

A GROUNDED THEORY APPROACH TO UNDERSTANDING
EDUCATOR PERSPECTIVES ON USING DATA TO
INFORM INSTRUCTION

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STEPHANIE R. BROYLES

Dr. Peggy Placier, Dissertation Supervisor

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The undersigned, appointed by the dean of the Graduate School, have examined the dissertation entitled

A GROUNDED THEORY APPROACH TO UNDERSTANDING EDUCATOR
PERSPECTIVES ON USING DATA TO INFORM INSTRUCTION

presented by Stephanie R. Broyles,

a candidate for the degree of doctor of education,

and hereby certify that, in their opinion, it is worthy of acceptance.

Dr. Peggy Placier

Dr. Emily R. Crawford

Dr. Bradley Curs

Dr. Sally Beth Lyon

Dr. Jimmy Sebastian

DEDICATION

To my husband, Neal, and my children, Garrett, Michael, and Emily, for your sacrifices, love, and support. To my parents, Joseph and Virginia, for instilling in me the belief that nothing is out of my reach. A special thanks to God for making this possible and for blessing me with such a wonderful family. I try not to ever let a day pass without counting my blessings and saying thanks.

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Abstract

Since the passage of the No Child Left Behind Act in 2001, which reauthorized the Elementary and Secondary Education Act of 1965, there has been an increased national focus on accountability in education (Jacobs, Gregory, Hoppy, & Yendol-Hoppey, 2009). This focus has developed into a movement that has become one of the central themes of the national dialogue around student achievement and school improvement. One result of this movement has been increased external pressures to demonstrate results as documented through data, which in turn requires educators to analyze and use data to inform instructional decision making. To meet these growing accountability requirements and facilitate the process of analyzing and using data, schools have implemented initiatives such as Professional Learning Communities (PLCs) and Response to Intervention (RtI). PLCs and RtI both provide structured support for using data to inform instruction. In spite of efforts such as these, the literature indicates that many educators feel ill equipped to analyze and use data and, further, that there may be several factors contributing to why they feel this way (Jacobs et al., 2009; Ronka, Lachat, Slaughter, & Meltzer, 2008). Although the literature identifies potential factors that may contribute to why educators may have certain perspectives on using data, little is known about the interrelatedness of these factors, which of these factors may be most important, or how best to address these factors through formal coursework or professional development.

The purpose of this study was to address the gap between how policymakers and educational leaders expect data to be used to inform instruction and how classroom-level educators internalize and implement these expectations. This study attempted to address

this gap by exploring educators' perspectives on using data, their views of their own data analysis skills, how they value and make meaning of data, and the characteristics of their training and/or organizational cultures contribute to these views. Research regarding educators' perspectives on using data for decision making should not only address a gap in the literature but also provide an impetus for the development of professional development programs to meet the needs of educators in both leadership and practitioner roles.

Chapter 1 – Introduction

Background for the Study

In the United States, agencies external to public schools and their local governing boards share responsibility for the quality of public education. These external agencies are typically government agencies at the local, state, and federal levels. The extent to which these agencies should be responsible for the quality of public education is disputed; however, it is widely agreed that there should be some shared responsibility since these agencies provide public schools with the funding and authority to operate (Aper, 2002; Newmann, King, & Rigdon, 1997). In recent decades there has been growing concern about the quality of public education in the United States and this concern has sparked a national dialogue about public school performance. The mantra of this national dialogue is accountability (Derthick & Dunn, 2009; Hanushek & Raymond, 2001) and the body of policy resulting from this dialogue can best be described as the accountability movement (Jacobs et al., 2009). Central to this movement are the ideas that accountability is demonstrated through data and that data should be used to inform instructional decision making (Jacobs et al., 2009; Young & Kim, 2010).

There are many examples of policy and policy stimuli related to the accountability movement, but the most noteworthy examples at the national level are the Elementary and Secondary Education Act (ESEA) of 1965, a report by the National Commission on Excellence in Education released in 1983 titled “A Nation at Risk,” and the No Child Left Behind (NCLB) Act passed in 2001. ESEA and NCLB both represent federal legislation passed to address concerns about the quality of public education across the nation, while

“A Nation at Risk” is a report that identified concerns and, because it captured the attention of the media and the public at large, served as a major stimulus for national policy.

The primary concerns identified by “A Nation at Risk” were the poor performance of students in America relative to their international counterparts, the achievement gap between white and minority students, high dropout rates among students from disadvantaged backgrounds, and overall low student achievement (Derthick & Dunn, 2009; Newmann et al., 1997). “A Nation at Risk” received so much public recognition that it eventually led to the passage of NCLB, which is the most recent reauthorization of ESEA and the defining legislation of the accountability movement. Prior to the passage of NCLB, national legislation had been moving only gradually toward a focus on accountability (Derthick & Dunn, 2009). NCLB, with its focus on outcomes rather than inputs (Goertz & Duffy, 2003) and on sanctions rather than rewards (Derthick & Dunn, 2009), ushered in a new era of education reform.

As a result of requirements imposed by federal legislation such as No Child Left Behind, states have developed a variety of responses including similar legislation, accountability mechanisms, and initiatives intended to support accountability mechanisms by providing structures or models to encourage data analysis and use. These responses have been widespread, with at least forty states increasing their accountability mechanisms during the 1980s (Newmann et al., 1997) and all fifty states implementing initiatives designed to provide more rigorous and challenging standards for students by the end of the 1990s (Goertz & Duffy, 2003). These initiatives addressed concerns about the quality of public education by striving to improve student achievement and they

addressed the call for accountability by including provisions for high-stakes testing to monitor student achievement.

While on the surface, state responses to federal legislation such as NCLB may seem fitting, these responses may actually serve to highlight a disconnect between the way schools actually operate and the way the accountability movement assumes schools can and should operate. All of the legislation related to the accountability movement is built on the premise that school improvement can be achieved through better accountability and that better accountability is demonstrated through using data to inform instructional decision making. By design, this premise is very similar to the ideas embodied in data-driven decision making, which is the central premise of the total quality management (TQM) movement that started in the United States in the 1980s as a way to demonstrate and improve quality in the manufacturing sector (J. A. Marsh, Pane, & Hamilton, 2006; Young & Kim, 2010). Although the TQM movement has experienced a great deal of success in the manufacturing sector and the corporate world at large, it may be primarily due to careful surveillance by customers and clients of the quality of outputs (Newmann et al., 1997). The importance of this surveillance is demonstrated when customers and clients demand better quality and choose a different supplier if their demands are not met. Essentially, businesses have to respond to these external pressures in order to stay in business. Building on this TQM principle, the accountability movement assumes that legislated external mandates will have the same impact on schools that external monitoring by customers and clients has on businesses (Newmann et al., 1997).

This assumption that external mandates will compel schools to improve student performance is actually a complex assumption that presumes some additional things to be true. First, it presumes that schools can run like manufacturers or other corporations and, not only can they run this way, but that they would also be more effective if they did (Derthick & Dunn, 2009; Young & Kim, 2010). Essentially, this suggests that improving student performance is no more complex than improving the quality of a manufactured product. Second, it presumes that there is a link between accountability and performance (Newmann et al., 1997). There is an implication in this presumption that schools can perform better than they do, but that they won't unless they are held accountable for their performance. Finally, it presumes that these external mandates will funnel down and be internalized by educators at the classroom level in schools (Katz, Sutherland, & Earl, 2005; Newmann et al., 1997). The expectation is that somehow this will serve as an impetus for teachers to try harder and that, in turn, will lead to improvements in student performance. Just like the presumption that there is a link between accountability and performance carries with it the implication that schools can perform better than they do, the presumption that external mandates will funnel down to classroom educators also carries with it the implication that they can perform better than they do.

Statement of the Problem

Prior to the passage of NCLB, national legislation had been moving only gradually toward a focus on accountability (Derthick & Dunn, 2009) and most states were soft on applying sanctions to underperforming schools. Since the passage of NCLB, states have been required to mandate that schools test more, report more, and set more rigorous improvement goals. States have also been required to apply heavier

sanctions more quickly to schools that do not meet their improvement goals (Goertz & Duffy, 2003). In the NCLB era of accountability, schools face a wide variety of sanctions ranging in severity from moderate to severe. At the moderate end of the spectrum, parents are given the choice to transfer students to better performing schools in the same district. At the more severe end of the spectrum, schools are branded as failures and are taken over and restructured (Derthick & Dunn, 2009; Goertz & Duffy, 2003). These provisions of NCLB have compelled states to develop high-stakes accountability mechanisms and, at the heart of these mechanisms, are state standardized assessments.

As a result of this emphasis on standardized assessments, schools have become so focused on state standardized test scores that, for many schools, these test scores have become the sole source of data for school improvement efforts (Flowers & Carpenter, 2009; Schmoker, 2003). In fact, since NCLB, standardized test scores have become the primary measure of school performance and, since accountability must be demonstrated through data, test scores have come to be synonymous with data (Jacobs et al., 2009; Young & Kim, 2010). Further, since the idea that data should be used to inform instructional decision making is one of the central tenets of the accountability movement (Jacobs et al., 2009; Young & Kim, 2010), there is an expectation that schools will use standardized test scores to inform instructional decision making. In view of the fact that instructional decision making is largely the responsibility of educators at the classroom level, the external mandates that require schools to use data are passed down by the various levels of administration to the classroom educator (Goertz & Duffy, 2003; Jacobs et al., 2009). In turn, these educators are presented routinely with a plethora of data such

as standardized test scores and are expected to make sense of them and use them to inform instruction. In essence, they are expected to be data literate (Ronka et al., 2008).

Due to the focus on sanctions in state accountability mechanisms developed for NCLB, schools are feeling tremendous pressure to demonstrate improvement. However, efforts to demonstrate improvement are really translating into efforts to prove compliance with schools collecting and reporting a plethora of data in addition to standardized test scores, but falling short of actually using the data to inform instructional decision making (Love, 2004; Newmann et al., 1997). In essence, they have become “. . . data rich, but information poor” (M. R. Davis, 2008; Ronka et al., 2008, p. 18). The literature suggests that there are three primary reasons why educators in these schools are not using data the way policy makers think they should. First, many educators report feeling ill equipped or ill prepared to analyze data (Earl & Katz, 2006; Flowers & Carpenter, 2009; Jacobs et al., 2009; Ronka et al., 2008; Williamson & Blackburn, 2009). Whether real or perceived, they do not think they have the skills necessary to analyze and use data. This may be due to a lack of training or experience (Earl & Katz, 2006; Flowers & Carpenter, 2009). Second, educators often mistrust data. Their feelings of mistrust range from simply feeling that their own intuition is more reliable to actually worrying that data can be skewed and used against them (Earl & Katz, 2006). Finally, educators may, for various reasons, fear data. When describing the way the prospect of using data makes them feel, educators use terms such as alert, alarm, and red flag (Jacobs et al., 2009). They quickly discover that data such as state standardized test scores serve more as red flags than as constructive inputs for instructional decision making. Further, educators may fear the prospect of being evaluated through data. Since educators are used to being in the

position of evaluating students, they may be frightened by the idea that data may serve as an indicator of their own performance relative to improving student achievement (Earl & Katz, 2006).

Purpose of the Study

The purpose of this study was to address the gap between how policymakers and educational leaders expect data to be used to inform instruction and how classroom-level educators internalize and implement these expectations. This study attempted to address this gap by exploring educators' perspectives on using data, their views of their own data analysis skills, how they value and make meaning of data, and the characteristics of their training and/or organizational cultures contribute to these views. Research regarding educators' perspectives on using data for decision making should not only address a gap in the literature but also provide an impetus for the development of professional development programs to meet the needs of educators in both leadership and practitioner roles.

Conceptual Framework

The conceptual framework for this study was developed from the body of theory surrounding organizational analysis and was used both as a lens through which to view the problem and as a buttress for the findings and implications. Organizational analysis theory provides an appropriate basis for the conceptual framework because even though the pressures of the accountability movement are being pushed down to individual educators in the classroom, the overarching goal of the movement is organizational-level school improvement. Further, since the root of the problem seems to be a disconnect

between the way schools actually operate and the way the accountability movement assumes schools can and should operate, the multiple perspectives of organizational analysis theory served as valuable tools for understanding the complexities of these differing perspectives.

Although schools are made up of individual educators, they really are educational organizations with “. . . complex social structures” (J. R. Davis, 2003, p. 20) and “. . . the circumstances of decision-making in educational organizations have become more complex and challenging” (Begley, 1999, p. 52). The accountability movement has contributed to the growing complexity of this decision-making by expecting schools to demonstrate accountability through data and, as such, to use data as the basis for instructional decision making (Jacobs et al., 2009; Young & Kim, 2010).

To understand how the accountability movement has contributed to the complexities of decision-making in educational organizations, educational leaders need a systematic way to analyze organizations and organizational situations, which is a key element of Donaldson’s (1998) definition of organizational analysis. In addition to needing a systematic way to analyze organizations, educational leaders also need to be able to use multiple perspectives or models as analysis tools (Bensimon, Neumann, & Birnbaum, 1989; Bolman & Deal, 2003; J. R. Davis, 2003; Donaldson, 1998; Tierney, 1988). Bolman and Deal refer to these multiple perspectives as frames and suggest that effective leaders “. . . need multiple tools, the skill to use each of them, and the wisdom to match frames to situations” (p. 18). They believe that the ability to apply multiple frames deepens a leader’s understanding of their organization and organizational situations. Likewise, Morgan refers to these multiple perspectives as metaphors and

posits that if leaders “. . . are not engaged in an active reading that embraces different points of view, much of the richness and complexity of organizational life is passing them by” (p. 350).

Specifically, the ability to use multiple perspectives in our analyses deepens our understanding of organizations and organizational situations because it allows us to see the same organization or the same situation in different ways (Morgan, 1997). Morgan explains that some perspectives will prove more useful than others because of the way “. . . they connect and resonate with the reality being observed” (p. 350). Donaldson (1998) agrees and adds that many fields of study have long rejected the idea that one theory or model can offer a complete explanation or solution. Being able to see the same situation in different ways is valuable because when we are faced with a decision-making situation there is often more than one acceptable alternative (Tierney, 1988). Additionally, the perspective we choose tends to influence what we see in our analyses (Bolman & Deal, 2003; Morgan, 1997). This does not mean that what we see is incorrect, just that certain aspects of a situation are emphasized with each different perspective we choose. Accordingly, each perspective “. . . tells its own story . . .” (Bolman & Deal, 2003, p. 40) and each “. . . provides a distinctive but partial view . . .” (Donaldson, 1998, p. 180).

Although the ability to use multiple perspectives in organizational analysis can provide educational leaders with a richer understanding of situations, an argument can be made for using a cultural or symbolic perspective in educational organizations. Bensimon et al. (1989) believe that “cultural and symbolic theories deserve serious attention because they present a view of leadership that is highly compatible with the characteristics of academic organizations” (p. v). These characteristics include things

such as a lack of “clear and measurable outcomes,” “ambiguity of purpose,” and “diffusion of power and authority” (Bensimon et al., 1989, p. v), which Weick (1976) suggests are inherent characteristics of educational organizations that derive from their tendency to be loosely coupled systems. Weick describes loosely coupled systems as systems with elements or functions that are “. . . tied together frequently and loosely” (p. 1). Key to Weick’s description is the idea that while events and decisions may impact multiple elements or functions of the system, each retains a separate identity. Davis (2003) also views educational organizations as loosely coupled systems suggesting that they “. . . appear to be an assemblage of various independent parts, varying from simple to complex” (p.25). The suggestion that educational organizations are loosely coupled systems supports the use of a cultural or symbolic perspective because when leaders utilize these perspectives in analyses they are viewing organizations as loosely coupled systems with ambiguous goals (Bensimon et al., 1989) and asking “what are the important parts and connections and how are they being regulated” (J. R. Davis, 2003, p. 25).

While an argument can be made for using cultural or symbolic theories to understand schools, the accountability movement seems to hold a view of schools that Morgan (1997) refers to as the “myth of rationality” (p. 146). Morgan posits that “modern organizations are sustained by belief systems that emphasize the importance of rationality, and their legitimacy in the public eye depends on their ability to demonstrate rationality and objectivity in action” (p. 146). For policymakers, the media, and the general public, rationality and objectivity in schools are demonstrated through using data to inform instructional decision making. Essentially, the legitimacy of schools in the

public eye depends on their ability to document results through data and to use that data to make improvements. Similar to Morgan, Bolman and Deal (2003) refer to this view as structural. From a structural perspective, schools are likened to factories and there is an emphasis on goals, specialized roles, formal relationships, rules, policies, procedures, and organizational hierarchies (Bolman & Deal, 2003). Similarly, one of the presumptions inherent in the primary premise of the accountability movement is that schools can run like manufacturers or other corporations and, not only can they run this way, but that they should run this way (Derthick & Dunn, 2009; Young & Kim, 2010). This is decidedly different than the way schools actually operate, and reconciling the differences between the structural way the accountability movement views schools and the cultural or symbolic way schools view themselves will be useful in understanding individual educator perspectives.

Though the multiple perspectives of organizational analysis theory served as a conceptual framework for developing an understanding of the problem and the findings, it is important to note that this body of theory may or may not fully explain the findings of this study. The reason for this is, as the term conceptual framework implies, because organizational analysis theories are grand theories and grand theories are conceptual (Corbin & Strauss, 2008). In other words, organizational theorists start with a concept and develop a theory that is abstract enough to be applied to the field of organizational analysis in general. Organizational theorists study organizations and the field of organizational analysis at a level that is more global than the everyday lives of individual educators. This study attempts to develop a substantive theory that is grounded in the

data of the everyday lives of educators, and which may or may not be explained by organizational analysis theory.

Research Questions

The following questions guided this study:

1. What are educators' perspectives on how they use data for instructional decision making?
2. How do educators view their own data analysis skills and the value of using data for decision making?
3. What characteristics of educators' training and/or organizational culture contribute to these views?

Design and Methodology

The design of this study is a qualitative study utilizing interpretive grounded theory methods for data collection and analysis (Bogdan & Biklen, 2007; Heppner & Heppner, 2004; Merriam, 1998). Grounded theory is a specific research methodology introduced by Glaser and Strauss in 1967 with the purpose of building theory that is grounded in data (Corbin & Strauss, 2008; Merriam, 1998). Theory may be substantive or formal (Corbin & Strauss, 2008), but this study seeks to build a substantive theory. Substantive theory differs from formal or grand theory in that it “. . . has as its referent specific, everyday-world situations . . .” (Merriam, 1998, p. 17) and, as such, is more practical than a formal or grand theory to everyday practice. More specifically, substantive theory is related to a specific area of inquiry, while formal theory is related to a conceptual area of inquiry. The pressure to use data to inform instructional decision

making and improve student performance has become a part of daily life for educators (Ronka et al., 2008); however, in spite of the pressure, the literature suggests that educators are falling short of actually using data (Crum, 2009; Love, 2004; Mokhtari, Rosemary, & Edwards, 2007/2008; Newmann et al., 1997; Ronka et al., 2008). A substantive theory developed from data related to educator perspectives on using data could have very practical implications for school leaders, district leaders, and even policymakers.

Data Collection Techniques

For the purpose of qualitative research “. . . data refers to the rough materials researchers collect . . .” (Bogdan & Biklen, 2007, p. 117) from a wide variety of sources including but not limited to interviews, observations, videos, documents, diaries, autobiographies, and memoirs (Bogdan & Biklen, 2007; Corbin & Strauss, 2008; Merriam, 1998). Qualitative data are richly descriptive and often take the form of words or pictures rather than numbers (Bogdan & Biklen, 2007; Merriam, 1998). Although there are many sources of data for qualitative research, Merriam posits that interviews are probably the most common source of data and often the only source of data. The reason interview data are so common in qualitative research is because the purpose of interviewing is to understand other people’s stories and what those stories mean to them (Seidman, 2006). Interviewing is a necessary part of qualitative research because we cannot observe how people feel or how they make meaning of their everyday lives (Merriam, 1998).

In this study, I wanted to develop a grounded theory to explain how educators internalize and implement external mandates to use data to guide instructional decision making. Since I could not observe how they feel or interpret how they feel from other source documents, I conducted digitally-recorded interviews as my primary source of data collection. My participants were purposefully selected to represent a stratified cross section of one particular school district, representing different grade levels, different subject areas, and different levels of experience teaching. I conducted semi-structured interviews, followed-up with probing questions, and continued interviewing until I seemed to have categorical saturation.

