, however the present results are heuristic in specifying potential causal relationships among teachers. Including a more diverse and nationally representative sample of teachers and administrators in future research would be beneficial and provide for greater confidence in the findings of the present study. A wider participant pool to make comparisons concerning organizational support, SEBD^{3}M, and engagement in data-driven decision-making would broaden the scope of the research as it relates to data-driven decision-making.

An additional limitation of the study concerns the administrative sample size. A larger sample of administrators would need to be included in order to conduct more definitive analyses. Perhaps the inclusion of additional districts would have increased the administrative sample size for a more in-depth analysis of administrative opinions on this topic.

One final limitation of the study related to the teacher instrument. The survey research methodology relies on responses of participants who choose responses based on self-reporting. The researcher is in position to assume that participants are giving honest assessments of SEBD^{3}M and honest responses about their opinions concerning organizational support, culture, and engagement in data-driven decision making. Therefore, the researcher is unable to independently verify that the given responses are the actual responses of participants. In addition, participants may respond with higher levels of agreement based on social desirability theory.

Directions for Future Research

The proposed model provides guidelines for the conditions conducive to data-driven decision-making in school. The combination of organizational support, collaborative support, culture, SEBD^{3}M, and engagement provide a roadmap to embrace data-driven decision-making as a school reform. While there was no difference in the SEBD^{3}M among elementary, middle, and high school teachers, the study provided the beginnings of a framework for understanding teacher opinions concerning data use processes in their schools.

Administrative approaches to data-use need to be examined to understand the conditions that may improve SEBD^{3}M for teachers. The specific behaviors or actions that encourage teacher engagement in data-driven decision-making activities is an area needing future exploration. The nuances of interactions surrounding data may make a difference in engagement in data-driven decision-making behaviors. For instance, the presence or absence of a school leader with expectations for data use in meetings about data may make a difference in levels of engagement among teachers.

Interventions for improving data analysis and interpretation skills are worth examining in future research. The present study provided evidence that there is a need for this training for in service teachers and administrators. Future research may be used to gather teacher and administrator opinions about what type of modalities they would prefer to get the most of this training as it applies to their role in the school. A comparison of computer-based tutorials, one-on-one coaching, and small group intervention might provide direction for planning activities that prepare teachers and administrators to become more effective data users in the future.

APPENDIX A – IRB Approval Letter

THE UNIVERSITY OF
SOUTHERN MISSISSIPPI

INSTITUTIONAL REVIEW BOARD
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NOTICE OF COMMITTEE ACTION

The project has been reviewed by The University of Southern Mississippi Institutional Review Board in accordance with Federal Drug Administration regulations (21 CFR 26, 111), Department of Health and Human Services (45 CFR Part 46), and university guidelines to ensure adherence to the following criteria:

- The risks to subjects are minimized.
- The risks to subjects are reasonable in relation to the anticipated benefits.
- The selection of subjects is equitable.
- Informed consent is adequate and appropriately documented.
- Where appropriate, the research plan makes adequate provisions for monitoring the data collected to ensure the safety of the subjects.
- Where appropriate, there are adequate provisions to protect the privacy of subjects and to maintain the confidentiality of all data.
- Appropriate additional safeguards have been included to protect vulnerable subjects.
- Any unanticipated, serious, or continuing problems encountered regarding risks to subjects must be reported immediately, but not later than 10 days following the event. This should be reported to the IRB Office via the "Adverse Effect Report Form".
- If approved, the maximum period of approval is limited to twelve months.
  Projects that exceed this period must submit an application for renewal or continuation.

PROTOCOL NUMBER: 17111504
PROJECT TITLE: An Examination of the Relationships Among Organizational Support, Self-Efficacy, and Engagement in Data-Driven Decision Making
PROJECT TYPE: Doctoral Dissertation
RESEARCHER(S): Kristal Pollard
COLLEGE/DIVISION: College of Education and Psychology
DEPARTMENT: Educational Research and Administration
FUNDING AGENCY/SPONSOR: N/A
IRB COMMITTEE ACTION: Exempt Review Approval
PERIOD OF APPROVAL: 11/16/2017 to 11/15/2018
Lawrence A. Hosman, Ph.D.
Institutional Review Board

APPENDIX B – Teacher Instrument

Teacher Instrument

For the following questionnaire items, "self-efficacy beliefs" refers to a person's belief in his or her ability to perform a task (Bandura, 1997). "Interim assessment data" refers to a district-wide assessments given 2-3 times a year to assess student mastery of state standards in a given subject area.