Data Analysis Methods

Data collected through interviews was transcribed and analyzed using Corbin and Strauss' constant comparative method, which they define as the “. . . analytic process of comparing different pieces of data for similarities and differences” (Corbin & Strauss, 2008, p. 65). This method was developed specifically for grounded theory and, as a method, its strength has been validated by its widespread use in all types of qualitative research designs (Merriam, 1998). Although it is widely used in other types of qualitative research, the constant comparative method really defines grounded theory research to the degree that it is difficult to separate the design from the method. In fact, the term constant comparative analysis has become so synonymous with the term grounded theory that other qualitative research designs are sometimes mistakenly referred to as grounded theory simply because they utilize the constant comparative method of data analysis (Merriam).

Limitations

There are two primary limitations to this grounded theory study. First, my interview participants were limited to one school district and, as such, are not representative of all school districts. In other words, the substantive theory developed in this study is grounded in the data of just one school district. This is significant because some might argue that I should have used a case study design and that the findings might not apply to educators in other settings. However, a case study was not the best design for this study because the findings are not particularly bound to the setting or context (Merriam, 1998), and I wanted to develop a substantive theory that may be transferable to other settings and contexts. Second, since I only analyzed data from interviews and I was only concerned with participant perspectives, I did not triangulate data. The aim of this study was to understand educator perspectives, not to validate that their perceived reality is the same as some other observable reality.

Significance of the Study

This study is significant to educational leaders, policymakers, and other stakeholders external to schools because the findings have implications regarding how to better support and encourage the use of data by classroom-level educators to inform instructional decision making. This is significant for two important reasons. First, the accountability movement as we know it today and the body of policy that defines it are here to stay for a while (Goertz & Duffy, 2003); and, as noted earlier, the ideas that accountability is demonstrated through data and that data should be used to inform instructional decision making are central to this movement (Jacobs et al., 2009; Young &

Kim, 2010). Within this body of policy that defines the accountability movement, there is a growing tendency to apply sanctions to schools that are not demonstrating through their data that they are meeting student performance goals (Derthick & Dunn, 2009). Because of this tendency toward school sanctions, educational leaders and others are recognizing the need to support and encourage educators in the use of data to inform instructional decision making. The second reason this study is significant is quite simply because as many researchers argue, there is real value in the idea of using data to inform instructional decision making (Bernhardt, 2009; Jacobs et al., 2009; Ronka et al., 2008; Schmoker, 2003; Williamson & Blackburn, 2009) and educators at the classroom level are in the best position to use data in ways that will have the most impact on instruction and learning (Schmoker, 2003).

Summary

As a result of external pressures to improve student achievement, classroom-level educators are increasingly being expected to use data to inform instructional decision making (Jacobs et al., 2009; Young & Kim, 2010). Further, there is evidence that using data to inform instruction results in improvements in student achievement (Bernhardt, 2009; Jacobs et al., 2009; Ronka et al., 2008; Schmoker, 2003; Williamson & Blackburn, 2009). However, despite this expectation and evidence in support of it, educators are falling short of actually using data (Crum, 2009; Love, 2004; Mokhtari et al., 2007/2008; Newmann et al., 1997; Ronka et al., 2008). Chapter two will explore what is known about how educators actually use data, why they may not be using data, and, in the absence of using data, what factors influence their decision making.

Chapter 2 – Literature Review

Introduction

Growing concerns about the quality of public education in the United States have sparked a national dialogue about public school performance, which has, in turn, led to the development of a body of policy known collectively as the accountability movement (Jacobs et al., 2009). Central to the accountability movement are the ideas that accountability is demonstrated through data and that data should be used to inform instructional decision making (Jacobs et al., 2009; Young & Kim, 2010). These ideas, which have shaped accountability policy, are modeled after ideas from the Total Quality Management (TQM) movement (J. A. Marsh et al., 2006; Young & Kim, 2010). In modeling ideas from TQM, the legislation of the accountability movement is built on an assumption that, while seemingly true for manufacturing, may not be true for education. For this study, the multiple perspectives of organizational analysis theory provided a lens through which to view this problem. While this lens may have been helpful in understanding the complex reality of meeting external mandates driven by policies built on the foundation of an ill-fitting assumption, it was important to consider what the research says about how educators are actually using data, why they may not be using data, and what opportunities they have to learn to use data. It was also important to consider what factors other than data are known to influence educator decision making.

Data-Driven Decision Making

Central to and implicit in the legislation of the accountability movement are the ideas that accountability is demonstrated through data and that data should be used to inform instructional decision making (Jacobs et al., 2009; Young & Kim, 2010). Not

coincidentally, these ideas are very similar to the ideas that are the basis of data-driven decision making, which is the central premise of the total quality management (TQM) movement that started in the United States in the 1980s as a way to demonstrate and improve quality in the manufacturing sector (J. A. Marsh et al., 2006; Young & Kim, 2010). As a result of this similarity, the accountability movement has borrowed the term data-driven decision making from the TQM movement and the term is now widely used in the dialogue surrounding standards-based school reform.

Since data-driven decision making in education is modeled after data-driven decision making in manufacturing even though schools are decidedly different than factories, it is important to develop a working definition for the term's use in education. The term is frequently defined in the empirical knowledge base and all of the definitions seem to share some common characteristics. The primary difference between the various definitions seems to be in their specificity. For example, Bernhardt offers a relatively general definition for data-driven decision making, defining it as “. . . the process of using data to inform decisions to improve teaching and learning” (2009, p. 24). Similar to Bernhardt, Weinstock also defines data-driven decision making in fairly general terms, describing it as using “. . . sophisticated technologies to gather data, sort and interpret it, and ultimately use it to pursue actions that bear higher academic achievement” (2009, p. 28). These definitions are general in the sense that they fail to specify what data are and how data are used. Crum (2009) puts forth a more specific definition, which includes language about gathering, analyzing, applying and sharing data. Her definition addresses the processes involved, but fails to identify the data. One of the more specific definitions found in the literature comes from Marsh et al. who note that data-driven decision

making in education “. . . refers to teachers, principals, and administrators systematically collecting and analyzing various types of data, including input, process, outcome and satisfaction data, to guide a range of decisions to help improve the success of students and schools (2006, p. 1).

For the purposes of this study, data-driven decision making is defined using the more specific definition offered by Marsh et al. There are two primary reasons for choosing this definition over others. First, this definition, while more specific, also has a broader scope than many of the other definitions found in the literature. In fact, many of the definitions seem to address using data only as a means to demonstrate accountability to external constituents and, as such, do not consider the broader implications of using data to guide school improvement efforts. The Marsh et al. definition seems to address more than just demonstrating accountability in that it refers to using data both to guide a range of decisions and to improve the success of students. The reference to using data to guide a range of decisions is important because it suggests that there are more uses for data in educational decision making than just raising standardized test scores. Similarly, the reference to using data to improve the success of students, when contrasted with other definitions that reference improving student achievement, suggests that data can also be used to benefit individual students and not just to benefit schools. The second reason for choosing the Marsh et al. definition was, quite simply, its reference to using various types of data. As with the other language of this definition, the acknowledgement that data are more than standardized test scores implies that there are broader uses for data-driven decision making than just meeting externally mandated performance goals related to standardized testing.

Although the Marsh et al. definition for data-driven decision making chosen for this study is one of the better definitions found in the empirical knowledge base, it is not without flaw. In fact, this definition, and all the others reviewed for this research study, may be inherently flawed in that they are all built on a foundational assumption borrowed from data-driven decision making as it applies to manufacturing, which may not hold true when applied to education. The assumption is that once data are used to identify an area that needs improvement that an educator, like an engineer in manufacturing, will know what needs to be changed and how it should be changed in order to achieve the desired improvements (Flowers & Carpenter, 2009; Jacobs et al., 2009; Williamson & Blackburn, 2009). However, knowing what adjustments should be made to instruction in order improve student success simply may not be as tangible as knowing what adjustment to make to a manufacturing process to improve the quality of a product. This flawed assumption, inherent in all the definitions, seemed to be a contributing factor to the problem under study.

How Data are Being Used

As a result of the standards-based school reform initiatives that are characteristic of the accountability movement, educators are increasingly expected to possess the professional knowledge necessary to use a wide variety of data to inform instructional decision making (Jacobs et al., 2009; Young & Kim, 2010). Not only are educators expected to know how to use data to inform instruction, they are also expected to know how to use data to affect improvements in student achievement and as a means of demonstrating and documenting those improvements (Mokhtari et al., 2007/2008; Young & Kim, 2010). As such, educators in many districts are faced almost daily with the

challenge of making sense of all of the various types of data that are available to them (Ronka et al., 2008). Although there is a growing expectation for educators to know how to use data to inform instruction and schools are responding by collecting more and more data, the literature suggests that many educators either cannot or do not use data-driven decision making as a matter of routine professional practice (Crum, 2009; Love, 2004; Mokhtari et al., 2007/2008; Newmann et al., 1997; Ronka et al., 2008). That is not, however, to suggest that educators do not use data at all. It is merely to suggest that they may not use data in the way data use is defined for data-driven decision making.

The literature indicates that the data educators are using can be grouped into two basic categories of data with very specific and limited uses. The first category of data being used involves data that schools are required to collect and report to external agencies, including student demographics and various standardized test scores (J. A. Marsh et al., 2006; Newmann et al., 1997; Pritz & Kelley, 2009; Weinstock, 2009; Young & Kim, 2010). The data in this category, particularly standardized test scores, are the data that are typically associated with the standards-based reform initiatives that are characteristic of the accountability movement and, consequently, most schools have put accountability systems in place for collecting and reporting these types of required data to external agencies (Newmann et al., 1997; Young & Kim, 2010). Because schools are held accountable for collecting, reporting, and making improvements related to these data, there is a lot of emphasis placed on these data. As a result, standardized test scores have become the primary source of data for continuous improvement for most schools (Flowers & Carpenter, 2009; Pritz & Kelley, 2009; Schmoker, 2003) and have even become synonymous with the term data (Jacobs et al., 2009; Young & Kim, 2010).

Although schools are collecting more and more of the types of data they are required to report to external agencies and making these data available to classroom-level educators (Love, 2004; Mokhtari et al., 2007/2008; Ronka et al., 2008), the data seem to be used specifically for the purposes of meeting external reporting requirements and setting school-level targets for continuous improvement. While school-level improvement targets are intended to influence classroom-level decision making, this is not necessarily what happens in practice (Flowers & Carpenter, 2009; Newmann et al., 1997; Pritz & Kelley, 2009; Schmoker, 2003). This apparent disconnect between intentions and practice is important because classroom-level educators are in the best position to improve the success of students and, in turn, to help schools meet school-level improvement targets.

The reasons these school-level improvement targets do not lead to classroom-level data-driven decision making may be linked to the fact that they are generally developed around standardized test score data. In a review of the literature on using assessments to improve instruction, Young and Kim (2010) found that most educators feel standardized test scores are of limited value to them because they often receive them after the students have advanced to the next grade, testing is done too infrequently, and standardized tests are not always aligned with their curriculum. Similarly, Marsh et al. (2006) cite timing as the primary reason educators do not find standardized test scores very useful, noting that tests are generally given in the spring and scores are received at the end of the year just before that cohort of students advances to the next grade.

While the expectation that school-level data-driven decision making will lead to classroom-level data-driven decision making (Bernhardt, 2009) has not necessarily lead

to classroom-level educators using accountability data to inform instruction (Flowers & Carpenter, 2009; Newmann et al., 1997; Pritz & Kelley, 2009; Schmoker, 2003), most of these educators do use data to some extent. The data classroom-level educators actually use can be grouped into a second category of data that includes data from a wide variety of classroom-level formative and summative assessments. Classroom-level formative and summative assessments are generally referred to as assessments *for* learning and assessments *of* learning, respectively (C. J. Marsh, 2007; Stiggins, 2002; Stiggins & Chappuis, 2006). Although the difference between formative and summative assessment is represented in the literature with a subtle change in prepositions, the difference is more than a simple issue of semantics. In defining these terms, the words *for* and *of* actually represent a significant conceptual difference and this difference is important to the discussion about data use.

The term formative assessment is used to refer to a wide variety of assessments, both formal and informal, that are used to support learning (Dorn, 2010; C. J. Marsh, 2007; Stiggins & Chappuis, 2006; Young & Kim, 2010). In its purest form, formative assessment is more of an instructional technique than an assessment technique in that the assessments are not graded and are used instead as ongoing tools for guiding instruction and for providing meaningful feedback to students (C. J. Marsh, 2007). In contrast, the term summative assessment is used to refer to a wide variety of assessments, both formal and informal, that are intended to be end measures of learning (Stiggins & Chappuis, 2006; Young & Kim, 2010). One of the reasons the difference between these two concepts is important to the discussion about data use is because the term formative assessment has made its way into the body of policy surrounding the accountability

movement (Dorn, 2010; Stecker, Lembke, & Foegen, 2008; Stiggins & Chappuis, 2006; Young & Kim, 2010). On the surface, the addition of the term formative assessment and the expectation that educators use formative assessments is positive. When used properly, data from formative assessments support classroom-level data-driven decision making in ways that standardized test data cannot. This is because, when used properly, formative assessments are timely, frequent, and aligned with the curriculum (Dorn, 2010; C. J. Marsh, 2007; Stiggins & Chappuis, 2006; Young & Kim, 2010).

Ironically, the inclusion of the term formative assessment in accountability policy has led, in practice, to a blurring of the conceptual difference between the terms formative and summative assessment, which is another reason that the difference between these two terms is important to the discussion about data use. In practice, policymakers and textbook publishers have begun to refer to frequent summative assessments as formative (Stiggins & Chappuis, 2006) and, further compounding this problem, there are very few classroom-level educators truly using formative assessments as a part of routine instructional practice (Black & William, 1998; C. J. Marsh, 2007; Stiggins, 2002; Young & Kim, 2010). In fact, educators, like policymakers and textbook publishers, may confuse some types of summative assessments with formative assessments. This is because the abilities to both distinguish between formative and summative assessment and to use formative assessment in its purest form require a broad base of foundational assessment skills and knowledge (Jacobs et al., 2009; C. J. Marsh, 2007; Stiggins, 2002; Stiggins & Chappuis, 2006; Young & Kim, 2010). Young and Kim (2010) argue that any assessment can be formative if it is used to support learning and that, intentions aside, assessments simply are not formative if they are not used to support learning. They

found in their review of the literature on using assessments to improve instruction that educators lack these assessment skills because they are not taught in schools of education or in ongoing professional development and, as such, that most educators use assessment data primarily for the specific and limited purpose of assigning grades.

In spite of the evidence in the empirical knowledge base that most of the data use in education is very specific and limited, there are isolated examples of educators using data to drive instruction. For example, Bernhardt (2009) describes how a California elementary school with high percentages of students that speak English as a second language and receive free or reduced lunches is using data-driven decision making to improve test scores in every subject, at every grade level, and for every subgroup. The success of that school can be attributed to a professional development program on data-driven decision making that administrators learned about at a workshop and then implemented school-wide. In a similar example, Beck (2008) details how a small, rural school district that uses data-driven decision making is experiencing steady gains in achievement test scores. This district has implemented a district-wide data-driven decision making program that involves bringing classroom-level educators together during the summer to systematically analyze data, plan instructional changes, and monitor progress. In these two examples, and others found in the empirical knowledge base, there is an important common thread and that common thread is that in schools where data are routinely and pervasively being used to inform instruction there is generally some type of school-wide or district-wide program in place to support and encourage data-driven decision making.

Reasons Educators May Not Use Data

While there is not a lot known about how educators use data to inform instruction or their perspectives on using data to inform instruction (Young & Kim, 2010), the literature does suggest that they may not be using data the way data use is defined for data-driven decision making (Crum, 2009; Love, 2004; Mokhtari et al., 2007/2008; Newmann et al., 1997; Ronka et al., 2008). Further, the literature identifies some potential reasons why educators may not use data to drive instruction, and these reasons can be grouped into three primary categories.

The first category involves possessing the necessary technical skills to analyze and use data. Many educators report feeling ill equipped or ill prepared to analyze data (Earl & Katz, 2006; Flowers & Carpenter, 2009; Jacobs et al., 2009; Ronka et al., 2008; Williamson & Blackburn, 2009). Essentially, whether real or perceived, many educators believe there is a deficit in their own skills and knowledge related to data analysis and use (Mokhtari et al., 2007/2008; Young & Kim, 2010). Interestingly, this belief does not seem to be limited to classroom-level educators. Young and Kim (2010) found in the literature that, when surveyed, only small percentages of educators in leadership roles reported feeling that they have the technical skills necessary to analyze and use data. This may be due to a lack of training related to using data or professional experience with using data (Earl & Katz, 2006; Flowers & Carpenter, 2009).

Along these same lines, the literature also indicates that many educators feel that the process of analyzing and using data is “overwhelming” (Flowers & Carpenter, 2009; Mokhtari et al., 2007/2008; Schmoker, 2003; Williamson & Blackburn, 2009); however, there is not strict agreement among the various authors regarding the source of this

feeling. Schmoker (2003) suggests educators feel this way because experts tend to overcomplicate data analysis and use, while Williamson and Blackburn (2009) attribute this feeling to the sheer amount of data available to educators. Similarly, Mokhtari et al. (2007/2008) and Flowers and Carpenter (2009) posit that this feeling stems from data analysis and use being a time consuming activity. Whether there is strict agreement or not on the basis of this feeling, there is probably some relationship between the feeling that data analysis and use is overwhelming and having the technical skills necessary to analyze and use data and, as such, it is being included in the first category.

The second and third categories are related to how educators may feel about data. There are two distinct but related terms used to describe these feelings in the literature. These terms, mistrust and fear, represent the second and third categories, respectively. Earl and Katz (2006) posit that educators often mistrust data and cite two reasons for this. First, most educators have a great deal of confidence in their own tacit knowledge about teaching and learning (Connelly & Clandinin, 1988) and this tacit knowledge is resistant to change (Sykes, 1999). When educators use data they are sometimes presented with information that is contradictory to or incongruent with what they tacitly believe to be true and, since they are confident in their own tacit knowledge, they feel it is the data cannot be trusted (Earl & Katz, 2006). In other words, they may feel that their own intuition is more reliable than the data. Second, many educators believe data can be skewed and used against them (Earl & Katz, 2006). Essentially, this is a belief that data can have more than one interpretation and that sometimes interpretations are based on a hidden agenda or, perhaps less nefariously, at least a desire to paint a certain picture.

Although educators may mistrust data because they believe it can be skewed and used against them, they may also fear it for the same reason. Another reason they may fear data is because data have become synonymous with standardized test scores (Jacobs et al., 2009; Young & Kim, 2010). When describing the way the prospect of using data makes them feel, educators use terms such as alert, alarm, and red flag; feelings which are thought to be associated with the high-stakes standardized testing that is characteristic of the accountability movement (Earl & Katz, 2006; Jacobs et al., 2009). Often, educators discover that data from these tests serve more as red flags than as constructive inputs to drive instructional decision making. Finally, educators may fear data because they may fear the prospect of being evaluated. Educators are used to being in the position of being evaluators and the prospect of being evaluated may be daunting. Particularly the prospect that their performance may be evaluated based on student performance data (Earl & Katz, 2006).

Why Data Should Be Used

Central to the accountability movement are the ideas that accountability is demonstrated through data and that data should be used to inform instructional decision making (Jacobs et al., 2009; Young & Kim, 2010). Consequently, there is a growing expectation that classroom-level educators should not only possess the technical skills necessary to use data, but that they should also routinely use data to drive instruction. The literature, however, suggests that this emphasis on data use has actually resulted at worst in data being used only for the purpose of demonstrating compliance (Love, 2004; Newmann et al., 1997) and at best in data also being used for the purpose of setting school-level improvement targets (Flowers & Carpenter, 2009; Pritz & Kelley, 2009;

Schmoker, 2003). While there is agreement in the literature that data can and should be used both to meet accountability requirements and to monitor progress towards meeting these requirements (Jacobs et al., 2009; Pritz & Kelley, 2009; Williamson & Blackburn, 2009; Young & Kim, 2010), the literature also suggests that there are other reasons to use data that may be more meaningful to classroom-level educators.

In fact, there are a variety of reasons for classroom-level educators to use data, all of which are directly related to the overarching goal of improving student success. One reason to use data is because when educators use the right data and use it effectively, data can help them understand what students know (Jacobs et al., 2009; Pritz & Kelley, 2009; Schmoker, 2003; Weinstock, 2009; Williamson & Blackburn, 2009; Young & Kim, 2010). While many educators trust the reliability of their own tacit knowledge over data (Connelly & Clandinin, 1988), there is evidence that data can reveal surprising information about what students do and do not know (Weinstock, 2009). Additionally, data can present a more precise picture of what students are learning. Where tacit knowledge may only offer broad or general insights into student learning, data can provide detailed information about students' strengths and weaknesses relative to specific content (Schmoker, 2003).