Please select the rating that best indicates your response. Only select one response.

I. Self-Efficacy Beliefs for Data-Driven Decision-Making

Please select the rating that best indicates your response concerning self-efficacy beliefs for data-driven decision-making. Rate your response on a scale of 1 to 9 with 1 being "Not At All" and 9 being "A Great Deal".	Not at all		Very little		Some degree		Quite a bit		A great deal
1. How confident are you in your ability to access interim assessment results for your students?	1	2	3	4	5	6	7	8	9
2. How confident are you in your ability to comprehend interim assessment reports?	1	2	3	4	5	6	7	8	9
3. How confident are you in your ability to interpret subtest or strand scores to determine student strengths and weaknesses in a content	1	2	3	4	5	6	7	8	9

area?									
4. How confident are you in your ability to use data to identify gaps in student mastery of curricular concepts?	1	2	3	4	5	6	7	8	9
5. How confident are you in your ability to use data to group students with similar learning needs for instruction?	1	2	3	4	5	6	7	8	9
6. How confident are you in your ability to use data to guide your selection of targeted interventions for gaps in student understanding?	1	2	3	4	5	6	7	8	9

II. Organizational Support for Data Use

Please select the rating that best indicates your response concerning organizational support for data use. Rate your response on a scale of 1 to 5 with 1 being "Strongly Disagree" and 5 being "Strongly Agree".	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
7. There is an expectation in my school that I analyze interim assessment data.	1	2	3	4	5
8. There is an expectation					

in my school that I use interim assessment data to inform my instructional decisions in the classroom.	1	2	3	4	5
9. There is a culture of trust among my grade level or department when it comes to discussions about the results of interim assessment data.	1	2	3	4	5
10. I take advantage of opportunities to meet with my colleagues to discuss the results of interim assessments.	1	2	3	4	5
11. Discussions about interim assessment data occur in a small group setting in my school.	1	2	3	4	5
12. I have received training on how to analyze and interpret my interim assessment data.	1	2	3	4	5

III. Collaborative Support for Data Use

Please select the rating that best indicates your response concerning collaborative support for data use. Rate your response on a scale of 1 to 5 with 1 being "Strongly Disagree" and 5 being "Strongly Agree".	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree
13. I analyze interim assessment data with my fellow teachers in my department.	1	2	3	4	5

14. I interpret interim assessment data with my fellow teachers in my department.	1	2	3	4	5
15. My fellow teachers share ideas about how they are using interim assessment data in their individual classrooms.	1	2	3	4	5
16. My fellow teachers generally have a positive outlook on interim assessment data collection in our school.	1	2	3	4	5
17. My fellow teachers generally support the idea of using interim assessment data to inform instructional decision-making.	1	2	3	4	5

IV. Engagement in Data-Driven Decision-Making

How often do you engage in each of the following activities? Please rate your engagement on a scale of 1 to 5 with 1 being "Never" and 5 being "Always".	Never	Rarely	Sometimes	Often	Always
18. I use interim assessment data to provide targeted feedback to my students about their performance.	1	2	3	4	5
19. I analyze interim assessment data to group my students based on strengths and weaknesses.	1	2	3	4	5
20. I analyze interim assessment data to remediate standards that	1	2	3	4	5

my class did not master.					
21. I analyze interim assessment data to enrich standards that my students have already mastered.	1	2	3	4	5
22. I make changes in instructional pacing based on student performance on interim assessments.	1	2	3	4	5

V. Demographic Information

Please provide the following information:

23. Gender:

_____Female
_____Male
_____Other

24. Ethnicity:

_____African-American
_____Caucasian American
_____Hispanic American
_____Asian-American
_____Other

25. Years of Teaching Experience:

_____0-2 years
_____3-5 years
_____6-10 years
_____11-15 years
_____16 years & above

26. Grade Level

_____Elementary (Pre-K through 5th grades)
_____Middle (6th through 8th grades)
_____High (9th through 12th grades)

27. I work at a school that is classified as:

_____Title I (at least 40% of student population comes from low-income families)
_____Non-Title I (less than 40% of student population comes from low-income families)

Thank you for completing this questionnaire.