Similarly, another reason to use data is because as educators develop a greater understanding of what students know and what they are learning they can, in turn, use that information to inform instruction (Jacobs et al., 2009; Pritz & Kelley, 2009; Williamson & Blackburn, 2009; Young & Kim, 2010). In the empirical knowledge base, the terms 'using data to inform instruction', 'using data to guide instruction', and 'using data to drive instruction' are all used interchangeably to refer to wide range of activities

and, as such, the terms will also be used interchangeably in this study. For instance, using data to inform instruction sometimes refers to using data to plan curriculum (Jacobs et al., 2009; Young & Kim, 2010). In other instances, however, using data to inform instruction refers to using data to shape instructional practices. Examples of instructional practices that might be shaped by data include things such as differentiating learning and grouping students for learning (Jacobs et al., 2009; Young & Kim, 2010). In some instances, however, using data to inform instruction simply refers to the imprecise and ill-defined goal of using data for making improvements in instruction (Pritz & Kelley, 2009; Williamson & Blackburn, 2009; Young & Kim, 2010).

A final reason to use data is to evaluate the effectiveness of instruction (Jacobs et al., 2009; Pritz & Kelley, 2009; Young & Kim, 2010). Using data to evaluate instructional effectiveness is very closely related to the other reasons cited for using data and, in fact, should be an integral part of the process of data-driven decision making. In practice, the process should be a continuous cycle of using data to understand what students know, using that information to plan curriculum and shape instructional practices, and then using additional student data to evaluate the effectiveness of the curriculum and instructional practices (J. A. Marsh et al., 2006).

What it Means to be Data Literate

Despite the evidence that many educators feel they lack the skills and knowledge necessary to analyze and use data (Mokhtari et al., 2007/2008; Young & Kim, 2010), data-driven decision making does not require sophisticated data analysis skills. In fact, classroom-level educators can easily learn to analyze and use data in ways that will have

the greatest impact on improving student success (Schmoker, 2003). Data-driven decision making does, however, require educators to be data literate.

Generally speaking, being data literate is defined as knowing how to use multiple types of data to inform decisions that lead to improving student success (Ronka et al., 2008), a definition which is barely distinguishable from the definition for data-driven decision making. In fact, the subtle distinction between these two definitions is that the definition for data literacy refers to knowing how to use data, while the definition for data-driven decision making refers to actually using data. As such, it is important to explore what ‘knowing how to use data’ means.

While being data literate can be defined simply and succinctly, what it actually means to know how to use data is complex and difficult to define. Even though there does not seem to be a simple and succinct definition for this phrase in the literature, there is a lot of discussion concerning what it means to use data well. Most of this discussion, however, is limited to addressing issues related to knowing how much of what data to use and, as such, falls short of actually addressing how to use data. Nonetheless, it is still necessary to explore this discussion in order to develop an understanding of what is known about what it means to be data literate or to know how to use data.

Several authors posit that being data literate involves knowing to use multiple sources of data (Bernhardt, 2009; Jacobs et al., 2009; Love, 2004; Young & Kim, 2010). Love (2004), for example, emphasizes using three sources of data or triangulating data. She contends that it is not good to draw conclusions from a single source of data and that two additional sources are necessary to validate the first source. Similarly, though they

do not use the term triangulation, Jacobs et al. (2009) hint at triangulation by arguing for the use of three sources of data. They suggest that using three sources of data develops a more comprehensive and more accurate portrayal of what students know. Others simply advocate for the use of multiple sources, citing similar reasons (Bernhardt, 2009; Young & Kim, 2010).

In addition to using multiple sources of data, there is much written about using different kinds of data (Bernhardt, 2009; Flowers & Carpenter, 2009; Jacobs et al., 2009; Love, 2004; Schmoker, 2003; Williamson & Blackburn, 2009; Young & Kim, 2010). One of the unintended consequences of the accountability movement is that standardized test scores have become synonymous with data to the degree that educators often do not realize that there are many other types of data that can and should be used in conjunction with test score data (Jacobs et al., 2009; Young & Kim, 2010). Some examples include data obtained from district or school-level assessments (Schmoker, 2003), student demographic data that is routinely collected in district and school-level information systems (Bernhardt, 2009; Jacobs et al., 2009), and data from formative classroom assessments (Williamson & Blackburn, 2009; Young & Kim, 2010). Other examples of data that are often overlooked in this context include perception data collected through survey instruments administered to a wide variety of stakeholders (Bernhardt, 2009; Flowers & Carpenter, 2009; Love, 2004) and other qualitative data collected through classroom observations and individual or focus group interviews (Love, 2004; Williamson & Blackburn, 2009; Young & Kim, 2010). Williamson and Blackburn (2009) believe so strongly in the value of this last type of data that they even recommend extending observations beyond the classroom. Specifically, they suggest collecting data

by following a student through a normal day and conducting what they refer to as a shadow study.

Besides using multiples sources of data and using different kinds of data, many authors support the idea of using disaggregated data or data that are broken down into specific subgroups of students, specific components of curriculum, or specific areas of instruction (Bernhardt, 2009; Flowers & Carpenter, 2009; Love, 2004; Ronka et al., 2008). Disaggregating data is useful in that it can help answer questions about specific areas of concern (Ronka et al., 2008). It can also identify which students are not being reached (Bernhardt, 2009) and what areas of instruction might be improved (Flowers & Carpenter, 2009). In short, using disaggregated data can reveal patterns, trends, and other important information.

While most of the discussion concerning what it means to be data literate is related to knowing how much of what data to use, there is also some discussion about using data that are high quality and about what makes data high quality. Quite simply, it is very important to use high quality data and high quality data are data that are complete and accurate (Katz et al., 2005; Ronka et al., 2008). Perhaps equally important is the notion that educators have to believe that data are high quality. It is not enough for data to be complete and accurate if educators do not believe data are complete and accurate (Ronka et al., 2008). Further, data have to have legitimacy with educators and have to be reflective of their own judgment (Young & Kim, 2010). Educators tend to reject data that are not reflective of their own judgment, which is likely because they are more confident in their own tacit knowledge than in data (Connelly & Clandinin, 1988) and because tacit knowledge is resistant to change (Sykes, 1999). In other words, they feel

that if some data and what they know to be true are not in alignment, it must be the data that are wrong.

Although most authors fall short of actually addressing how to use data, there are some that hint at how to use data. For example, there is wide agreement in the literature that the process involves asking questions (Katz et al., 2005; Mokhtari et al., 2007/2008; Ronka et al., 2008; Williamson & Blackburn, 2009). In fact, Katz et al. (2005) and Williamson and Blackburn (2009) contend that the process starts with asking questions in order to identify the purpose for using data, while others advocate for asking questions to guide the collection and analysis of data (Mokhtari et al., 2007/2008; Ronka et al., 2008). It is important to note, however, that most of these authors do not offer much practical advice on what questions to ask, how to ask them, or how to get answers.

The other example found frequently in the literature is related to possessing the technical skills necessary to analyze and use data (Katz et al., 2005; Newmann et al., 1997; Ronka et al., 2008; Young & Kim, 2010). Katz et al. (2005) specify that these skills are skills in statistical and measurement concepts, while others are not specific and simply refer to these skills as data analysis skills (Newmann et al., 1997; Ronka et al., 2008; Young & Kim, 2010). Ronka et al. (2008) and Young and Kim (2010) also suggest that assessment literacy is a component of this skill set, particularly noting the importance of knowing how to use formative assessment feedback. However, as with using questions in the process, there is not much practical advice on what these technical skills actually are or on how to apply them.

Interestingly, most of the discussion about possessing the technical skills necessary to analyze and use data is tied not just to data literacy but also to data capacity. The reason for this may be because, as Ronka et al. (2008) argue, effective data use will not occur unless schools address capacity. Data capacity is not clearly defined in the literature, but the term seems to refer to how data literate a school is collectively (Newmann et al., 1997; Ronka et al., 2008; Young & Kim, 2010). There does seem to be a fair amount of advice in the research regarding how to build capacity.

First, it is important for educational leaders to be technical experts in analyzing data and to serve as data coaches (Ronka et al., 2008; Young & Kim, 2010). Educational leaders that are experts in analyzing data are better able to facilitate discussions about using data, guide accurate analysis, and identify the instructional implications of analysis (Young & Kim, 2010). Along these same lines, it is also necessary to build these skills faculty-wide through formal professional development and technical assistance from data coaches (Newmann et al., 1997; Ronka et al., 2008; Young & Kim, 2010).

Second, it is important to build structured time for collaborative data analysis into the school calendar (J. A. Marsh et al., 2006; Newmann et al., 1997; Ronka et al., 2008; Young & Kim, 2010). Not only is it important to have this dedicated time, it is also important for educational leaders to facilitate the meetings that take place during this time. As data coaches, they should help keep these meetings focused on what can be done in classrooms to make improvements based on data (Young & Kim, 2010).

Finally, it is important to develop technology that facilitates using data (J. A. Marsh et al., 2006; Newmann et al., 1997; Young & Kim, 2010). The systems that are

used to collect, store, analyze, and report data are becoming increasingly important in developing data capacity in schools. As these systems are developed, educators need to be taught to manipulate them and to use them to get reports (Young & Kim, 2010).

Educator Decision Making

Educators routinely make a wide variety of decisions as a matter of professional practice (Klimczak, Balli, & Wedman, 1995; Parker, 1984). These decisions can range from what topics to teach and how to sequence them to what specific examples to use when teaching. In fact, making decisions is such a routine part of their professional practice that educators are often characterized as decision makers (Klimczak et al., 1995).

Additionally, some might argue that educators are not just decision makers, but that they are also skilled decision makers. While educators make a lot of decisions as a part of planning curriculum and instruction, they also find themselves making a lot of quick decisions in reaction to unplanned and unpredictable interactions with students (Parker, 1984; Schoenfeld, 1998). Further, they make a lot of these decisions in an environment that is in flux and under conditions that are uncertain (Helsing, 2007). In spite of all this, there is research to support the idea that the decisions educators make influence student achievement in positive ways (Parker, 1984).

It would seem reasonable to expect then, that since educators are skilled at making decisions that influence student achievement positively, that they would also be skilled at using data to inform these decisions. Not only would it seem reasonable to expect, it is exactly what is increasingly being expected of educators in response to standards-based reform (Mokhtari et al., 2007/2008; Young & Kim, 2010). However,

whether because they do not have the skills or perhaps because they do not see the value, educators are not, as expected, using data to inform these decisions (Crum, 2009; Love, 2004; Mokhtari et al., 2007/2008; Newmann et al., 1997; Ronka et al., 2008). Since what is expected is not what is happening, it is important to understand what actually influences educators' decision making.

The literature indicates that there are several factors that influence educators' decision making and that these factors, while different, are closely related and somewhat intertwined. Educators' beliefs, for example, are one such factor (Schoenfeld, 1998; Young & Kim, 2010). What educators believe, along with their goals, are important determinants of the decisions they make and why they make them (Schoenfeld, 1998). Their beliefs also influence what they embrace and what they reject (Young & Kim, 2010). Similarly, educators' personal experiences are another such factor. Not only do their personal experiences influence their decisions, their personal experiences also shape their beliefs about teaching in general (Klimczak et al., 1995). Personal judgment is another factor that influences decision making and fits with beliefs and personal experiences. Over time, educators form impressions of students based on their interactions with them and these impressions are the basis of the judgments they make (Young & Kim, 2010). Educators place a high level of importance on these judgments when making decisions (Herman & Dorr-Bremme, 1983).

A final factor that influences educators' decision making is knowledge. Educators draw on the domains of subject matter knowledge and pedagogical content knowledge when making decisions (Klimczak et al., 1995; Sandholtz, 2005; Schoenfeld, 1998). In fact, to be successful, educators must develop expertise in both their subject

matter and pedagogy along with an understanding of how the two interact (Klimczak et al., 1995). Their knowledge of subject matter and pedagogy is not static and, therefore, most educators continue to develop expertise in both of these areas throughout their careers (Sandholtz, 2005). Educators rely heavily on both subject matter knowledge and pedagogical knowledge to inform instructional decisions such as making adjustments to instruction (Klimczak et al., 1995; Schoenfeld, 1998).

It is important to note that, collectively, all of these factors that influence decision making are a part of educators' tacit knowledge. Tacit knowledge, which is difficult to share with others, can include beliefs and judgments along with knowledge of subject matter and pedagogy (Nonaka & Takeuchi, 1995). Collectively, tacit knowledge is the single most important factor influencing educator decision making (Connelly & Clandinin, 1988).

Formal Coursework and Professional Development

At the heart of understanding how data-driven decision making can be addressed through formal coursework and professional development is the notion of understanding educators as learners (Love, 2004). In this context, learning refers not only to the acquisition of knowledge but also to how the learner makes meaning of newly acquired knowledge, and to the idea that knowledge is created and re-created through construction of meaning by the learner (Katz et al., 2005). In other words, the construction of knowledge occurs when learning is internalized by the learner (Nonaka & Takeuchi, 1995).

Since learning involves creating knowledge, it is important to understand what is meant by knowledge. While some might use the terms knowledge and information interchangeably, knowledge is really more complex than information and can be defined as “. . . a dynamic human process of justifying personal belief toward truth” (Nonaka & Takeuchi, 1995, p. 58). Further, knowledge is primarily tacit, rather than explicit, and is difficult to share with others. In fact, in order to be shared, tacit knowledge must be converted to explicit knowledge (Nonaka & Takeuchi, 1995).

Paradoxically, these basic tenets of learning and knowledge that should underpin any successful formal coursework or professional development on using data directly parallel and support one of the reasons educators may not use data in the first place. As noted earlier, educators often trust their own tacit knowledge over data (Connelly & Clandinin, 1988) and this tacit knowledge is resistant to change (Sykes, 1999). Seemingly, many educators see data as information rather than knowledge since they are not making meaning of it and internalizing it. Consequently, when presented with data that are contradictory or incongruent with their tacit knowledge, the data are easily rejected (Earl & Katz, 2006).

Further complicating the development and delivery of successful coursework and professional development on using data is the idea that, since knowledge is created through the construction of meaning by the learner (Katz et al., 2005), knowledge comes with experience. Moreover, the research does indicate that experience is better than formal coursework or professional development and that educators, particularly pre-service educators, need experiences in settings that support frequent practice of using data (Jacobs et al., 2009). Not only is learning through experience better, it is also what

happens most often in practice. However, as is the norm with the profession in general, the reality is that most of this practice happens in isolation and educators are left to figure it out on their own through trial and error (Young & Kim, 2010). Another reality is that this sometimes results in educators developing practices for using data to inform instruction that have flaws (Katz et al., 2005).

Despite the importance of experience, there is evidence that both formal coursework and professional development contribute to helping educators begin to understand how to use data and, accordingly, to helping them feel more confident about using data (Jacobs et al., 2009; Young & Kim, 2010). Unfortunately, there is also evidence to suggest that educators do not have a lot of opportunities to participate in formal coursework or professional development on using data and, further, that many of the opportunities that do exist may be less than optimal (Katz et al., 2005; Pritz & Kelley, 2009; Ronka et al., 2008; Young & Kim, 2010).

The discussion related to formal coursework on using data, similar to the actual availability of this coursework, seems to be very limited. It is mentioned primarily in reference to pre-service educators and only a small percentage of pre-service educators report receiving this type of coursework (Young & Kim, 2010). Not only is formal coursework for pre-service educators weak on addressing the issue of using data, it is also weak on addressing the more specific issue of using data to inform instruction (Young & Kim). Quite simply, it fails to provide guidance on translating data analysis into meaningful instructional improvements. Also, this formal coursework is not consistently relevant to classroom practices and often does not address the needs of educators (Young & Kim).

The discussion related to professional development on using data, if not the actual availability of such professional development, is not as limited as the discussion related to formal coursework on using data. In fact, as with formal coursework on using data, only a small percentage of educators report receiving professional development on using data (Young & Kim, 2010). However, the need for professional development on this topic is widely acknowledged (Katz et al., 2005; Pritz & Kelley, 2009; Ronka et al., 2008; Young & Kim, 2010), even if it is not necessarily well defined. Further, while there is not a lot known about what good professional development on using data should include, Young and Kim (2010) contend that, at minimum, it should be consistently applicable to classroom practices, be grounded in specific subject matter, and address assessment literacy.

There are, however, a few isolated examples in the empirical knowledge base of frameworks for professional development on using data. For example, Williamson and Blackburn (2009) suggest a four-step process that involves determining what you want to know, deciding how to collect data, analyzing data, and setting priorities and goals. Similarly, Flowers and Carpenter (2009) recommend a five-step process with steps that include reviewing your school improvement plan, determining how data will be used, identifying relevant data, examining and discussing the data, and setting goals and evaluating progress. Ronka et al. (2008), on the other hand, propose using questions to guide the inquiry and analysis and refer to this framework as the essential questions approach.

Although these frameworks all outline a structured process intended to facilitate the development of data-driven decision making skills among educators, they all

fail to address how to actually analyze data and how to use the results of analyses to improve instruction. In fact, these frameworks seem to be built on the assumptions that educators already know how to analyze and use data and that they only need a structured process to ensure that data is used routinely and consistently in support of school-wide improvement goals.

Summary

While there is research to support the idea that using data-driven decision making can influence student achievement gains (Bernhardt, 2009; Jacobs et al., 2009; Ronka et al., 2008; Schmoker, 2003; Williamson & Blackburn, 2009), most educators fall short of actually using data to inform instruction (Crum, 2009; Love, 2004; Mokhtari et al., 2007/2008; Newmann et al., 1997; Ronka et al., 2008). That is not to say, however, that educators do not use data at all. Their use of data is just very specific and limited and they do not have many opportunities to participate in formal coursework or professional development aimed at broadening these skills.

Although the literature identifies potential factors that may explain why educators have certain perspectives on using data, little is known about the interrelatedness of these factors, which of these factors may be most important, or how best to address these factors through formal coursework or professional development. This study attempts to generate a better understanding of some of these factors in order to potentially inform professional development on using data to inform instruction.

Chapter 3 – Research Design and Methodology

Introduction

As noted in the literature review section, there is not a great deal in the literature regarding educator perspectives on using data to inform instructional decision making. Further, while the limited literature available on the topic identifies potential factors that may contribute to why educators may have certain perspectives on using data, it seems little is known about the interrelatedness of these factors, which of these factors may be most important, or how best to address these factors through formal coursework or professional development. This deficit in the literature suggests that there is not an empirical knowledge base for educational practitioners, educational leaders, professional developers, or educational researchers to draw on and build upon.

Through my research, I wanted to address the gap between how policymakers and educational leaders expect data to be used to inform instruction and how classroom-level educators internalize and implement these expectations. More specifically, I wanted to understand educators' perspectives on using data, their views of their own data analysis skills, how they value and make meaning of data, and how their educational backgrounds or organizational cultures shape these views. Qualitative methods were most appropriate for this type of inquiry for a number of reasons.

First, generally speaking, qualitative research is “undertaken because there is a lack of theory, or existing theory fails to adequately explain a phenomenon” (Merriam, 1998, p. 7). As noted above, little is known about educators' perspectives on using data to inform instruction, why they have certain perspectives, or what can be done to support

and develop desired perspectives. I wanted, through my research, to make a contribution to the limited empirical knowledge base. Second, since there is a disconnect between the way external policy makers think educators should use data and educators perspectives on using data, it is important to understand this phenomenon from the perspectives of the educators. Qualitative research seeks to understand a phenomenon “from the informant’s own frame of reference” (Bogdan & Biklen, 2007, p. 2). In fact, Merriam (1998) notes that this is a key concern of qualitative research. Third, the primary source of data for this study was interview transcripts, which are descriptively rich. In qualitative research, data often take the form of words or pictures rather than numbers (Bogdan & Biklen, 2007; Merriam, 1998). Finally, for this study, I was the primary instrument for collecting data, which is characteristic of most forms of qualitative research (Bogdan & Biklen, 2007; Merriam, 1998).

Design and Methodology

The design of this study is a qualitative study utilizing interpretive grounded theory methods for data collection and analysis (Bogdan & Biklen, 2007; Heppner & Heppner, 2004; Merriam, 1998). Grounded theory is a specific research methodology introduced by Glaser and Strauss in 1967 with the purpose of building substantive theory that is grounded in data (Corbin & Strauss, 2008; Merriam, 1998). This is in contrast to other qualitative designs that simply seek to provide rich, thick description or identify basic themes (Corbin & Strauss, 2008). That being said, it is important to note that grounded theory methods have become so widely used that the term grounded theory is often used very loosely to refer to any type of qualitative study that utilizes grounded theory methods for data analysis (Merriam, 1998). In fact, Corbin (2008) even

acknowledges the value of grounded theory methods to other types of qualitative research studies noting the challenges data analysis presents to all qualitative researchers. However, in this study I will attempt to actually develop a substantive theory that is at least grounded in the data from my setting and context.