APPENDIX C – Administrator Instrument

Administrator Instrument

For the following questionnaire items, self-efficacy beliefs refers to a person's belief in his or her ability to perform a task (Bandura, 1997). Interim assessment data refers to a district-wide assessments given 2-3 times a year to assess student mastery of state standards in a given subject area.

Please select the rating that best indicates your response. Only select one response.

VI. Self-Efficacy Beliefs for Data-Driven Decision-Making

Please select the rating that best indicates your response concerning self-efficacy beliefs for data-driven decision-making. Rate your response on a scale of 1 to 9 with 1 being "None At All" and 9 being "A Great Deal".	Not at all		Very little		Some degree		Quite a bit		A great Deal
28. How confident are you in your ability to access interim assessment results for your school?	1	2	3	4	5	6	7	8	9
29. How confident are you in your ability to comprehend interim assessment reports for your school?	1	2	3	4	5	6	7	8	9
30. How confident are you in your ability to interpret subtest or strand scores to determine overall strengths and	1	2	3	4	5	6	7	8	9

weaknesses in a given subject area at your school?									
31. How confident are you in your ability to use data to identify gaps in student mastery of curricular concepts for each subject area?	1	2	3	4	5	6	7	8	9
32. How confident are you in your ability to use data to set academic goals for your school?	1	2	3	4	5	6	7	8	9
33. How confident are you in your ability to use data to guide your selection of instructional resources and materials for targeted interventions to address gaps in student understanding?	1	2	3	4	5	6	7	8	9

VII. Organizational Support for Data Use

Please select the rating that best indicates your response concerning organizational support for data use. Rate your response on a scale of 1 to 5 with 1 being "Strongly Disagree" and 5 being	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

“Strongly Agree”.					
34. I expect teachers in my school to interpret interim assessment data.	1	2	3	4	5
35. I expect teachers in my school to use interim assessment data to inform instructional decisions in their classrooms.	1	2	3	4	5
36. I emphasize the importance of data to inform instructional decisions to my teachers and staff.	1	2	3	4	5
37. There is a culture of trust among grade levels when it comes to discussions about the results of interim assessment data.	1	2	3	4	5
38. I provide teachers with opportunities to discuss the results of interim assessment data with their colleagues.	1	2	3	4	5
39. Discussions about interim assessment data occur in a small group setting in my school.	1	2	3	4	5
40. I have received training on how to analyze and interpret interim assessment data.	1	2	3	4	5

VIII. Collaborative Support for Data Use

Please select the rating that best indicates your response	Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

concerning collaborative support for data use. Rate your response on a scale of 1 to 5 with 1 being "Strongly Disagree" and 5 being "Strongly Agree".					
41. My fellow administrators generally have a positive outlook on interim assessment data collection in our schools.	1	2	3	4	5
42. My fellow administrators generally support the idea of using interim assessment data to inform instructional decision-making.	1	2	3	4	5
43. I analyze the results of interim assessment data with other school leaders in my school.	1	2	3	4	5
44. I interpret the results of interim assessment data with other school leaders in my school.	1	2	3	4	5

IX. Engagement in Data-Driven Decision-Making

How often do you engage in each of the following activities? Please rate your engagement on a scale of 1 to 5 with 1 being "Never" and 5 being "Always".	Never	Rarely	Sometimes	Often	Always
45. I use interim assessment data to provide targeted feedback to my teachers about their performance.	1	2	3	4	5
46. I analyze interim					

assessment data to identify school-wide strengths and weaknesses.	1	2	3	4	5
47. I analyze interim assessment data to make decisions related to personnel.	1	2	3	4	5
48. I use interim assessment data to determine professional development activities for teachers at my school.	1	2	3	4	5
49. I use interim assessment data to recognize student growth in proficiency levels.	1	2	3	4	5

X. Demographic Information

Please provide the following information:

50. Gender:

_____Female
_____Male
_____Other

51. Ethnicity:

_____African-American
_____Caucasian-American
_____Hispanic/Latino American
_____Asian-American
_____Other

52. Years of Administrative Experience:

_____0-2 years
_____3-5 years
_____6-10 years
_____11-15 years
_____16 years & above

53. Grade Level

_____Elementary (Pre-K through 5th grades)
_____Middle (6th through 8th grades)
_____High (9th through 12th grades)

54. I work at a school that is classified as:
   _____Title I (at least 40% of students are from low-income families)
   _____Non-Title I (less than 40% of students are from low-income families)

Thank you for completing this questionnaire.

REFERENCES

Amendum, S., Conradi, K., Pendleton, M. (2015). Interpreting reading assessment data: moving from parts to whole in a testing era. *Intervention in School and Clinic*, 51(5), 284-292.

Athanases, S., Bennett, L., & Wahleithner, J. (2013). Fostering data literacy through pre service teacher inquiry in English Language Arts. *The Teacher Educator*, 48, 8 28.

Bambrick-Santoyo, P. (2012). *Leverage Leadership: A Practical Guide to Building Exceptional Schools*. Jossey-Bass. San Francisco, CA.

Bandura, A. (1971). *Social learning theory*. New York: General Learning Press.

Bandura, A. (1997). *Self-efficacy beliefs: the exercise of control*. New York: W.H. Freeman and Company.

Bandura, A. (2001). Social cognitive theory: an agentic perspective. *Annual Review of Psychology*, 52, 1-26.

Boyoung, K., Rhee, E., Ha, Gyuyoung, Y., Joonyoung, Y., Lee, S. (2016). Tolerance of uncertainty: links to happenstance, career decision self-efficacy beliefs, and career satisfaction. *Career Development Quarterly*, 64(2), 140-152.

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

Brodie, K. (2014). Learning about learner errors in professional learning communities. *Educational Studies in Mathematics*, 85(2), 221-239.

Brunner, C. et. al. (2005). Linking data and learning: the grow network study. *Journal of Education for Students Placed At Risk*. 10(3), 241-267.

Chesnut, S. & Burley, H. (2015). Self-efficacy beliefs as a predictor of commitment to the teaching profession: a meta-analysis. *Educational Research Review*, 15, 1-16.

Chiesa, R., Massei, F., Guglielmi, D. (2016). Career decision-making self-efficacy beliefs change in Italian high school students. *Journal of Counseling & Development*, 94, 210-224.

Coburn, C. & Turner, E. (2011). Research on data use: a framework and analysis. *Measurement*, 9(4), 173-206.

Collinson, V., Cook, T. & Conley, S. (2006). Organizational learning in schools and school systems: improving teaching, learning, and leading. *Theory Into Practice*, 45(2), 107-116.

Common Core State Standards Initiative. (2017). Common Core State Standards. Retrieved from http://www.corestandards.org/.

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

Datnow, A. & Hubbard, L. (2016). Teacher capacity for and beliefs about data-driven decision-making: A literature review of international research. *Journal of Educational Change*, 17, 7-28.

DuFour, R. (2015). How PLCs do data right. *Educational Leadership*, 73(3), 22-26.

DuFour, R. (1998). *Professional learning communities at work: Best practices for enhancing student achievement*. Bloomington, IN: National Educational Service.

Dunn, K, Airola, D., Lo, W. (2013). 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, Airola, D., Lo, W., & Garrison, M. (2013). What teachers think about what they can do with data: development and validation of the data-driven decision-making efficacy and anxiety inventory. *Contemporary Educational Psychology*, 38, 87 98.

Elias, R. (2008). Anti-intellectual attitudes and academic self-efficacy beliefs among business students. *Journal of Education for Business*, 84(2), 110-117.

Farley-Ripple, E. & Buttram, J. (2014). Developing collaborative data use through professional learning communities: early lessons from Delaware. *Studies in Educational Evaluation*, 42, 41-53.