When Glaser and Strauss introduced grounded theory in 1967, their work was the only one of its kind and there was only one grounded theory. Since that time, there have been several evolutions and interpretations of grounded theory (Corbin & Strauss, 2008). The design of this study is based on the interpretation of grounded theory presented by Corbin and Strauss in the third and most recent edition of the *Basics of Qualitative Research*. This most recent edition, written after the passing of Strauss, presents an updated interpretation of grounded theory that takes into account contemporary thinking about qualitative research while attempting to remain true to the vision of grounded theory held by Strauss until his death (Corbin & Strauss, 2008). Ironically, the book serves almost as a how-to guide on data analysis for qualitative researchers. This is ironic because the book seemingly addresses a problem similar to the problem identified in this study only for a theoretical rather than a practicing audience, and for a different context.

This somewhat prescriptive, how-to approach may be explained by Corbin's philosophical assumptions concerning research and reality. Corbin (2008) notes that although she attempts to take contemporary thinking on qualitative research into consideration and dislikes being labeled a post-positivist, that she still believes that research should contribute to the empirical knowledge base and that it should be practical. While her beliefs regarding research are very pragmatic, her beliefs regarding

reality are very complex. Corbin (2008) believes that the world is complex, that there are no simple explanations for things, that reality is made up of events that occur due to a variety of factors coming together and interacting, that these events mean different things to different individuals, and that this meaning can be interpreted different ways by different researchers. Corbin's latest interpretation of grounded theory is an attempt to reconcile her practical view of research with her complex view of the world. Quite simply, she provides researchers a straight-forward, how-to guide for using a complex research methodology designed to explain very complex interactions between individuals and events.

In summary, a grounded theory approach was a good choice for the design of this study for at least two reasons. First, and foremost, grounded theory methodology aligns well with the study's research questions, which is an important determinant for research design (Corbin & Strauss, 2008). In this study I wanted to not only understand the gap between how policy makers and educational leaders expect data to be used and how educators internalize and implement these expectations but to also understand some of the factors that explain this gap. In other words, I wanted to focus on "why," at least for my setting and context, and "why" is a question best answered through the development of a substantive theory grounded in data. Second, my views regarding research and reality align well with Corbin's, which is another important determinant for research design (Merriam, 1998). I wanted my research to contribute to the empirical knowledge base and, more importantly, to inform practice. Although the view policymakers hold of using data to inform instructional decision making may not actually result in improving student performance, I do believe there is value in using data. I would like for my

findings to contribute to the development of a professional development initiative to address the effective use of data to inform instructional decision making. With that practical aim in mind, I know that there is not a simple explanation for why educators have certain perspectives on using data. Their perspectives are the result of the events that make up their everyday experiences and their individual understanding of those events. Corbin's interpretation of grounded theory provided a structured way for me to apply a complex research methodology to a complex research problem. Additionally, since different researchers can interpret the meaning of the same data in different ways, grounded theory methodology provided guidelines for how I approached my role as the primary research instrument.

Researcher's Role

In all qualitative methodologies, the researcher is the primary research instrument and, because researchers are people, all the data analysis is, to some extent, shaped by the researcher's own worldview, values, experiences, and perspectives (Merriam, 1998). While this can be viewed as a weakness of these methodologies, there are things the qualitative researcher can do ensure the trustworthiness of a study's findings. The issue of trustworthiness will be addressed in the methodology section later in this chapter.

Although the researcher as the primary research instrument can be viewed as a weakness of qualitative methodologies, this role of the researcher can also be viewed as a strength. The researcher, being human, has "the ability to pick up on subtle nuances and cues in the data that infer or point to meaning" (Corbin & Strauss, 2008, p. 19). Qualitative researchers refer to this ability as sensitivity (Corbin & Strauss, 2008; Merriam, 1998) and it is likened to the human trait of intuition. This ability allows

qualitative researchers to “. . . be sensitive to the context and all the variables within it, including the physical setting, the people, the overt and covert agendas, and the nonverbal behavior” (Merriam, p. 22).

Another strength of the researcher as the primary instrument is the reflexivity the researcher brings to the process (Bogdan & Biklen, 2007; Corbin & Strauss, 2008). When interacting with participants in the data collection process, a researcher will invariably have emotional responses to the data being collected. Some of these responses are conveyed to the participants and, to some extent, may shape the participants’ responses. The researcher and participants are said to “. . . co-construct the research . . .” (Corbin & Strauss, 2008, p. 31). While some opponents argue that this is a weakness similar to the one noted earlier about the researcher’s own views shaping the data analysis, this too can be addressed by taking steps to ensure the trustworthiness of the study’s findings. Further, reflexivity has proponents who view it as absolutely essential to the qualitative research process (Corbin & Strauss, 2008). Qualitative researchers are trained to study complex problems involving human participants. These human participants have experiences and stories to share, but may not know much about participating in a research study. Reflexivity on the part of the researcher may serve to guide participants through the inquiry and to help them reveal to the researcher what is important.

In addition to the strengths already mentioned, it should also be noted that for this study in particular, my professional role within the setting of my study was a benefit to my roles of researcher and primary research instrument. Since my study participants were selected from the school district where I work, I have knowledge of their setting and

other contextual factors that might contribute to their perspectives. Plus, since the participants either know me or know of me, they might have been more willing to participate in the study and quicker to open up during the inquiry. Some might argue, however, that my professional role within the setting of my study could have instead been a detriment to my roles of researcher and primary research instrument because study participants might have been more hesitant to share insights with me that might be perceived as negative by district administrative personnel. I do not, however, think that this is a concern. My research problem does not involve issues that are sensitive or controversial. The interview questions I asked participants are not likely to subject even the most forthcoming participants to any undue risk or harm. Additionally, the informed consent form (see Appendix A) I prepared for this study assured study participants that their participation is voluntary and confidential and that even their identities will be protected (Seidman, 2006).

Setting

The participants for this study were selected from the school district where I work, a small to mid-sized district in a rural Midwestern town. The district has three elementary schools, one middle school, one junior high school, one high school, and one area career and technical center that serves high school students and adult students both from inside the district and from several other districts within a fifty-mile radius. The district also has early childhood, adult literacy, and basic education programming. Data from the 2010 census indicates that the total population for the district's service area is 30,939 and, according to statistics publicly available on the state department of elementary and secondary education's website, the district's enrollment is 4,020 students

in grades kindergarten through 12 and forty-one in pre-school. Almost ninety percent of the enrolled students are reported as white and a little over forty-six percent of them qualify for free or reduced lunch. The district has a student to teacher ratio of 20:1 and a student to administrator ratio of 237:1. Average salaries for administrators and classroom-level educators are \$85,049 and \$46,199, respectively, which are slightly higher than state averages. Conversely, the average annual expenditure per pupil is \$8,041, which is slightly lower than the state average. The assessed value of the district is around \$377 million and the adjusted tax rate is approximately \$3.17.

Participants

According to statistics publicly available on the state department of elementary and secondary education's website, the district currently has approximately 269 full-time certified educators teaching grades kindergarten through 12. The data are disaggregated by building and an analysis of the building-level data indicates that the number of educators at each grade level ranges between approximately seven and nine percent of the total. In other words, staffing levels appear to be fairly consistent across the grade levels. Further, the educators have an average of thirteen years of teaching experience and almost sixty percent hold master's degrees or higher.

With the assistance of an internal district contact who has greater access to more detailed staffing demographics than are publicly available, potential participants were purposefully selected to represent a stratified cross-section of this school district. Qualitative research does not test hypotheses and, as such, qualitative researchers cannot generalize their study findings. Similarly, qualitative researchers do not study statistically random samples that are representative of a larger population. The

alternative for qualitative researchers is to purposefully select participants to represent a cross-section of the study population and to conduct in-depth interviews until they reach data saturation across their selected sample (Seidman, 2006).

The selection criteria for this study included years of experience, subject matter, and grade level. I attempted to select a sample that is representative both of the various levels of experience among district educators and the various subjects and grade levels taught in the district. I wanted to understand educator perspectives on using data in general because I want my findings to support the development of a professional development initiative to address the effective use of data to inform instructional decision making. Through the selection of a stratified cross-section, my participants, even though they will only represent one school district, are more likely to be representative of other educators in other districts. Although I am not able to generalize my findings, I did attempt to make them transferrable because I want my research to inform practice.

My initial contact with potential participants was through an email briefly describing my research project (see Appendix B), how I got their names and contact information, and asking for a short face-to-face meeting for the purpose of further discussing their potential participation in my research (Seidman, 2006). My initial email communication did not solicit any commitment from potential participants regarding participation in the research itself. Since I work in the same district as my study participants and have an email address that is familiar to them, an initial contact by email seemed to be well received. In the short face-to-face meeting that followed my initial contact by email, I attempted to recruit participants both by generating interest with a better description of the scope of the project and by assuring them that their time

commitment will be minimal and that their voluntary participation will be confidential (see Appendix C). I also used this initial meeting as an opportunity to assess whether potential participants seemed to be suitable candidates for my research (Seidman, 2006). I looked specifically for familiarity with and interest in my research problem, any bias towards being too eager to participate, and potential to interview well. Through this two-pronged approach I attempted to recruit a larger pool of participants than I actually needed (Seidman, 2006).

While I attempted to recruit a larger pool of participants than I actually needed, I did not establish a set number of participants ahead of time. Qualitative researchers generally agree that it is not only usually acceptable but also often necessary to wait and establish the number of participants during the study. These researchers, however, have divergent opinions on how that number should be arrived at eventually. Some argue for using an emergent design and letting new dimensions discovered through interviewing indicate when additional participants are needed. Others argue for using purposeful sampling with the aim of maximum variation and letting participants indicate when additional participants are needed through a snowballing process (Seidman, 2006). Because I want my findings to be transferrable, I used the latter method and utilized the snowballing process until I reached data saturation across my selected sample (Seidman, 2006).

Methods

As noted earlier, this qualitative study utilized interpretive grounded theory methods for data collection and analysis (Bogdan & Biklen, 2007; Heppner & Heppner, 2004; Merriam, 1998). More specifically, and as with the design of this study, the

methods are based on the interpretation of grounded theory presented by Corbin and Strauss in the third and most recent edition of the *Basics of Qualitative Research*.

Data Collection Techniques

For the purposes of this study, data were collected through face-to-face interviews with the selected participants on an individual basis. Although Corbin and Strauss (2008) note that one of the strengths of qualitative research is that there are many sources of data, they also recognize the legitimacy of using just one source of data depending on the problem being investigated and whether or not the researcher is concerned with triangulating data. Merriam (1998) not only concurs with Corbin and Strauss on this point but also posits that interviews are often the single best source of data for qualitative studies. There are at least two reasons why interviewing was the best method for collecting data for this study. First, and foremost, interviewing was the best way to investigate the problem that is central to this study since, through my research, I want to understand my participants' perspectives relative to the problem. This was best accomplished through interviewing because a person's perspectives on an issue are not easily observed through action or inferred from a document. Second, because my purpose was to understand the participants' perspectives, I was not concerned with triangulation and instead used other methods to check the trustworthiness of my data. Quite simply, the aim of this study was to understand my participants' perspectives, not to validate that their perceived reality is the same as some other observable reality.

Interviews conducted as a part of qualitative research can range from highly structured to completely unstructured, but most qualitative researchers prefer less structure over more (Bogdan & Biklen, 2007; Corbin & Strauss, 2008; Merriam, 1998;

Seidman, 2006). Highly structured interviews, which are sometimes referred to as standardized interviews, are very similar to oral surveys in that all of the questions and the order of the questions are determined ahead of time, participants are all asked the same questions in the same order, and the questions tend to be closed-ended and designed to elicit very specific responses (Merriam, 1998). On the opposite end of the spectrum are completely unstructured interviews, which are interviews where the researcher might simply say, “Tell me about...” (Corbin & Strauss, 2008; Merriam, 1998; Seidman, 2006). The interview protocol for this study is semi-structured, representing a point somewhere near the middle of the structure spectrum (Bogdan & Biklen, 2007; Merriam, 1998). Since structure can refer both to the questions asked and to the process for asking them, it is important to discuss what is meant by semi-structured in the context of this study.

For this study, semi-structured means that interviews were conducted using a set of flexibly worded, open-ended questions developed ahead of time and posed in a predetermined order. Since I was interested in developing a theory that is grounded in the data, it was important to have guiding questions (Corbin & Strauss, 2008) that focus participants on talking about these perspectives. However, that being said, I was careful not to bias the questions toward the support of any particular theories in the existing empirical knowledge base. I was not interested in testing theory but rather in developing theory and, as such, the literature was not used to shape the inquiry but rather to shape the discussion regarding the findings of the inquiry.

While the structure and the content of the questions may seem like the most important factors to consider, the predetermined order of the questions also merits consideration. The order was such that initial questions are concerned with participants’

general perspectives on the broad topic of using instructional data, while later questions are concerned with participants' specific experiences using instructional data. The reason for this funneling approach to questioning participants is twofold. First, starting with broad questions about the topic in general is a good way to set the tone for the interviews as this type of questioning is likely to be viewed as very nonthreatening and, as such, to put participants at ease. Second, starting with broad, general questions is a good way to get participants thinking about the topic without leading them. Having participants that are at ease and thinking about the topic facilitates more effective and expedient interviews. Since the order of the questions was predetermined, it was necessary to conduct pilot interviews with individuals similar to potential participants from my study population. Piloting allowed not only for fine tuning of the order but also of the structure and content (see Appendix D).

In addition to the open-ended questions, probing questions were also used during the interviews to check for researcher understanding, to further explore participant meaning, and to unpack new topics that emerged. Although Seidman (2006) expresses unease with the term probing, noting negative connotations associated with it, the practice of asking unplanned, exploratory questions based on participant responses is commonly referred to as probing (Bogdan & Biklen, 2007; Merriam, 1998). Since the term probing is widely recognized by qualitative researchers, this study will also use the term.

Unlike the questions for the interviews, the probes were not determined ahead of time. While it is possible to determine potential probes ahead of time, Merriam (1998) notes that it is virtually impossible to determine all of the probes that will be used ahead

of time. The reason for this is, quite simply, because probes are dictated by the participants' responses to the interview questions and, it is important to note that there are a few types of responses in particular that bear probing (Bogdan & Biklen, 2007; Merriam, 1998). First, although qualitative researchers try to avoid questions that will yield a response of yes or no, sometimes, that is exactly how a participant responds. This may be the direct result of a poor question or it may be indicative of a participant's interviewing skills, but, either way, it can be addressed with a probe. Second, sometimes a participant's meaning may be unclear to the researcher. In this situation, the researcher might ask a participant to clarify what they mean or even to provide examples of what they mean, both of which are common probes. Finally, sometimes a participant's response will include a reference to a topic or issue that has not yet been brought up by other participants. In such a case, the researcher uses probes to discover the role the new topic or issue might play in the problem under study.

While most participants in this study were interviewed one time utilizing the semi-structured interview protocol developed for this study along with appropriate probes, I did reserve the right to ask participants to submit to unplanned follow-up questions if deemed necessary or beneficial as a result of data analysis. Corbin and Strauss (2008) advocate for analyzing interview data immediately after an interview rather than waiting until the end when all of the interviews are completed. Through this process of constant, comparative analysis, concepts may emerge that warrant follow-up questioning for further exploration. Follow-up questioning was conducted via email, on the telephone, or in person depending on the breadth and depth of the proposed follow-up questions.

All of the interview data collected for this study were digitally recorded and manually transcribed by the researcher. Qualitative researchers generally express support for recording interviews with an audio recording device such as a digital recorder; however, emphasis on the importance of audio recording varies among researchers. Seidman (2006), for example, is emphatic that interviews should be recorded so that they can be transformed into written texts to study. Similarly, Bogden and Bilken (2007) strongly recommend audio recording if interviews are lengthy or if interviews are the primary method of data collection for a study. Merriam (1998), however, stops short of recommending audio recording, but does note that it is by far the most common method used by qualitative researchers for recording interview data.

Digitally recording and transcribing the interviews made it possible to preserve an exact record of the participants' words by creating written texts of them (Merriam, 1998; Seidman, 2006). The ability to create written texts of the interview data was particularly beneficial to this study since this study is concerned with participant perspectives, used interviews as the primary method for collecting data about those perspectives, and used constant, comparative analysis of the data to develop a grounded theory around those perspectives. Because the researcher, as both a human and the primary research instrument, does to some degree shape the data analysis (Merriam, 1998), it is important that the analysis start with verbatim texts of the participants' words rather than paraphrased or summarized texts created and shaped by the researcher (Seidman, 2006).

Additionally, there are other benefits to preserving an exact record of the participants' words both with audio recordings and transcriptions of those recordings. First, preserving the words of the participants is equivalent to preserving the original

study data. This can be useful if, later, during analysis, something seems unclear in a transcript. The researcher can simply return to the original source data to check for accuracy. Similarly, the researcher can use the original source data to demonstrate faithfulness to the data if there is ever an accusation that study data were mistreated or exploited (Seidman, 2006). Second, letting study participants know that there will be an exact record of their responses and that they will have access to it may help participants to feel better about participating in the study. Knowing that their words will be recorded and transcribed exactly, participants can interview with confidence that anything they say will be treated responsibly (Seidman, 2006). Finally, reviewing audio recordings and the transcribed records of those recordings can help a researcher improve their own interview skills (Merriam, 1998; Seidman, 2006).

Although qualitative researchers generally express support for recording interviews with an audio recording device because of the benefits mentioned earlier, there are a couple of potential minor drawbacks to audio recording worth mentioning. The first of these is the potential for the audio recording equipment to malfunction during the interview (Merriam, 1998). While there was a small possibility this could have happened, digital recording equipment used today is fairly reliable. To eliminate the risk of this happening, I tested my equipment before each interview and always had back-up power sources for my digital recorder such as additional batteries and an AC adapter. The second of these is the potential for participants to feel uneasy because they are being recorded. However, as noted earlier, recording also benefits the participants; and qualitative researchers who express support for audio recording note that participants generally forget about the device pretty quickly (Merriam, 1998; Seidman, 2006).

After each interview, the audio recording from the interview was manually transcribed by the researcher. Corbin and Strauss (2008) advocate for analyzing interview data immediately after an interview rather than waiting until the end when all the interviews are completed, and the written text of participants' word created through transcription is the best database for this analysis (Merriam, 1998). For the most part, the interviews were transcribed verbatim in their entirety for reasons I have already articulated. The only things that were omitted from the transcripts was information that might identify participants, unnecessary utterances such as "um" and "ah," and fillers such as "you know" (Heppner & Heppner, 2004). While this was a tedious and time consuming project, there are some very practical reasons for the researcher performing this task. One reason is that researchers who do their own transcription become intimately familiar with their data (Merriam, 1998; Seidman, 2006). Another reason is that if there is anything in the audio recordings that is difficult to decipher the researcher, who conducted the interviews, might be able to fill in any missing data (Merriam, 1998). Finally, paying someone to transcribe the audio recordings would be very costly since it is likely to take four to six hours to transcribe ninety minutes of audio recording (Seidman, 2006).

Data Analysis Methods

For the data to be meaningful to the end users of this study, it was necessary for the researcher to analyze the data and to present the end users with the results of that analysis. Corbin and Strauss define analysis as the "... process of examining something in order to find out what it is and how it works" (2008, p. 46) or, in this case, to find out what perspectives educators have about using data for instructional decision making and

what factors might contribute to those perspectives. This study seeks to build a substantive theory grounded in the data on educators' perspectives and, as such, utilized methods conducive to building a grounded theory (Corbin & Strauss, 2008; Merriam, 1998).

Data analysis began as soon as the first data were collected with the analytic process of writing memos. Corbin and Strauss (2008) advocate for analyzing interview data immediately after an interview rather than waiting until the end when all of the interviews are completed, and for writing memos from the first analytic session forward. Although there are many types of memos used in qualitative research, Corbin and Strauss (2008) feel that researchers should worry less about type and more about the actual process of writing them. They contend that worrying about the type of memo and what form it should take can interfere with the “. . . generative fluid aspect of memoing” (2008, p. 118). Although I agree that it is important not to worry too much about type, I also feel that it is important to give the end users of this study a basic idea of what types of memos were used and how they were used.