Farley-Ripple, E. & Buttram, J. (2015). The development of teacher capacity for data use: the role of teacher networks in an elementary school. *Teachers College Record*, 117, 040309, 222-241.

Farrell, C. (2015). Designing school systems to encourage data use and instructional improvement: a comparison of school districts and charter management organizations. *Educational Administration Quarterly*, 51(3), 438-471.

Fauske, J. & Raybould, R. (2005). Organizational learning theory in schools. *Journal of Educational Administration*, 43(1), 22-40.

Gasse, R., Vanlommel, K., Vanhoof, J., & Petegem, P. (2017). The impact of collaboration on teachers' individual data use. *School Effectiveness and School Improvement*, 28(3), 489-504.

Gonzalez, J. (2001). Merging organizational learning with learning theory—a task for the 21st century? *Journal of Structural Learning & Intelligent Systems*, 14(4), 355 370.

Gullo, D. (2013). Improving instructional practices, policies, and student outcomes for early childhood language and literacy through data-driven decision-making. *Early Childhood Education*, 41, 413-421.

Halverson, R., Grigg, J., Prichett, R., & Thomas, C. (2007). The new instructional leadership: creating data-driven instructional systems in school. *Journal of School Leadership*, 17, 159-193.

Hoaglund, A., Birkenfield, K. & Bluiett, T. (2014). Data meeting model: developing data focused pre-service teachers. *Reading Improvement*, 51(3), 313-318.

Hoover, N. & Abrams, L. (2013). Teachers' instructional use of summative student assessment data. *Applied Measurement in Education*, 26, 219-231.

Huguet, A., Marsh, J, & Farrell, C. (2014). Building teachers' data use capacity: insights for strong and developing coaches. *Education Policy Analysis Archives*, 22(52), 1-30.

IBM Corp. (2016). IBM SPSS Statistics for Windows, Version 24.0, Armonk, NY: IBM Corp.

Ittner, A., Helman, L., Burns, M., McComas, J. (2015). Data drive these coaches. *Journal of Staff Development*, 36(2), 20-46.

Jacobs, J., Gregory, A., Hoppey, D., & Hoppey, D. (2009). Data literacy: understanding teachers' data use in a context of accountability and response to intervention. *Action in Teacher Education*, 31(3), 41-55.

Jacobsen, R., Synder, J., & Saultz, A. (2014). Informing or shaping public opinion? The influence of school accountability data format on public perceptions of school quality. *American Journal of Education*, 121, 1-27.

Jimerson, J. (2014). Thinking about data: exploring the development of mental models for 'data use' among teachers and school leaders. *Studies in Educational Evaluation*, 42, 5-14.

Jimerson, J. & Wayman, J. (2015). Professional learning for using data: examining teacher needs & supports. *Teachers College Record*, 117, 1-36.

Kirwan, C. (2013). *Making sense of organizational learning: Putting theory into practice*. Burlington, VT. Gower.

Kunsting, J., Neuber, V., & Lipowsky, F. (2016). Teacher self-efficacy beliefs as a long term predictor of instructional quality in the classroom. *European Journal of Psychology of Education*, 31(3), 299-322.

Lange, C., Range, B., & Welsh, K. (2012). Conditions for effective data use to improve schools: recommendations for school leaders. *International Journal of Educational Leadership Preparation*, 7(3), 1-11.

Lent, R. Brown, S., & Hackett, A. (1994). Toward a unifying social cognitive theory of career and academic interest, choice, and performance. *Journal of Vocational Behavior*, 45, 79-122.

Levin, J. & Datnow, A. (2012). The principal role in data-driven decision-making: using case study data to develop multi-mediator models of educational reform. *School Effectiveness and School Improvement*, 23 (2), 179-201.

Little, J. (2012). Understanding data use practice among teachers: the contribution of micro process studies. *American Journal of Education*, 118(2), 143-166.

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

Mandinach, E. & Gummer, E. (2015). Data-driven decision-making: components of the enculturation of data use in education. *Teachers College Record*, 117, 1-8.

Mandinach, E, Parton, B., Gummer, E., Anderson, R. (2015). Ethical and appropriate data use requires data literacy. *Phi Delta Kappan*, 96(5), 25-28.

Mandinach, E. & Jimerson, J. (2016). Teachers learning how to use data: a synthesis of the issues and what is known. *Teachers and Teacher Education*, 60, 452-457.

Marsh, J., Bertrand, M., & Huguet, A. (2015). Using data to alter instructional practice: the mediating role of coaches and professional learning communities. *Teachers College Record*, 117, 1-40.

Marsh, J. & Farrell, C. (2015). How leaders can support teachers with data-driven decision-making: a framework for understanding capacity building. *Educational Management Administration & Leadership*, 43(2), 269-289.

Muthén, L.K., & Muthén, B.O. (1998-2017). Mplus User’s Guide. Sixth Edition. Los Angeles, CA: Muthén & Muthén.

Murray, J. (2014). Critical issues facing school leaders concerning data-informed decision-making. *Professional Educator*, 38(1), 14-22.

Noyce P., Perda, D., & Traver, R. (2000). Creating data driven schools. *Educational Leadership*, 57(5), 52-27.

Park, V., Daly, A., & Guerra, A. (2012). Strategic framing: how leaders craft the meaning of data use for equity and learning. *Educational Policy*, 27(4), 645-675.

Preacher, K. & Hayes, A. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, 40(3), 879-891.

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

Saka, M., Bayram, H., & Kabapinar, F. (2016). The teaching processes of prospective science teachers with different levels of science-teaching self-efficacy beliefs belief. *Educational Sciences: Theory & Practice*, 16(3), 915-941.

Schwanenberger, M. & Ahearn, C. (2013). Teacher perceptions of the impact of the data team process on core instructional practices. *NCPEA International Journal of Educational Leadership Preparation*, 8(2), 146-162.

Rallis, S. & Macmullen, M. (2000). Inquiry-minded schools: opening doors for accountability. *Phi Delta Kappan*, 81(10), 766-773.

Scott, S. (2013). Sociocultural theory. Retrieved August 28, 2016 from http://www.education.com/reference/article/sociocultural-theory/.

Schilkamp, K. & Kuiper, W. (2010). Data-informed curriculum reform: which data, what purposes, and promoting and hindering factors. *Teaching and Teacher Education*, 26, 482-496.

Senge, P. (1990). *The Fifth Discipline: The Art & Practice of the Learning Organization*. New York: Currency Doubleday.

Sikes, K. A. (2008). *Investigating Teachers Perceptions of the Data-Driven Decision Making Process at a Georgia Elementary School*. (Doctoral dissertation).Retrieved from ProQuest Dissertations and Theses Global. (3319940).

Skaalvik, E. & Skaalvik, S. (2014). Teacher self-efficacy beliefs and perceived autonomy: relations with teacher engagement, job satisfaction, and emotional exhaustion. *Psychological Reports: Employment Psychology & Marketing*, 114(1), 68-77.

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

U.S. Department of Education (2015). Every Student Succeeds Act. Retrieved from https://www.ed.gov/essa?src=ft.

U.S. Department of Education, Office of Planning, Evaluation and Policy Development (2007). *Teachers' use of student data systems to improve instruction*. Washington, DC: Author.

U.S. Department of Education, Office of Planning, Evaluation and Policy Development. (2010). *Teachers' ability to use data to inform instruction: challenges and supports*. Washington, DC: Author.

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

Vanlommel, K., Van Gasse, R., & Petegem, P. (2017). Teachers' decision-making: data based on intuition driven? *International Journal of Educational Research*, 83, 75 83.

Vanlommel, K., Vanhoof, J., & Petegem, P. (2016). Data use by teachers: the impact of motivation, decision-making style, supportive relationships, and reflective capacity. *Educational Studies*, 42(1), 36-53.

Watson, C. (2014). Effective professional learning communities? The possibilities for teachers as agents of change in schools. *British Educational Research Journal*, 40(1), 18-29.

Wayman, J. (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.

Wells, C. & Feun, L. (2012). Educational change and professional learning communities: a study of two districts. *Journal of Educational Change*, 14, 233-257.

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