For the purposes of this study, two basic types of memos were used. The first type was written immediately following each interview and contained the researcher's basic impressions of the participant and the flow of the interview in general (Corbin & Strauss, 2008; Heppner & Heppner, 2004). These memos were important to the analysis since the interviews were conducted over a period of time, and it would have been difficult to remember these initial impressions later and even more difficult to ascribe them to a particular participant. Not only would it have been difficult to remember these impressions because time had elapsed, it would also have been difficult to remember

them because they would have been reshaped in the researcher's mind by concepts that emerged through the constant analysis of data. The second type were written throughout the analytic process and are a written record of the analysis itself (Bogdan & Biklen, 2007; Corbin & Strauss, 2008). Qualitative researchers have a tendency to want to analyze interview data directly on the transcripts of the interviews by recording codes near the verbatim text they represent and writing notes in the margins. While this is a valid step in the analytic process, analysis is too complex and involves too much cumulative thought to be developed and tracked in the margins of interview transcripts (Corbin & Strauss, 2008). Memos written throughout the analytic process provide a means for developing and tracking very complex analyses and create an audit trail other researchers can follow to retrace the process by which the researcher arrived at the findings.

While the analytic process of writing memos provided a mechanism for developing and tracking the data analysis, they did not facilitate the analysis itself. Analytic tools, or “. . . the mental strategies that researchers use when coding” (Corbin & Strauss, 2008, p. 58) were used to facilitate the analysis or coding of the data. Although there are many analytic tools, Corbin and Strauss note that two in particular, asking questions and making comparisons, are the tools they use because they are the most relevant to analysis. As such, these two tools were the primary analytic tools used in this study to facilitate data analysis.

Asking questions is an analytic tool that can be used at every stage of analysis and is, essentially, just what it sounds like. There are no right or wrong questions, and the questions do not have to be complex, abstract, or theoretically significant. In fact, when

analyzing data researchers often ask simple questions such as who, what, when, where, how, and with what consequences (Corbin & Strauss, 2008). Researchers also ask questions related to time and space such as with what frequency or duration and how much space. Asking questions is an analytic tool that helps get analysis started or back on track (Corbin & Strauss, 2008).

Making comparisons is an analytic tool that involves comparing one piece of data with another and can refer to comparing one participant's response to a question with another participant's response to the same question or to comparing one participant's response to a question with that same participant's response to a different question (Corbin & Strauss, 2008). Making comparisons allows a researcher to see similarities and differences in the data or, in other words, to discover both patterns and variations. Making comparisons helps force any biases or assumptions the researcher holds to the surface. And, most importantly, making comparisons also helps the researcher make meaning of the data, move the analysis from description to abstraction, and see linkages between categories, concepts, and dimensions (Corbin & Strauss, 2008). Additionally, making constant comparisons, or the constant comparative method, is the defining feature of grounded theory research designs (Merriam, 1998).

The actual analysis was performed through a process of coding the data for concepts derived from the data and grouping those concepts into categories. Corbin and Strauss (2008) define concepts as words that stand for ideas contained in the data and note that they are interpretations made by the researcher, or the product of data analysis. Concepts are the basis of the constant comparative method and can vary in levels of

abstraction. In fact, categories are merely higher-level concepts which are used to group lower-level concepts according to shared properties (Corbin & Strauss, 2008).

Just as categories can vary in levels of abstraction, the levels of analysis can vary as well. Analysis can range from a superficial, surface analysis that merely skims the top of the data to an in-depth analysis that digs deep beneath the surface of the data (Corbin & Strauss, 2008). The more superficial the analysis is, the less likely it is to uncover anything that is not already known. Since I wanted to develop a grounded theory that will contribute to the empirical knowledge base, I performed an in-depth, microanalysis of the data. The coding for an in-depth, microanalysis is not any different than for a superficial, surface analysis. It is simply more detailed and, as such, tends to uncover more possible meanings in the data and facilitate the development of theory (Corbin & Strauss, 2008).

The theory itself was developed throughout the analytic process and started with the writing of the very first memo and concluded with the writing of the findings. As noted earlier, the data analysis was developed and tracked through written memos and, in order to move the analysis towards the development of a theory, these written memos were sorted and reviewed to identify linkages and relationships among the higher-level concepts or categories (Corbin & Strauss, 2008; Merriam, 1998). This process continued until a central or core category that explains the linkages and relationships among all the categories was identified. The identification and development of this explanatory core category is, in essence, the development of the grounded theory and is what differentiates the findings of a grounded theory study from the findings of other types of qualitative research studies (Corbin & Strauss, 2008). In other words, after coding my data on

educator perspectives for concepts and grouping those concepts into higher-level categories, I attempted to identify the one category that not only explains these educators' perspectives but also explains how all of the categories that emerged through analysis are related to each other.

Trustworthiness

In addition to collecting, recording, and analyzing the data, it was also necessary to assess the quality of the data obtained in this study. Since I would like for my research findings to contribute to the development of a professional development initiative to address the effective use of data to inform instructional decision making, it is important for educational leaders and practitioners alike to be able to trust my findings.

Traditionally, the findings of qualitative research are considered to be “. . . trustworthy to the extent that there has been some accounting for their validity and reliability . . . “

(Merriam, 1998, p. 198); however, Corbin and Strauss (2008) and Seidman (2006) express concerns about using the terms validity and reliability when discussing qualitative research. Corbin and Strauss note that the “. . . terms carry with them too many quantitative implications . . .” (2008, p. 301) and Seidman concurs noting concerns about the epistemological assumptions underlying the terms. While I generally agree with Corbin and Strauss and Seidman on this point, there do not seem to be any other terms widely used and recognized by qualitative researchers to use in place of the terms validity and reliability. To address this, I will use Merriam's (1998) approach, which is to consider validity and reliability to be necessary approaches to demonstrating the more pertinent issue of trustworthiness.

Merriam (1998) posits that qualitative researchers should be concerned with both internal and external validity, describing the former as having to do with the match between reality and the research findings and the latter as having to do with the generalizability of the research findings. Merriam does, however, acknowledge the paradoxical nature of ensuring internal validity in qualitative studies since one the underlying epistemological assumptions of qualitative research is that reality is constructed by individuals interacting with the world around them and there is not one observable reality. Similarly, Merriam discusses the difficulties associated with ensuring external validity or generalizing findings since, unlike quantitative studies with experimental designs, qualitative studies do not utilize methods such as random sampling or attempt to control for sample size or sample equivalency.

That being said, employing strategies to ensure both internal and external validity was important for demonstrating the trustworthiness of my findings. I did, however, approach the problem of ensuring internal and external validity carefully as both are, generally speaking, somewhat contradictory to the aims of this research study. Ensuring internal validity was problematic because I was interested in understanding participant perspectives, but not in validating that their perspectives match some observable reality. Likewise, ensuring external validity was incongruous because I was interested in the potential for transferability rather than generalizability. I approached the problem of ensuring internal and external validity as being equivalent to ensuring the quality of my findings. Validity, however, is not my only hallmark of quality as Corbin and Strauss (2008) warn that quality findings also have to be innovative, thoughtful, and creative.

In this study, I used three basic strategies for ensuring internal validity. First, as my findings emerged during analysis, I shared them with the participants and asked participants if what was emerging seems to be in line with their perspectives on the issue under study. This is commonly referred to as member checking and can be done as described or by actually giving participants copies of their individual interview transcripts to review (Corbin & Strauss, 2008; Heppner & Heppner, 2004; Merriam, 1998). I did not ask participants to review their individual interview transcripts because they are very lengthy and most participants would not want to commit the time necessary to review them. Additionally, most participants would not be accustomed to reading verbatim transcripts of their own responses to questions and may have been shocked at how difficult they are to follow or that some of their responses even seem unintelligible. These participants might have felt inclined to request unnecessary grammatical or editorial revisions to their individual transcripts. Similarly, as I analyzed data I compared the responses of participants against each other (Corbin & Strauss, 2008; Merriam, 1998). Second, I employed a form of peer examination by asking professional colleagues to review my findings as they emerged (Merriam, 1998). This was primarily my dissertation advisor whom I worked closely with throughout my study, but might have also included my dissertation committee members or others from my doctoral cohort or my professional setting. Finally, I disclosed all of my researcher biases at the outset of the study including my assumptions regarding reality and my theoretical orientation (Merriam, 1998), both of which have already been disclosed earlier in this chapter.

While I had three explicit strategies for ensuring internal validity, my approach to ensuring external validity was not as prescriptive. Instead of having explicit strategies, I

attempted to ensure external validity primarily through the writing of my research. More specifically, I attempted to provide rich, thick description of my participants, their responses, and their situations so that end users of my study can judge for themselves whether my findings might be transferrable to their own situations (Merriam, 1998). Additionally, although my study participants were limited to one school district, I attempted to achieve as much variation among participants as possible through purposeful sampling. Variation among participants can help ensure external validity by producing results that apply to a broader range of individuals and situations (Merriam, 1998).

In addition to internal and external validity, Merriam (1998) also suggests that qualitative researchers should be concerned with reliability, describing it as “. . . the extent to which research findings can be replicated” (1998, p. 205). However, as with internal and external validity, Merriam concedes that the idea of reliability, at least in the traditional sense, is incongruous with qualitative research. The reasons for this, according to Merriam, are similar to the ones she cites in her discussion regarding the incongruity of internal and external validity with qualitative research. Essentially, Merriam argues that the traditional idea of reliability is based on the assumption that there is one observable reality and that repeated studies of it will yield the same findings. Because qualitative studies assume that there is not one observable reality, achieving this type of reliability is nearly impossible. Merriam also notes that, unlike quantitative studies with experimental designs, the designs of qualitative studies do not include the controls necessary to replicate research findings. That being said, Merriam posits that reliability in qualitative studies does not have to mean that other researchers could

replicate the findings, but rather that other researchers would concur that the findings are consistent with the data collected. This is achieved by disclosing the researcher's biases and assumptions, describing the researcher's relationship to the study participants and the criteria used to select them, and creating a solid audit trail regarding the data collection and analysis (Merriam, 1998). Earlier in this paper I disclosed my biases and assumptions and my relationship to the study participants and the criteria used to select them. In the course of my research, I created a solid audit trail other researchers could use to authenticate my data collection and analysis processes and techniques.

Limitations

As noted in chapter one, there are two primary limitations associated with the design of this study. First, my interview participants were limited to one school district and, as such, are not representative of all school districts. In other words, the substantive theory developed in this study is grounded in the data of just one school district. This is significant because some might argue that I should have used a case study design and that the findings might not apply to educators in other settings. However, a case study was not the best design for this study because the findings are not particularly bound to the setting or context (Merriam, 1998), and I wanted to develop a substantive theory that may be transferable to other settings and contexts. Additionally, some might argue that I should have studied multiple sites as a strategy for ensuring external validity (Merriam, 1998). As discussed earlier in this chapter, I addressed this by attempting to achieve as much variation among participants as possible through purposeful sampling and, this variation contributes to ensuring external validity. Second, since I only analyzed data from interviews and I was only concerned with participant perspectives, I did not

triangulate data. Although triangulation is a recognized strategy for ensuring internal validity (Merriam, 1998), it is contradictory to the aim of this study since the aim of this study was to understand educator perspectives, not to validate that their perceived reality is the same as some other observable reality. In order to minimize the impact of this limitation, I used three other strategies to ensure internal validity.

Summary

Through semi-structured interviews with a cross-section of teachers in one school district followed by a rigorous analysis process, this study attempted to develop a grounded theory to explain the gap between how policymakers and educational leaders expect data to be used to inform instruction and how classroom-level educators internalize and implement these expectations. This study is important because little is known about this topic. The findings may have implications regarding how to better support and encourage data-driven decision making by classroom-level educators.

Chapter 4 – Findings

Introduction

The findings presented in this chapter are based on the analysis of data collected through digitally recorded interviews with fifteen total participants over a two-month period. The interviews were conducted face-to-face, primarily in the researcher's office or the participants' classrooms. One participant did request to be interviewed at a local eatery and that request was granted. Although participant selection, data collection, and data analysis were all conducted in accordance with methods outlined in chapter three of this study, specifics regarding the final participants selected and the final progression of data analysis are provided in the introduction of this chapter for the purposes of ensuring trustworthiness and facilitating transferability of these findings.

Final Participant Selection

Approximately seventy-five participants were solicited for potential participation in this study. Of those seventy-five, twenty-five expressed interest in participating and were recruited as potential participants. The interviews began immediately after the initial twenty-five potential participants were recruited. The final fifteen participants were selected because they were fairly representative of the study population, there was a high level of variation among them, and the interviews reached data saturation. At least one of the final fifteen participants was selected through the snowball method.

As noted in chapter three, the study population consists of approximately 269 full-time certified educators distributed fairly evenly over grades K through 12. The study population has an average of thirteen years of teaching experience and almost sixty

percent hold master's degrees or higher. Comparatively, the fifteen participants are also fairly evenly distributed over grades K through 12, have an average of sixteen years of teaching experience, and sixty percent hold master's degrees or higher. In addition to supporting the idea that the participants are fairly representative of the study population, these factors also provide support for the idea that there is a high level of variation among participants. Moreover, there are other factors that point to a high level of variation among participants. First, although the participants have an average of sixteen years of experience, that experience ranges from two years on the low end to thirty-two years on the high end. Second, while sixty percent of participants hold a master's degree or higher, there are participants in the sample with bachelor's degrees, master's degrees, and even specialist's degrees. Finally, in addition to being distributed fairly evenly over grades K through 12, participants are also distributed fairly evenly among buildings and subject areas. In the lower grade levels, there is at least one participant representing each of the grades between first and fifth. In the upper grade levels, there is at least one participant representing each of the subject areas of art, communication arts, math, and science. Each of the six buildings in the district is represented by at least one participant, with five participants from the elementary schools, three from the middle school, three from the junior high school, and four from the high school (see Figure 1 for a summary of the final participants selected).

Figure 1. Summary of final participants.

Building Assignment			Level of Teaching Assignment			Specific Teaching Assignment			Educational Background		
Building	#	%	Level	#	%	Subject/Grade	#	%	Education	#	%
Elementary School #1	2	13.33%	Elementary	5	33.33%	Art	1	6.67%	Bachelor's+	6	40.00%
Elementary School #2	1	6.67%	Middle	3	20.00%	Comm Arts	2	13.33%	Master's+	9	60.00%
Elementary School #3	2	13.33%	Jr. High	3	20.00%	Math	2	13.33%			
Middle School	3	20.00%	High	4	26.67%	Science	3	20.00%			
Jr. High School	3	20.00%				SPED	1	6.67%			
High School	4	26.67%				Grade 1	1	6.67%			
						Grade 2	1	6.67%			
						Grade 3	1	6.67%			
						Grade 4	1	6.67%			
						Grade 5	2	13.33%			
Totals	15	100.00%		15	100.00%		15	100.00%		15	100.00%

In keeping with both the study design and institutional requirements for protecting human subjects in research, all participant identifiers were removed at the time of transcription. For the dual purposes of clarity and convenience, the codes P1 through P15 were assigned to the participants in place of their names and in lieu of pseudonyms. The codes are merely a way to identify each of the fifteen individual participants and the only

significance in them is that they were assigned in the same order as the interviews were conducted. For continuity, those same codes will be used in this chapter to refer to each of the individual participants.

Final Analytic Progression

As described in chapter three, data analysis began with the first data collected and concluded with the writing of the findings. The following is a brief, step-by-step overview of the progression of the analytic process. Participants were interviewed following the interview protocol designed for this study and each interview was digitally recorded. Handwritten notes were taken during each interview and developed into memos afterwards. Verbatim, color coded transcripts of the digitally recorded interviews were typed as soon after each interview as possible. Running notes identifying possible concepts and things to follow-up on were kept throughout the transcription process and served as the starting point for coding the data for analysis. The data were coded directly on printed copies of the transcripts in three or four iterations. The coded data were comparatively analyzed in two ways. First, a matrix was created with Microsoft Excel that compared each participant's responses to the individual interview questions (see Appendix E for an example). Second, documents were created with Microsoft Word for each of the concepts that emerged through coding (see Appendix F for an example). These documents compare each participant's responses by concept and actually contain color-coded segments of the interview transcripts. The final analysis was developed through the processes of comparing data, asking questions, and writing reflective memos until the concepts were grouped into categories and one explanatory category was identified. After the analysis was complete, participants were sent a written member

check that contained both a summary of each participant's responses to the individual interview questions and a summary of the categories that emerged during analysis. Feedback from the member check was also incorporated into the analysis and is, therefore, reflected in the findings.

Although the study design did not include provisions for collecting data from any source other than interviews and was not concerned with triangulation, two documents were collected during the interviews and are included as appendices G and H, respectively. The first document (see Appendix G) is a spreadsheet used to collect common assessment results and report them to the district curriculum superintendent. The reason this document was collected is because it was either mentioned directly or at least referred to by every single participant that was interviewed and, as will be discussed further in this chapter, contributes greatly to how participants in this study view using data. The second document (see Appendix H), titled "Common Assessment Evaluation Form," was described by P4 as a set of criteria used during data analysis to evaluate the clarity and efficacy of the test questions that generated the data. In keeping with both the design and the aim of this study, these documents were not used to validate participant perspectives but rather to further understand them.

How Data are Defined

During analysis, the ways participants defined data were identified as important concepts and were grouped into a category termed "data definition." This category was then developed into a collective participant definition of the term data. Discussion of this collective participant definition is being presented prior to the discussion of each of the three research questions because of its significance to each of them.

Participants in this study were asked to identify the kinds of data related to student learning that they have available to them. All of the participants indicated the availability of a wide variety of data related to student learning, which can be grouped into three basic categories of data. The first two categories are the same two categories that were found in the literature review and discussed in chapter two. Data in these two categories can be characterized as either the data schools are required to collect and report to external agencies or the data obtained from various classroom-level formative and summative assessments, respectively. The third category of data is distinctly different from what was found in the literature, and data in this category can be characterized as data obtained from standardized test preparation tools and assessments.

Category One: Accountability Data

The first category of data, which are data schools are required to collect and report to external agencies, are primarily student demographic data and state standardized test scores. Only two of the participants, P1 and P3, identified student demographic data as a source of data. P1 said that demographic data were available from the state reporting system, while P3 said demographic data were available from the school information system and noted that these data indicated whether “. . . a student may have an IEP or that kind of thing, or the kind of family situation they may come from. . .” In contrast, eleven of the participants cited state standardized test scores as a source of data.

Participants from the elementary or middle school settings referred to the state achievement tests students are required to take in grades three through eight, whereas participants from the high school setting referred to specific end-of-course (EOC) assessments required for certain subjects and taken primarily in grades nine and ten. It is

important to note, however, that while state standardized test scores were frequently cited as a source of data related to student learning, there was very little indication that these data are being used to inform instruction.

Category Two: Classroom-Level Data

The second category of data are data obtained from various classroom-level formative and summative assessments. A little more than half of the participants identified classroom observations, daily work, homework, quizzes, or unit tests as sources of data. Quizzes and tests were cited as sources of data the most frequently among this group, with all of them citing one or both. Most of these participants described having performed some type of item analysis on quizzes and tests for the purpose of determining whether or not to re-teach concepts. Classroom observations, daily work, and homework are included in this category because they are classroom-level data; however, they were not cited as sources of data as frequently as quizzes and tests. Only two participants, P3 and P4, described classroom observations as data. P3 said that data collected from classroom observations were used to make immediate modifications to the curriculum and/or instruction, noting that “the students are either getting it or not and then you correct right then and there on the spot and help them to be successful.” P4, on the other hand, indicated that these data were used to identify students that needed individual or extra help. Similarly, only four participants identified daily work or homework as sources of data. All four of these participants described having graded this work routinely and frequently for the purpose of determining whether to spend more time on a concept or to proceed with the next concept.

There are two interesting things to note about this second category of data. First, although it is highly likely that all of the participants interviewed use classroom-level data, only slightly over half of them identified the items in this category as data. Further, while it is also likely that all of the participants use data from formative assessments, none of them described anything that was purely formative as a source of data. A few participants did, however, indicate that they used data from the summative assessments they cited as sources of data in formative ways. P4 explained, “. . . and I know it’s not truly formative if there’s a grade attached to it. I will also tell you that students will not do the assignment if there is not a grade attached to it.” Second, when they described the way they used graded daily work, homework, quiz, and test data, most participants described having used these data to evaluate the class as a whole. Specifically, participants indicated that these data were summarized into averages by item and some benchmark average ranging between fifty and seventy percent was used to determine whether to spend more time on a concept, move on to a new concept, or re-teach concepts.

Category Three: Standardized Test Preparation Data

The third category, which are data obtained from standardized test preparation tools and assessments, includes data both from test preparation software and common assessments. A little over half of participants identified a variety of computer-based test preparation programs as sources of data. These participants reported that they used data from these programs for the purposes of grouping students and predicting and improving students’ scores on state standardized tests. P12 described having used data from these programs to identify students with similar needs and group them for remediation.

Likewise, P14 reported having used these data at the beginning of the year to determine Response to Intervention (RtI) groups and then on an on-going basis to make adjustments to RtI groups. P6 and P13 also talked about having used data from these programs to group students; however, these participants described having used these data to place students in diverse cooperative learning groups. Almost all of the participants who reported that they used data from these programs noted that instructional materials in these programs were aligned with state mandated grade-level expectations (GLEs) or course-level expectations (CLEs), that these programs gave students exposure to and practice with questions similar to what they would encounter on state standardized tests, that these programs provided them with a wide variety of data summarized in chart or graph format, and that the data from these programs were highly predictive of how students will perform on state standardized tests.

While a little over half of participants identified computer-based test preparation programs as sources of data, nearly all of the participants identified common assessments as a source of data. In fact, fourteen of the fifteen participants cited common assessments as a source of data, and the one participant that did not represents a subject area that does not have an associated state standardized test. In general, participants acknowledged that common assessments were aligned with state mandated GLEs or CLEs, were intended to help standardize local curriculum, served as a tool for predicting and improving scores on state standardized tests, and were required by the district. Thirteen of the participants described the common assessments they used as locally developed; however, several of these thirteen participants indicated having had limited or no involvement in developing them either because they were developed ahead of their time or by a separate curriculum

team. One participant, P6, reported recently switching from locally developed common assessments to purchased, third-party common assessments. The reason given was that questions on the third-party assessments were structured more like state standardized test questions than were questions on the locally developed assessments. Similarly, thirteen participants described the common assessments they used as primarily containing only multiple choice questions and these participants generally indicated that they used Scantron technology to grade these assessments. Likewise, thirteen participants indicated that they administered common assessments on a quarterly basis and most said that this was the minimum required by the district. One participant, P4, reported that all unit tests administered in common classes were common assessments. All fourteen of the participants who cited common assessments as a source of data indicated that these data were analyzed collaboratively with either a grade-level or department-level professional learning community (PLC) or a curriculum team. They further indicated that the results of this analysis were summarized in the Excel spreadsheet provided by the district and reported to the district curriculum superintendent.

Although the data in this third category might be viewed as classroom-level data because they are collected as a part of normal classroom routine, these data actually comprise a distinctly different category that lies somewhere between category one and category two and is intended to link these two categories. There are at least three reasons these data are distinctly different. First, while data in category one are collected in response to mandates by agencies external to the school district and data in category two are collected as a matter of routine classroom practice, data in category three are collected in response to mandates external to the classroom but internal to the school

district. Second, while data in category one are collected to demonstrate accountability to external agencies and data in category two are collected to inform classroom practice, data in category three are intended to inform classroom practice in ways that will positively impact demonstrated external accountability. Finally, although the curriculum and instruction that drive category two data are supposed to be aligned with the state standardized tests that are characteristic of category one data, participants in this study placed far more value on category two data and consistently described these data as more meaningful. Accordingly, the value these participants placed on category three data fell somewhere in the middle of this spectrum. In other words, the further the mandate gets from the classroom, the less participants value the data from the mandate (see Figure 2). This is important because this value spectrum is the inverse of the way policymakers and administrators intend for these categories of data to be used and, ultimately, to be valued (see Figure 3).

Figure 2. Relationship of perceived value and mandates.

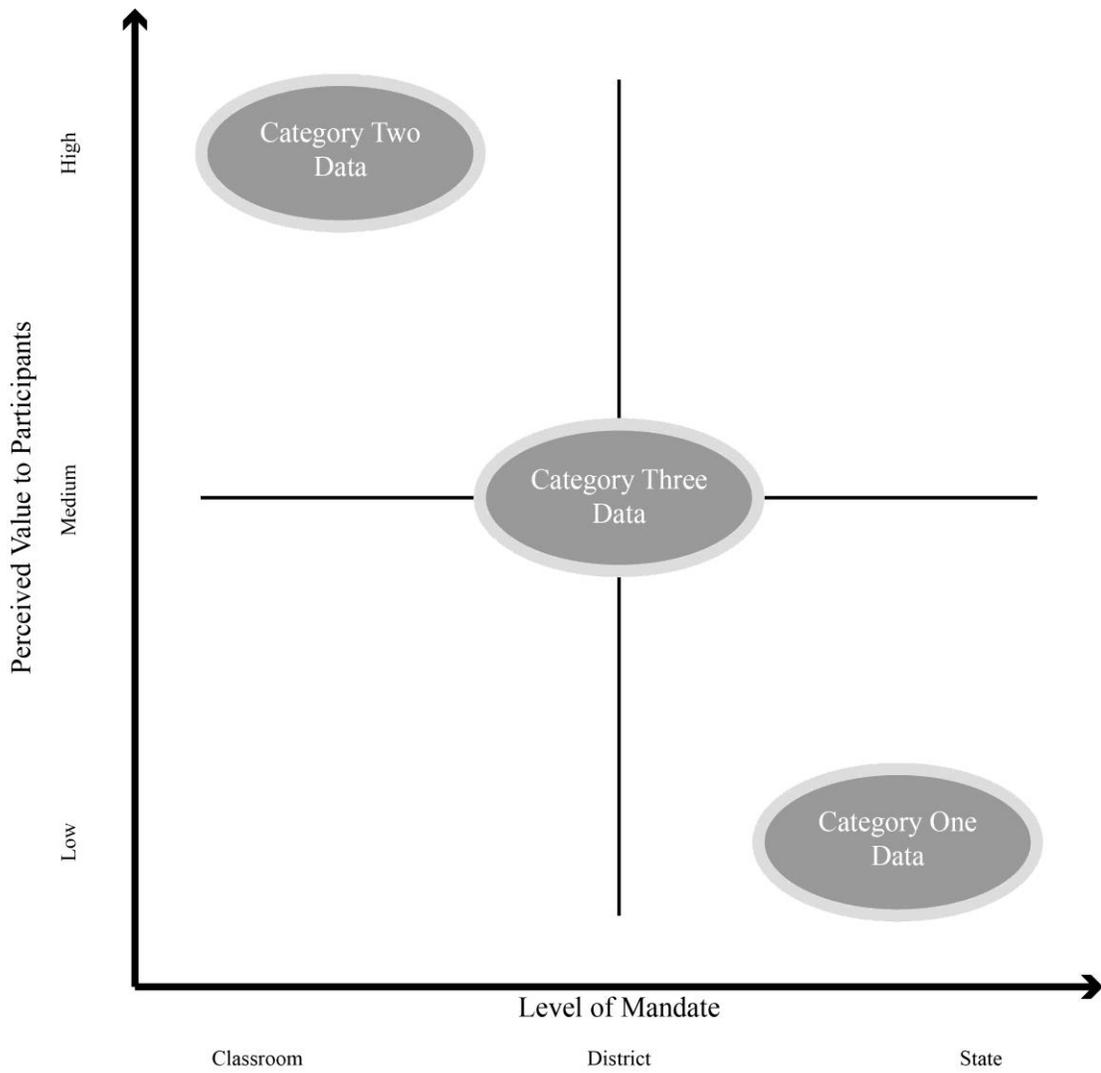
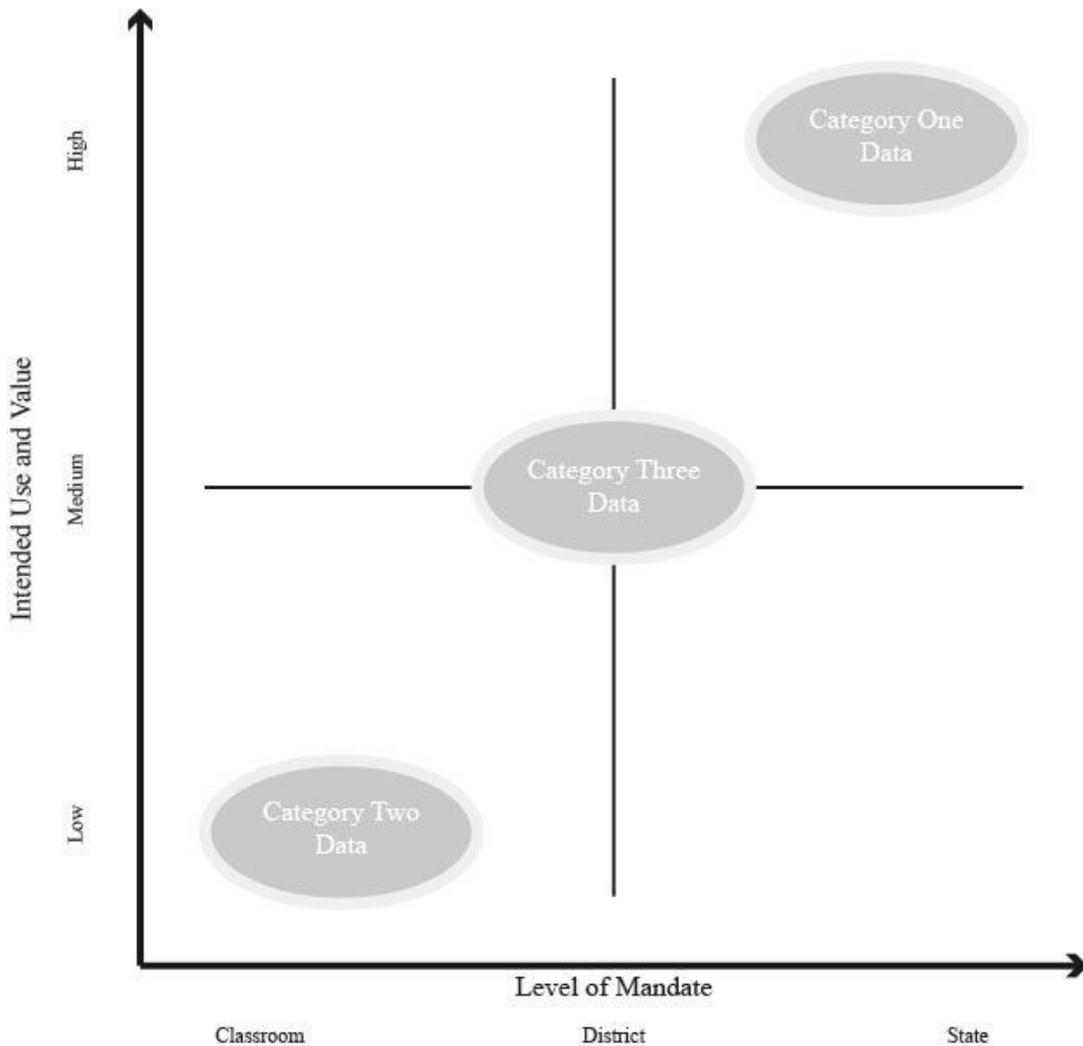


Figure 3. Intended use and value.



In addition to being distinctly different than what was found in the literature, category three is also significant because it explains the way participants in this study define data. Category three data were, in general, cited far more frequently by participants than any other data, and common assessments, in particular, were the single most commonly cited source of data. The reason for this seems to be because the school district has emphasized common assessments to the point that they have become synonymous with data for these participants. Participants reported that there was a push in this school district to standardize curriculum and the delivery of curriculum to the

extent that students could move seamlessly from one classroom to another at the same grade level and in the same subject area. They also reported that there was a push for high scores on state standardized tests. As a result, common assessments seemed to be the primary focus of the grade-level and department-level PLCs and the curriculum teams. There was time built into the calendar throughout the school year for these teams to meet and analyze common assessment data, they were provided with supports to assist with analysis, and there was an expectation that they report the results of their analysis to the district curriculum superintendent. Participants described common assessment data as the only data they were asked for directly and, as such, they were hesitant to call items in category two data. P15 noted that items in category two were not viewed as “valid” data by others, while P7 described these items as “informal” data. In fact, category two data were largely extrapolated from participant responses regarding how they actually make changes to instruction.

Data Definition

As a result of this focus on common assessments, the participants in this study define data in general in the same way they define common assessment data specifically, which is as percentages that summarize class averages for an item or items on a summative assessment. The application of this definition can be seen not only in their comments regarding using common assessments but also in their comments related to using classroom-level data from category two. Further, the way these participants define data is an important consideration in the discussion related to each of the three research questions of this study.

Discussion of Research Question One

The first research question that guided this study was: What are educators' perspectives on how they use data for instructional decision making? The aim was to understand not only how participants perceive their own use of data to inform instruction but also what explains how they perceive their own use of data. The discussion around this question overlaps the discussion around how participants define data and how they define data also explains how they perceive their own use of data. Further, the way participants define data is also an integral part of this discussion because their perceived use of data is based on what they define as data. This study found that concepts related to participant perspectives could be grouped into two distinct but related categories, which involve how data are analyzed and how the results are used.

How Data are Analyzed

Participants in this study view data analysis as separate but related to using data to inform instruction and, as with data itself, they *define data analysis very narrowly*. In fact, participants in this study generally define the data analysis they do as the process of summarizing the number of correct or incorrect responses to an item, converting that sum to a percentage, and then comparing that percentage against an established benchmark. One thing that is significant about this definition is that data analysis does not begin with what participants define as data. Instead, participants generally defined the process of collecting and converting raw inputs into what they defined as data as part of data analysis.

Another thing that is significant about this definition is that participants clearly view data analysis primarily as a *mathematical process*, with nine of them directly

referring to analysis as involving math or, more specifically, statistics. For example, when asked to characterize their own data analysis skills, P2 and P7 both described having strong math skills, while P8, P11, and P13 all described having weak math skills. P11 specifically stated, “I am horrible at math, so unless it’s given to me as a percentage already I’m horrible at figuring up my data.” Further, when probed about analyzing data, P3 gave an example that involved finding a statistical correlation and P5 referred to finding standard deviations. Similarly, P10 described having taken a lot of statistics courses in graduate school and expressed regret that there was not enough time to do more in-depth analysis of data than simply finding averages.

A final thing that is significant about this definition is that participants generally view data analysis as involving some type of *item analysis*. Almost all of the participants described having performed item analyses, but there were variations in their descriptions related to frequency, level of formality, and level of collaboration. These variations seemed to be tied closely to the source of data for the item analysis and participants primarily identified daily work, homework, quizzes, unit tests, and common assessments as the sources of data for item analyses.

As noted earlier, when asked to identify the kinds of data related to student learning that they have available to them, four participants cited *daily work* and *homework* as data, a little over half of the participants cited *quizzes* and *unit tests* as data, and almost all of the participants cited *common assessments* as data. All four of the participants who cited daily work and homework as data indicated that they analyzed these data pretty much on a daily basis, that the analysis they performed was informal, and that this was a solitary activity. I characterized the analysis as informal because these

participants essentially said that they graded the daily work or homework and then scanned through the graded papers looking for high incidences of incorrect answers on individual items. One of these four participants, however, described having used a slightly more formal process. P4 noted having used a simple tally sheet while grading to track not only the number of incorrect responses to each item but also to jot down notes regarding why students seemed to miss these items.

Quizzes and unit tests.

The majority of participants who cited quizzes and unit tests as data said that they analyzed these data much in the same way as daily work or homework, just not as frequently since they did not have the opportunity to collect these data as frequently. P4 and P7, though, both described something slightly different than the others. P7 said that unit tests were given department-wide approximately every two weeks and that data from these tests were discussed “informally amongst the teachers” in that department. Interestingly, these tests were this participant’s individual unit tests, not common assessments, and this participant viewed the act of discussing them informally amongst colleagues as analysis. Similarly, P4 also described analyzing unit test data collaboratively; however, P4 indicated that all of the unit tests in common classes were common assessments and that data from these unit tests were analyzed at department-level PLC meetings utilizing the Excel spreadsheet provided by the district for analyzing common assessments. Further, P4 noted that sometimes the analysis was done outside of PLC meetings stating that “. . . we do that, since there’s just three of us, pretty easily through email.” P4 was asked how unit test data for classes that were not common were analyzed. P4 indicated that these data were analyzed using the same Excel spreadsheet

used for common assessments, but that this was a solitary activity. It is important to note that while P4 strongly advocated for the exclusive use of common assessments in common classes, P4 also expressed that unit test data from common classes were slightly less useful than unit test data from classes that were not common and cited two reasons for this. First, P4 noted that “. . .when you’ve got three different people doing it, one person may, another person doesn’t for whatever reason, and so I think the data may be a tad more skewed.” Essentially, this participant was referring to the fact that although the assessments were common, the instruction they measured was not. Second, P4 described having to wait to use unit test data from common classes since these data were analyzed collaboratively, but indicated that unit test data from classes that were not common could be used immediately.

Common assessments.

All of the participants who cited common assessments as data indicated that they analyzed these data at least quarterly, that the analysis they performed was formal, and that this was a collaborative activity. In fact, all but one of these participants said that these data were only analyzed once per quarter, which was also identified as the minimum requirement. The only participant who indicated that these data were analyzed more frequently than quarterly was the participant who indicated that all of the unit tests for common classes were common assessments. I characterized the analysis as formal because the participants all said they used the same process and what they described was a very structured process. Almost all of these participants reported that the common assessments they administered contained only multiple choice items and that they used Scantron technology to grade them. After the assessments were graded, participants

noted that the results were entered into the Excel spreadsheet provided by the district and that this spreadsheet summarized the number and percentage of incorrect responses for each item on a separate row. They further noted that this spreadsheet allowed them to see at a glance how their summarized results for any given item compared with others in their grade level or department. Approximately half of participants reported that they entered their own data directly into the Excel spreadsheet, while the other half reported that they forwarded their data to someone in their grade level or department for this purpose. Finally, all of these participants reported that they analyzed these data with their grade-level or department-level PLC teams or with their curriculum teams during structured time that was built into the calendar for this purpose. They noted that these teams met and compared the results for each item against some established benchmark and then decided collaboratively what to do with the results.

How Results are Used

While participants view how they use the results of data analysis as using data to inform instruction, how they use results is a distinct category that can be separated from data analysis in the context of using data to inform instruction. The reason for this is because a little over half of the participants indicated that they used data from computer-based test preparation programs to inform instruction, but none of these participants said they analyzed these data. In fact, these participants generally agreed that one of the benefits of using these programs was that the programs provided them with analyzed data. Further, at least three participants directly indicated that although they did not feel confident in their data analysis skills, they did feel confident in their ability to use data that were already analyzed. For example, P11 stated, “. . . but once I have the

percentages I can use that very easily to work with my instruction to modify it however I need.” Essentially, participants view using analyzed data as necessary in using data to inform instruction, but they do not view the process of analyzing it as necessary. Moreover, while understanding how participants view data analysis is important, it is how they view what they do with the results of analysis that is really the crux of the matter.

The conundrum.

In addition to being the crux of the matter, how participants view what they do with the results of analysis is also very complex. Most participants in this study provided at least one example of how they used the results of analysis or, more specifically, how they used data to inform instruction, but most were not able to describe how the results had actually informed instruction. P1 described this conundrum as follows:

. . . I feel pretty adequate at interpreting data. It is another thing getting just numbers to the actual classroom. That’s the hardest thing, I think, is, okay, we can interpret a paper with all these descriptions or all these numbers on here, but what does that mean for the kids, for teaching? That’s the hardest part.

Similarly, in response to a probe on this topic, P5 said, “How to teach it differently? Big ole huge question. That’s the question we’re always facing.” What P1 and P5 were both saying was that although data informed them of problems, data did not necessarily tell them how to fix the problems. It is the challenge of knowing how to use results that creates the complexity in how participants view their use of results.

As with data analysis, participant descriptions of how results were used seemed to be closely tied to the source of data. The general ways participants said they used results were to group students, to review or re-teach concepts, or to modify instruction for future students. Participants indicated that they primarily used data from computer-based test preparation programs to group students, while they used data from daily work, homework, quizzes, and unit tests to determine whether to review or re-teach concepts. Since most participants only administered common assessments quarterly, data from these assessments were generally used to make changes to instruction for future students.

Frequency of use.

How participants used data from computer-based test preparation programs to group students was described earlier in this chapter in the section on how participants define data. What was not described in that section was how frequently the participants used these data or how exactly these data informed their grouping decisions. Participants who used data from these programs generally said that they collected student data pretty much on a daily basis. In fact, some participants indicated that they were required to have students use these programs for at least thirty minutes a day. Participants did not necessarily use the data as frequently as they collected it, but they did suggest that they used it very routinely. Participants said that these programs provided them with analyzed data summarized in charts and graphs, and that these data indicated things such as reading level or proficiency with specific GLE or CLE concepts in tested areas. Whether they used these data to group students together with similar needs or to create diverse cooperative learning groups, the participants essentially used these data to create instructional groups around reading levels or specific GLE or CLE concept areas.

Is it the assessment?

How participants used data from daily work and homework was also described earlier in this chapter in the section on how participants define data. As previously noted, participants who cited daily work and homework as sources of data for instructional decision making indicated that they used these data pretty much on a daily basis to determine whether to spend more time on a concept or to move on. There are a couple of things that are important to note about the way participants said they used these data. First, participants mainly used these data to evaluate groups of students as a whole. They indicated that they scanned through graded papers and looked for high incidences of incorrect answers on individual items, which were characterized by these participants as incidences greater than thirty percent. Second, participants primarily used these data to determine the pace of instruction and the need to review, not necessarily to modify the instruction.

How participants used data from quizzes and unit tests differed from how they used data from common assessments; however, there was one thing about the way they used data from all three of these sources that was similar. This similarity was a step in the process that occurred after the data were analyzed and the weak items were identified, but before the data were used to inform instruction. Basically, participants said that between these two actions they evaluated the quiz, test, or common assessment questions that pointed to weak areas for clarity and efficacy. At least half of the participants brought this up during the interviews and most were asked additional probes for the purpose of trying to understand exactly how they determined if a question was well written and effective. P6 and P11 both said that they “just knew” if a question was a poor

question and P6 attributed this specifically to experience. Further, P6 described a poor question as a “teachable moment,” noting that the students might encounter poor questions on state achievement tests. P4 and P10 both indicated that they sometimes they solicited feedback from students to determine if a question was poorly constructed. P4 sometimes said to students, “Tell me what you were thinking when you answered this one. What do you think this question asked you?” Similarly, P10 sometimes asked students, “What do you think that question meant? What was that question asking?” Further, P4, P10, and P11 all indicated that sometimes students pointed out questions that were unclear during testing. There was one additional method for evaluating questions that was identified, but it seemed to be used specifically to evaluate common assessment questions. P4, P5, and P10 all said they discussed the questions students missed with their grade-level or department-level colleagues to determine if any of them were poorly constructed. These participants referred to this as a “professional conversation.” When asked if there were any criteria used to guide this professional conversation, P4 said they used the “Common Assessment Evaluation Form,” P5 said they evaluated the distracters in questions, and P10 said they looked for trends in incorrect answers. It is important to note that the “Common Assessment Evaluation Form” is actually a form for documenting the results of the professional conversation and does not include criteria for evaluating questions.

Participants generally stated that they rewrote any questions that they determined to be poor questions and did not use the student results from those questions to inform instruction. Results from questions that seemed to point to weak areas and seemed to be well constructed, however, were used to inform instruction.

Review or re-teach?

Participants indicated that the way they used data from quizzes and unit tests was primarily to determine whether or not to review or re-teach concepts. Participants who said they reviewed concepts in response to these results said that they either went back over the same lesson or went over the quiz or test questions that triggered the review. At least four participants indicated that they used these data in this way, and half of them indicated that they re-tested after reviewing. While only a small number of participants directly mentioned using these data to determine whether or not to review concepts, eleven of the fifteen participants said they used these data to determine whether or not to re-teach concepts. In fact, P6 specifically stated that this was the primary way these data were used, noting that the purpose of using these data was to “inform re-teaching opportunities.” Participants who said that they re-taught concepts in response to these results described a variety of re-teaching strategies. Some said that they tried differentiation to account for different learning styles, while others said they asked colleagues for tips on teaching certain concepts. Some indicated they simply covered additional material related to certain concepts in order to give the students more instruction, more practice, or both. Most participants indicated that they used more than one of these re-teaching strategies and many said that they re-tested after re-teaching.

Participants indicated that the main way they used data from common assessments was to make changes to instruction for future students. Most participants said that common assessment results were not timely enough to be used for re-teaching; however, they generally used the same strategies to modify instruction for future students as were used for re-teaching. In other words, when participants talked about making

changes to instruction they said that they differentiated instruction, asked colleagues for tips on teaching certain concepts, or covered additional material related to certain concepts. What was different was that they implemented these changes with future students, not the students who precipitated the changes. Another thing that was different was that they collaborated with colleagues on their grade-level or department-level PLC teams and decided together how to change instruction.

Significantly, how participants view their use of results from quizzes, unit tests, and common assessments is very complex. Most participants described a process for using these results that started with analyzing data or accessing analyzed data and ended with changing instruction. Participants were able to describe what data they used to make changes and what changes they made, but not how they knew what to change. Data merely identified problems or weak areas and the participants were left with the challenge of figuring out what instructional changes to implement to address them, a challenge P1 described as follows:

It's not going to tell us why they're low. It's not going to tell us if it's a teacher problem or a student problem. It can't interpret home lives. It just shows you that the scores are low and that's it. You still have to figure out what happened and what you need to do to get these scores up.

On the surface, how participants described changes they made seemed somewhat arbitrary. For example, P10 and P13 described adding hands-on and visual activities to instruction in response to data, but both of them acknowledged that the reason they had chosen differentiation as a strategy was not specific to the data. They chose

differentiation because they viewed it as a good strategy to try, not because the data indicated that they were not addressing all of the learning styles. There were many other similar examples in the data that involved the use of the other re-teaching strategies. While how participants decided what to change may appear somewhat arbitrary on the surface, when pressed to really explain it they attributed the changes they made to intuition, experience, and their relationships with students.

Summary

The purposes of the first research question were to understand educator perspectives on how they use data for instructional decision making and what explains these perspectives. This study found that participants had very narrow definitions for data, data analysis, and using data to inform instruction. Most data participants referred to were percentages, and those percentages generally represented class averages for items on summative assessments. None of the participants described anything that was purely formative as a source of data, and many were hesitant to refer to classroom-level data as data. Additionally, with the exception of the examples related to using data to group individual students, all of the participants described using data to make changes for groups of students as a whole. Finally, data were used primarily to re-teach or make instructional changes for future students, and there was very little evidence that data informed the actual changes.

This study also found that these perspectives were explained by how participants perceived that they were expected to use data. The district used grade-level and department-level PLCs and curriculum teams to facilitate the collaborative use of data, and there seemed to be a clear expectation that the scope of work for these teams was to

develop and use common assessments aligned with GLEs or CLEs. As such, the district put supports in place to make it easier for these teams to analyze and use these data. The supports encouraged both the development of common assessments that mainly contained multiple choice items and a very specific method for analyzing data. In other words, these supports started to define what these data looked like and how they were used and, because there was such a strong emphasis on common assessments, this eventually shaped the definition and use of data in general.

Discussion of Research Question Two

The second research question that guided this study was: How do educators view their own data analysis skills and the value of using data for decision making? The purposes of this question were to understand whether or not participants feel they have the skills necessary to analyze and use data to inform instruction and what kind of value they assign to using data to inform instruction.

How Participants View Their Skills

The participants in this study were asked how they would characterize their own skills to analyze and use data, which are two activities that they clearly view as separate but related. Interestingly, participants generally based their answers to this question exclusively on how they characterized their skills to analyze data. This is interesting because these same participants did not view analyzing data as absolutely necessary for using data, nor were they able to explain how data actually informed instruction. In fact, eleven of the fifteen participants based their answers to this question solely on how they characterized their skills to analyze data. The other four participants answered this question in two parts, referring first to their skills to analyze data and then to their skills

to use data. Further, there did not seem to be any relationship between whether or not participants viewed analysis as a mathematical process and whether or not they referred exclusively to their analysis skills when answering this question. In other words, the participants in this study tended to relate the term *skills* to analysis rather than to using results to inform instruction.

How participants characterized their skills was also generally the same. Twelve of the fifteen participants described their skills as adequate, good, or better than average. Specifically, two participants said their skills were adequate, nine participants said their skills were good, and one said her skills were better than average. Three of these participants, however, attached qualifiers to their answers. P2 and P3 noted that their skills were good as long as the data were classroom-level data, while P4's caveat was that data had to come from questions that were well-written. The three other participants described their skills as weak. P8, for example, said, "I don't think my own skills are up to par," while P13 said, "I don't know that I have a lot of data skills." There did seem to be a relationship between whether or not participants viewed analysis as a mathematical process and how they characterized their skills since all three of these participants described having weak math skills.

Although how participants view their own data analysis skills was included as part of a research question that guided this study, this study found that these views are not an important factor in understanding the research problem. This question was included because the literature I reviewed for this study indicated that it might be one of the reasons educators do not use data. It is not significant because participants in this study tended to associate skills only with analysis and the majority characterized their skills as

good. Additionally, as noted earlier, this study found that analysis and use could be separated in practice and that educators were comfortable with the idea of using data that were already analyzed. While how participants view their skills is not significant when considered at face value, the inquiry around this question did uncover something significant. The thing that is significant is that participants in this study do not generally view using results as a skill, and there are two reasons this is significant. First, most of the participants were unable to describe how data actually informed instruction. In the process they described, there was generally a gap between using data to identify weak areas and the subsequent changes to instruction. Second, a skill is something that can be taught. If participants do not view using results as a skill, then they may not view this as something that they can be taught.

How Participants Value Using Data

The second part of research question two was concerned with how participants value using data for decision making and, unlike the first part of research question two, this line of inquiry did prove to be important for understanding the research problem. There was one over-arching theme in participants' value-related statements and that theme was that they all perceive using data as important. More specifically, they perceive using data as important to someone other than themselves. For example, when asked if there was anything additional that might help me better understand educator perspectives on using data, P11 replied, "The thing you need to know is that educators know that it is really important, but we can't find the time to do it." Similarly, P15 answered, "Well, it's not my favorite thing to do, but it is important. I do understand the

importance of it.” Quite simply, these two participants, as well as most others in this study, do not personally value using data to inform instruction.

In addition to this over-arching theme, several concepts emerged during analysis of participants’ value-related statements. These concepts can be grouped into two categories, which are *time* and *usefulness*. Concepts related to time emerged far more frequently during analysis than any other concepts, and, besides being prevalent, these concepts were also very easy to identify since participants generally clearly expressed that they were talking about *time*. Concepts related to usefulness were not as prevalent or as easy to identify and categorize, but they are equally important to this discussion.

Time: It takes time to analyze data.

A little over a third of participants said that it takes a lot of time to analyze data and described this as a factor that limits their use of data. At least two of these participants acknowledged that the district built structured time into the calendar for them to meet with their teams and analyze data, but both expressed that they did not feel it was enough time. P15, for example, said, “I think the biggest problem is just the time. I think that they try to give us time with our early morning meetings and things like that, but it’s just hard.” P15 went on to describe feeling that it might be a full-time job for one person and noted, “I just don’t think there’s time to do that with the regular classroom.”

Similarly, at least three of these participants said they did not have time to analyze data because of the amount of time involved in planning and grading. P5 said, “I don’t believe that I possess the time that a lot of it takes,” and went on to note that “. . . planning and grading consume almost every waking hour that we have.” Likewise, P11 talked

about not having enough time each day for planning and grading and described the time constraint as follows:

We have to teach all day and we're only given forty-seven minutes for plan time and, you know, that's a gob amount of time to sit there and analyze data and grade your papers . . . you spend either hours and hours after school or hours and hours at home planning for your school day and you miss out on time with your kids . . . or, you put something off, and usually it's analyzing the data.

Interestingly, P5 and P11 both attempted to quantify these demands on their time and gave estimates of how much time it took to grade a single paper and how many papers per week they typically graded.

Time: It takes time to use the results.

While a little more than one third of participants described the time it takes to analyze data as a problem, almost the same number of participants described the time it takes to use the results as a problem. This is because, as noted earlier, participants largely associated using results with re-teaching and, further, many of them described feeling pressured to standardize curriculum and the delivery of curriculum to the extent that students could move seamlessly from one classroom to another at the same grade level and in the same subject area. Essentially, around a third of participants did not feel that they had time to use data because they did not feel that they had time to re-teach concepts.

One of these participants, P2, gave an example of having tried to use more data and explained that “. . . a lot of the time I would go back and go over something and

that's when I found that I started getting behind some of the other teachers because they weren't." This same participant went on to say that "... if I let the data completely drive my instruction I wouldn't have time to teach everything." P6 also described having had to limit how much data drove instruction, noting, "I reached a point, because we're so limited in our instructional time, that I would just take the questions that most kids had missed and we'd talk about them again." P4, on the other hand, described having cut things out of the curriculum that seemed to be "... the least important or that would be the least damaging to students" in order to have time to re-teach. This same participant acknowledged, "... it takes time to go back and re-teach and sometimes you don't have that time. It's true."

Time: Data are not always timely.

Similar to what was found with regard to analyzing data and using the results, approximately one third of participants indicated that sometimes it is difficult to use data to inform instruction because data are not timely. P4, for example, said, "... but sometimes, see, you're too far away from it to go back." Likewise, P15 noted, "... it's a fast world ... by the time you analyze something, we've moved on to something else completely." While these two participants were talking about using data in general, two other participants, P10 and P11, more specifically referred to data from common assessments. For instance, P10, explained:

Unfortunately, it's kind of an after-the-fact data collection and it's not a perfect system, but you kind of look for two, three, four-year trends in your data ... it seems bad to say, but students will be sacrificed or they will not get that particular objective that particular year ...

Along the same lines, P11 said, “. . . to me, with the common assessment . . . we’re done with teaching the unit so, therefore, we don’t really go back to teach anything else.”

Interestingly, the participants who indicated that timeliness was a factor were fairly evenly divided on whether they referred in their examples to using data in general or using common assessment data specifically. This is probably because, as noted earlier, the participants in this study define all data the same way they define common assessment data and, as such, some of them assign the same value to all data that they assign to common assessment data.

Usefulness: Data do not tell the whole story.

Approximately half of the participants in this study talked about how data do not tell the whole story. These participants said that data have a narrow focus and that data can be skewed by factors ranging from students’ test taking abilities to their health or disposition on test day. Many of these participants described feeling frustrated because data do not reflect all of the growth students experience in their classrooms. P1 said, “It is easy to get lost in the numbers and the data and this is what is says, and to lose what is being done in the classroom, the impacts.” Similarly, P2 noted, “. . . well, I know as an educator I get frustrated with the numbers sometimes . . . sometimes a number doesn’t reflect exactly what you did in your classroom.” Likewise, P3 said, “I can’t give you a spreadsheet that shows the improvement that happened, the learning that happened in my classroom. It’s not a numbers kind of thing.”

Additionally, a few of these participants reported feeling that educators are judged unfairly by others on the basis of data that do not tell the whole story. P1, for example,

said, “. . . the public or politicians see numbers and the media says we’re failing and teachers are taking the blame for that, getting a bad rap.” P2 also expressed concerns about this as follows:

. . . with some of the things they’re talking about in the legislation about teachers being judged on how their kids perform on tests and looking at the data from that . . . sometimes that’s not exactly everything because as a teacher you teach a lot more than that. There’s a lot more that goes on in the classroom besides that and I think to judge someone based on a number isn’t completely accurate.

While only a few of these participants specifically expressed concerns about data being used to judge them unfairly, the others seemed to also share these concerns. The basis for this conclusion is that when these participants talked about data not telling the whole story, they all referred exclusively to data used for external accountability.

Usefulness: Individual students get lost in data.

Another concept that emerged during analysis is the idea that individual students get lost in data, and approximately one third of the participants in this study identified this as a factor that limits the usefulness of data. These participants essentially said that teaching should be individualized and that each student should get the instruction or interventions they need to be successful. P8, for example, described this concern as follows:

Sometimes I think we kind of get so lost in the data that we just forget about the individual students. I know I’ve been very frustrated in the past having students that are struggling in my classroom and trying to find a place where they fit

because their test score is this and it's not that, so they don't fit in there, and I think those kids get lost a lot because we try to stick to certain data.

Similarly, P10 said that data were good for determining if a question was poorly written or if there was something missing from instruction, but noted:

And really, to be effective to the individual it has to be individualized . . . from an individualized point of view, it's got to be . . . it's got to have their name on it. If you're going to make a change in that student then you need to know the data about that student, not just the class average.

Interestingly, while only one third of the participants expressed concerns about individual students getting lost in data, all of the participants defined data and described using data in terms that clearly indicated they did not view it as a tool for helping individual students.

Usefulness: Data for someone else.

Most of the participants in this study indicated that they primarily used data because they felt they were expected to use data, and approximately half of the participants said that the data they used were actually for someone else. In other words, they not only felt they had to use data, but they also felt the data were not particularly useful to them. These participants specifically described the purposes of these data as predicting and raising standardized test scores and generally referred to common assessment data. In fact, most participants said that their grade-level or department-level teams had goals related to improving test scores.

In fact, a few of these participants expressed very clearly that they felt data were for someone else. P6, for instance, said, “I think the underlying thing is that data is what needs to drive your instruction in order for your kids to perform well and to meet AYP and all those other things we’re expected to do.” Another participant, P5, commented:

. . . and recording it, and analyzing it, and doing all those things is really just to satisfy somebody somewhere else. The analysis and all of that is to prove something. For a lot of us it feels like we’re simply proving what we’re doing. And, I get that there has to be accountability . . . I think it can be done differently . . . It’s not an effective way to prove whether or not I’m accountable for doing what I’ve been tasked to do with all these different personalities. It’s just something else to do.

Although the tone of these two participants’ comments is very different, there is an important similarity in what they both said. They both essentially said that data are used to meet external expectations for improving test scores, and the reason for the difference in their tone can be attributed to their views related to this expectation. P6 seemingly sees improving test scores as one of the goals of education, while P5 clearly sees improving tests scores as a way to prove that you are meeting the goals of education. Interestingly, P6 related this goal of education to performance rather than to learning.

Usefulness: Data limits learning.

A little over one-third of participants directly expressed concerns about how using data is limiting learning, and many of the participants that did not express these concerns did, in their comments about using data, provide support for the existence of these

concerns. The participants who directly expressed these concerns said that data were limiting the breadth and depth of learning by placing a strong emphasis on GLEs or CLEs and certain tested subjects. Some of these participants said that GLEs and CLEs were being emphasized to the extent that other concepts were being cut out, while others said that the GLEs and CLEs themselves were being taught with a very narrow focus. Further, at least one of these participants said that certain subjects were being emphasized to the detriment of others.

At least half of these participants described either not being allowed to or not having time to teach concepts that were not GLEs or CLEs. P14, for example, said that the unit tests that came with the textbooks were very useful because they included concepts that they were not required to teach. When asked to describe a concept they were not required to teach, P14 responded, "It's not a GLE, and if we teach things that are not GLEs that's a way to get in big trouble by our principal." Another participant, P12, said that they were moving from GLEs to the newly adopted Common Core next year and noted that a particular concept that had been a GLE was not part of the Common Core at that grade level. This participant lamented that fact that they would not be able to teach this concept next year because they would have to follow the Common Core, but did note that the concept is part of the Common Core for a higher grade level.

A few of the participants said that not only was using data narrowing the focus to just concepts that were GLEs or CLEs, but that it was also resulting in those concepts being taught in very specific and limited ways. P3 summarized this as follows:

. . . data, I think it, at least the stuff that they're asking for, holds them back and keeps kids from learning as much as they should or could . . . because they have to get those test questions covered. They have to make sure the kids know these particular facts, in a certain way, by a certain time, and sometime people's brains just don't work that way.

P3 gave an example to illustrate this that was related to a specific math GLE. P3 noted that when students are taught to use a ruler in math class that they are taught to measure a straight line that is provided for them. This participant went on to explain that although students do well when they are tested over this GLE, that they do not know how to actually apply using a ruler to other types of problems.

Finally, at least a couple of the participants expressed feeling that as a result of the focus on using data to improve test scores that certain subjects were being emphasized to the detriment of others. The elementary and middle school participants described having to focus more time on tested subjects, while the junior high and high school participants referred to a general feeling that subjects that did not have a standardized test associated with them were less important than subjects that did. P3 in particular noted that administrators in this district referred to non-tested subjects as non-core and that this was frustrating. In fact, P3 said, “. . . don't say I am not a core class because core means it's crucial, it's important. When you say I'm non-core, you're saying I'm not important.”

Summary

The purposes of the second research question that guided this study were to understand whether or not participants feel they have the skills necessary to analyze and

use data to inform instruction and what kind of value they assign to using data to inform instruction. This study found that participants generally related the term *skill* to analyzing data rather than to using data to inform instruction, and that most participants felt that their skills were good. Further, this study found that whether or not a participant felt that their skills were good is not an important factor in understanding the research problem. What is important in understanding the research problem is that not only do participants associate the term *skill* with data analysis, but that they also do not view using results as a skill.

In contrast, the way participants value using data to inform instruction is important in understanding the research problem and is explained by concepts that can be grouped into two categories: *time* and *usefulness*. There were three concepts related to time and most of the participants in this study cited at least one of these concepts as a factor that limited their use of data. Essentially, participants said that analyzing data takes a lot of time, using data takes a lot of time, and data are not always timely. Two participants, P12 and P14, brought up another time related issue that was not discussed because only two participants mentioned it. The issue they brought up was that collecting data takes time or, more specifically, that the frequent testing required for collecting data takes time away from instruction.

Similar to *time*, this study found that there were four concepts related to *usefulness* and, as with *time*, most of the participants in this study cited at least one of these concepts as a factor that limited their use of data. Participants in this study did not place personal value on data either because they felt that data did not accurately reflect the learning that took place in their classrooms or because they felt that data did not reflect the needs and

growth of individual students. Additionally, participants saw using data as something they did for someone else and for the express purposes of predicting and improving test scores. Finally, they indicated that these very specific purposes for using data limited both the depth and breadth of learning.

Discussion of Research Question Three

The final research question that guided this study was: What characteristics of educators' training and/or organizational culture contribute to these views? The purposes of this question were to understand whether or not participants had participated in any professional development or formal coursework related to using data to inform instruction and, if so, how they perceived the value of that training. Since one of the aims of this study was to help shape future professional development on using data, it was important to find out what types of training educators are already getting and how useful these trainings are to them. Another purpose of this question was to understand the role of organizational culture in educators' perspectives on using data since organizational culture may be a factor in both addressing the research problem and in developing future professional development.

Professional Development

Participants in this study were asked to describe any professional development they had participated in that was related to using data to inform instructional decision making. Nine of the fifteen participants in this study said that they had never had any professional development on using data to inform instruction, while the other six indicated that they had, at some point, participated in professional development on this topic.

No professional development.

Of the nine participants who said that they had never had any professional development on using data to inform instruction, two of them said that they had learned about using data through participation in collaborative teams. P1 noted that he was a member of a Positive Behavior Support (PBS) team and said, “. . . it’s not actually that I took a class or anything to know that, we’re learning at the meetings.” Similarly, P2 said the following about department-level PLC meetings that were facilitated by a curriculum specialist:

. . . we have one person that collects all of our data . . . we would go over it and we would discuss what we’re supposed to do with it and so we never really had a formal training on how to do it, but she kind of led us through how to read all the data . . . here’s all these charts, here’s all these graphs . . . let’s compare it, see how everybody did.

Interestingly, when P1 and P2 were asked later in their interviews to describe any supports that were in place in their respective buildings to help improve data analysis skills or to facilitate analyzing and using data, they both described these collaborative teams as supports.

The seven other participants who said they had never had any professional development on using data to inform instruction generally said that they were not aware of any opportunities for professional development of this type in their buildings or in the district. P8, for example, was asked an additional probe about whether or not this type of professional development was ever offered in her building or in the district and she

responded, “Not that I’m aware of.” Another participant, P11, was asked a similar probe to which she replied, “I’m sure we’ve probably had something in the building, but nothing’s coming to mind. No, nothing really stands out.” At least one participant, P3, said that if she wanted to get professional development on this topic that there would be both encouragement and financial support from administration in the district.

Some professional development.

As noted earlier, six of the fifteen participants in this study said that they had, at some point, participated in professional development on using data to inform instructional decision making. Three of these participants said that it had been more than a few years since they had participated in any professional development of this type. One of these participants, P4, indicated that she had received a lot of professional development on this topic several years earlier when the district first implemented PLCs, but noted that she had not had any in the past five years. Another one of these participants, P6, noted that she had been a curriculum director in a different district and had participated in a great deal of professional development on using data in that position. This same participant said that she had not participated in any professional development on this topic since she was hired by this district. Finally, the last of these three participants, P7, said that she had been focused on her own personal professional development goals for the last few years and acknowledged that she had not been participating in much professional development that did not directly support those goals.

The three other participants who indicated that they had, at some point, participated in professional development on using data all described more recent experiences. Two of these three participants, P12 and P14, said that they had received

training fairly recently on using one or more of the various standardized test preparation software programs licensed by the district. In fact, P14 noted that she was one of a select few who went to outside training on using these programs and that she, in turn, provided similar training to others in her building. It is important to note, however, that the professional development P12 and P14 described was not actually related to using data to inform instruction. The training these two participants described was specific to using these programs with students and generating reports of students' results. The last of these three participants, P5, did not provide any examples of recent training. This participant simply said, "For the last ten years at least, almost everything that's professional development is related to using data to improve instruction. Almost everything."

Although there were not a lot of similarities in the professional development experiences of these six participants, they were all asked about the value of the experiences they described. All six of these participants were generally positive about professional development they had participated in on using data. P4, the participant who said she had been involved with implementing PLCs in the district, said, "The first that we went to was not very good, in my opinion. They threw . . . it was a ton of data, but they didn't tell us how to get it . . . they've really gotten so much better as we've gone to training more recently." While P4 used the phrase "more recently" when describing the way the training had improved over time, she also noted that it had been at least five years since she had participated in any such training. P6, the participant who once was a curriculum director in another district, described a variety of experiences including workshops offered by the state department of education and by the education department of a major public university. With regard to the university workshops, P6 said, ". . . she

was fabulous as to gearing your instruction, or your curriculum and instruction, to fueling student performance.” The four other participants were also similarly positive about professional development they had received, even if the professional development was not actually about using data to inform instruction.

Formal Coursework

Along with professional development, participants in this study were asked to describe any formal coursework they had taken that was related to using data to inform instructional decision making and, similar to professional development, the majority (11 of 15) reported that they had never had any formal coursework on this topic. Most of these eleven participants simply said that their degree programs had not included any such coursework; however, two of the eleven participants applied caveats to their answers. P10 said that he had taken a statistics course as a part of his master’s degree, but noted that it was specific to understanding subject matter data rather than classroom data. Another participant, P11, reported that although she had not had any courses on how to use data, her capstone course for her master’s degree program had required her to use data. Specifically, P11 described having been required to conduct action research in her classroom and, as a part of her action research, having used classroom data to make changes to instruction.

While the majority of participants said they had never had any formal coursework on using data to inform instruction, one participant said she may have taken coursework on this topic and three participants said they had taken coursework on this topic. P3, the participant who expressed uncertainty with regard to this question, indicated that she had earned a master’s degree about twelve years earlier. This participant said that she

vaguely remembered a course in her master's program that might have been on using data, but explained, "... we had to do data, but it wasn't numbers. It was that you observe, you write down, and then you reflect. I can't remember what it was called, but we did do some of that."

The three participants who said they had taken coursework on using data to inform instruction indicated that this coursework had been part of graduate degree programs. P5 said that she had earned a master's degree in curriculum and instruction and "... that was all about, the entire realm of it was about using data to improve instruction." Another participant, P8, said that she had taken a course on this topic while earning a master's degree in education, but referred to this course as a course on evaluation specific to SPED. P8 also noted that this course had not been very useful to her both because it was specific to SPED and because she had taken it too early in her career. Finally, P15, said that she had completed a specialist's degree in administration that had included several courses on using data, but noted that the courses were "a little different." This participant went on to describe courses where she had studied cases or scenarios and used qualitative data such as interview data to answer research questions.

Although the only participants who had taken any coursework on using data to inform instruction all hold master's degrees or higher, they were not representative of all participants in this study with graduate degrees. In fact, among the participants who said they had never taken any coursework on this topic, there were at least five with graduate degrees. Interestingly, at least one of these participants, P6, has a master's degree in curriculum and instruction. This is interesting because P5, the participant who reported the most formal coursework on this topic, also has a master's degree in curriculum and

instruction and said that her whole degree program had been about using data to improve instruction. P6 explained that the reason her master's degree in curriculum and instruction had not included coursework on using data was because she had completed it many years earlier and things had changed a lot since then. Further, with the exception of P6, how long it had been since participants completed their degree programs did not seem to have any bearing on whether or not their programs had included coursework on this topic. It is also important to note that P6 is quite likely an outlier since she is definitely the only participant in the study to have earned a graduate degree prior to the standards-based reform movement and possibly the only participant to have earned any degree prior to this movement.

Organizational Culture

As noted earlier, one of the purposes of the third research question was to understand the role of organizational culture in educators' perspectives on using data to inform instructional decision making. It is important to point out that, because organization culture is complex, this study was only interested in understanding the characteristics of organizational culture that might contribute to these perspectives and not the overall organizational culture. In an attempt to identify these characteristics, participants were asked about the expectations they felt to use data and the supports that were in place to help them meet those expectations.

Pressure to use data.

The participants in this study generally characterized the expectations they felt to use data as pressure, and the amount of pressure they felt to use data was very closely associated with the grade-level or subject area they taught. Participants representing

lower grade levels or non-tested subject areas generally felt less pressure to use data than did participants representing upper grade levels or tested subject areas. The one exception to this was P14, the participant from the elementary school that was in school-improvement status due to low standardized test scores. Although P14 represented a lower grade level, she felt intense pressure to use data. P14 identified her school's RtI program as the source of that pressure and explained that her principal had implemented a very structured and comprehensive RtI program. In fact, she said that every student was placed into an RtI group, that there was ongoing evaluation of the RtI groups, and that every certified faculty member worked with one of the RtI groups for thirty minutes each day. While P14 acknowledged this had been beneficial and that scores were improving, she also said, “. . . sometimes I think it's too much . . . let me teach.”

Regardless of the level of pressure participants felt to use data, the only data they associated with expectations were common assessment data. Fourteen of the fifteen participants in this study identified common assessment data as one of their primary sources of data, and most of these participants indicated that these were the only data they were specifically expected to use. Further, the expectation that they use common assessment data was so well defined that participants accepted that it was a requirement. Participants also generally accepted that common assessments were intended to help standardize local curriculum and serve as a tool for predicting and improving scores on state standardized tests. In fact, as noted earlier in this chapter, this study found that the push for common curriculum and the focus on data from common assessments shaped the way these participants defined all data.

In addition to shaping the way participants defined data, this push shaped the way participants perceived the district's expectations, especially for those who felt pressured by those expectations. Several participants representing tested areas in upper grade levels, along with the participant representing the elementary school in school reform status, described the district as *data driven*. P4, for example, said, "That is what we're about is using data to figure out what we need to fix." Likewise, P5 noted, ". . . we are data driven. I mean we do focus on figuring out what's going right, what's going wrong, and fixing it." While neither of these participants said specifically what they were trying to "fix," what they were both acknowledging was the overarching expectation for high test scores that caused participants to perceive the district as *data driven*. There were other participants in this study who made comments similar to those of P4 and P5, and there were even some who specifically identified the expectation for high test scores. In one such example, P7 said, ". . . they expect high test scores, and so there's always a push to pick up, you know, wherever we're weak and improve it."

Resistance to using data.

At least two participants acknowledged that there had been some resistance to collecting and using required data or, more specifically, common assessment data. The two participants who mentioned resistance represented both upper grade levels and tested areas. P4, for example, said that there had been problems across the district getting some of the classroom-level educators to administer the common assessments and report the results. P4 noted that team leaders that were having issues with this could talk to whichever administrator was responsible for evaluating that educator.

Similarly, P10 said, “There is an expectation that you should be looking at it and making changes; however, there is some resistance sometimes to making changes. Change is difficult.” This participant was referring specifically to using common assessment data, but gave at least three examples of general resistance within his curriculum team. In one example, P10 said that a particular grade-level team had been slow to develop common assessments and that they continued to work at “a snail’s pace” even after the situation had reached a point that they were told they had to get it done and given extra professional development time to do it. Another example P10 provided also involved a grade-level team within his curriculum team. This particular team only gave one common assessment per semester even though the minimum requirement was one per quarter. P10 said that this team continued to give one common assessment per semester even though the curriculum specialist told them they were not meeting the minimum requirement. P10’s final example was about resistance within his own grade-level team to collecting data that resulted in inconsistent data. He attributed this resistance to the idea that “. . . people are aware, you know, that sometimes we collect data just to collect data. We really don’t use it as much as we should.”

Supports.

Participants in this study were asked if there were any supports in place in their buildings to improve data analysis skills or to facilitate data analysis and use. The supports that participants identified included grade-level or department-level PLC teams, testing teams, curriculum teams, curriculum specialists, the district’s instructional technology facilitator, calendar time for analyzing data, Scantron technology, and the Excel spreadsheets used to track common assessment data. While participants identified

a number of supports, most of these supports were cited by only one or two participants. Interestingly, the only support that was cited by more than a couple of participants was the Excel spreadsheets used to track common assessment data. One third of participants identified this spreadsheet as a support and almost half of them identified the instructional technology facilitator who created the spreadsheet as a support.

Most of the supports identified by participants were only cited once or twice, but most of the participants who identified supports cited more than one. Further, approximately a third of participants were not able to identify any supports at all. When asked if there were supports in place, P3 responded, “Not really that I am aware of that’s out there, like come, we want you to focus on data. I haven’t seen anything like that.” Similarly, P8 noted, “I don’t really feel that there is that, in ours. Not to say that there isn’t, but I haven’t really seen anything like that.” Another participant, P11, replied, “Not that I know of. I feel like we are on our own to try to figure it out.”

Structured collaboration.

All of the participants in this study described being involved in a great deal of structured collaboration as the district had embraced the PLC model several years earlier and applied it consistently to grade-level, department-level, and curriculum teams. These teams served as the foundation for the district’s professional development plan and, as such, there was a great deal of time built into the calendar for them to meet. All of the participants in this study were on at least one of these teams. In fact, participants generally said that they met almost weekly with one of these teams and that the primary purposes of these teams were to collaboratively analyze data and figure out how to use

the results to inform instruction. One participant summed this up as follows: “And, we collaborate, collaborate, collaborate. We spend a lot of time talking to each other.”

Additionally, a few participants in this study said that they were on Positive Behavior Support (PBS) teams. Although the PBS model is somewhat different than the PLC model, it does focus on using data. Since this emerged in one of the early interviews, participants were probed on the topic of PBS. All participants acknowledged that their schools were PBS schools and that they received PBS data from someone, even if they were not on a PBS team. The data they all said they received were data on “the big five,” and how they received these data was generally as a handout at a faculty meeting or as an attachment to an email. When asked about “the big five,” almost none of the participants could even name the five categories represented in “the big five.” Further, whether they were on a PBS team or not, participants said these data were not beneficial to them. For example, a participant who was actually on a PBS team, P1, said that one of the reasons PBS was implemented was to improve attendance rates district-wide. However, when probed about expectations related to PBS data, P1 explained, “Not a whole lot we can do here in the classroom. As far as that data, there’s not much we can do as a teacher. I think that’s more the administrators’ responsibility.”

Feedback from administration.

Although participants in this study said that they were required to use common assessment data and that they were given structured time for this purpose, a third of them also said that they did not get any feedback from administration with regard to these data. These participants were not only frustrated by this lack of feedback, but also concerned that it signaled that these data were not really important. P8, for example, said, “I mean

that's one of the things I feel like is kind of a negative on data because I feel like we do this, but then we don't ever really see anything about what happens to it." Likewise, P10 noted, "... to be honest with you, I'm not quite sure what happens with the data even when we kind of collect it. It just kind of sits . . ." Another participant, P11, said, "I don't feel like anybody else looks at it and looks at what we're doing besides us because we don't get any pats on the back . . ." A final noteworthy comment on this topic was made by P14. P14 commented, "That's one of my biggest complaints. We do all that work grading those tests and entering them into the spreadsheets and posting them . . . and then we never hear anything on them."

Summary

The purposes of the final research question were to understand whether or not participants had participated in any professional development or formal coursework related to using data to inform instruction and, if so, how they perceived the value of that training. This study found that most participants had never participated in any formal professional development on using data to inform instruction and, those who had, had not participated in any within the last five years. Further, some of the professional development participants felt that using data to inform instruction was actually only about using standardized test preparation software. This study also found that an even greater number of participants had never had any formal coursework related to using data to inform instruction and, those who had, had taken it as part of a graduate degree program. While the participants who had received professional development on this topic generally described it in positive terms, the participants who had taken formal coursework on this topic generally described it in more neutral terms.

Another purpose of this final research question was to understand the role of organizational culture in participants' perspectives on using data. Analysis revealed that concepts related to pressure to use data, organizational supports, structured collaboration, and feedback all contributed to participant perspectives on using data. This study found that participants characterized expectations to use data as pressure and that the amount of pressure they felt to use data was related to their grade-level or subject area. This study also found that in spite of efforts by the district to put supports in place in the form of structured collaboration, many participants did not view the collaborative teams as supports. Finally, but no less importantly, there was a noted lack of feedback from administration related to common assessment data that caused some participants to question whether using data was really valued.

Summary

Through constant comparative analysis of transcripts of semi-structured interviews with fifteen participants, this study identified concepts and categories important to understanding the research problem and the three research questions that guided this study. These findings point to a substantive theory grounded in the data of this study, which will be discussed in chapter five. This discussion will also explore the implications of this theory for practice and future research and how this theory is supported by the current empirical knowledge base. Although this study was not guided by literature in the empirical knowledge base, it was my intention that this study support and contribute to this knowledge base.

Chapter 5 – Substantive Theory and Implications

Introduction

As noted in chapter one, the purpose of this study was to address the gap between how policymakers and educational leaders expect data to be used to inform instruction and how classroom-level educators internalize and implement these expectations. This study attempted to address this gap by exploring educators' perspectives on using data, their views of their own data analysis skills, how they value and make meaning of data, and the characteristics of their training and/or organizational cultures contribute to these views. The research problem that signaled the need for this study was a growing body of evidence indicating that, despite increasing expectations to use data (Jacobs et al., 2009; Young & Kim, 2010), educators are not using data driven decision making as a part of routine professional practice (Crum, 2009; Love, 2004; Mokhtari et al., 2007/2008; Newmann et al., 1997; Ronka et al., 2008).

Three research questions guided this study and the findings related to each of these questions were presented in chapter four. In this chapter I will develop a substantive theory grounded in the data supporting the findings. I will also discuss the implications of the findings and the substantive theory for both practice and future research.

Substantive Theory

Many concepts emerged during analysis of the data, which were grouped into several categories. These categories and the concepts within them were analyzed until they could be grouped into one explanatory category that offered a theory about these

participants' perspectives on using data to inform instruction. This theory is a complex theory that, while grounded in data from practice, shares a conceptual relationship with the epistemology of constructivism. Pragmatically, this epistemology explains what participants believe about how students learn and what they believe about how learning is measured. Together, these beliefs are the basis of the substantive theory.

Beliefs About How Students Learn

What participants believed about how students learn is embedded in many of the concepts included in the discussion of the second research question. These concepts were grouped into two categories, which were *time* and *usefulness*. Concepts related to time emerged more frequently than any other concept in this study. Participants said they did not have *time to analyze data* or to *use the results* to inform instruction. They also said that data often were not timely. Although it is tempting to accept these statements at face value, time is not an issue that merits singular attention. One reason for this is because while participants said they did not have time to analyze data, they also acknowledged that there was a lot of structured time built into the school calendar for this purpose. Another reason for this is that, in spite of protestations about time, participants clearly indicated that they found time to accomplish very time consuming activities when they believed the activities were *useful*. As such, *time* is an issue only when considered in the context of *usefulness*. Further, concepts categorized as usefulness not only give meaning to the issue of time, these concepts also help explain participant beliefs about student learning. These beliefs define *the role of the classroom-level educator* and *the nature of learning*.

The role of the classroom-level educator.

The idea that *individual students get lost in data* was a concept that emerged during analysis and was grouped into the category of *usefulness*. Since this study was about understanding participant perspectives on using data, it would be logical to assume that participants were thinking of complications related to individualizing instruction. Analysis, however, indicated that this concept was much less about individualizing instruction than it was about *relationships* with students. In fact, only one participant actually linked this concept to individualizing instruction, while the rest linked it to relationships with students or *knowing* students on an individual level. Moreover, later iterations of data analysis revealed linkages to the importance of relationships and knowing individual students throughout all participant transcripts.

For participants in this study, knowing students on an individual level means understanding their prior knowledge and beliefs, their rate of learning, and what they are learning. While it may be unlikely that any of these participants would describe themselves formally as constructivists, their conception of knowing students has constructivist underpinnings (Abdal-Haqq, 1998; Powell & Kalina, 2009; Sirotnik, 2004). Further, constructivist paradigms not only emphasize the importance of relationships, these paradigms also define the role of the classroom-level educator in these relationships as that of a facilitator or guide (Abdal-Haqq, 1998; Powell & Kalina, 2009) and there is evidence that study participants defined their roles similarly embedded in their beliefs about the nature of learning.

The nature of learning.

As noted in the previous section, what participants believed about the nature of learning provides evidence that they viewed themselves as facilitators or guides in the learning process. Similar to their beliefs about the importance of relationships, this aligns with a constructivist paradigm. Specifically, what participants believed about the nature of learning can be interpreted from two important concepts that emerged during analysis and were categorized as *usefulness*. These concepts were that *data do not tell the whole story* and *data limits leaning*.

A number of participants in this study expressed concerns that *data do not tell the whole story*. These participants associated these concerns with feelings that data do not necessarily reflect how students have grown and that data do not capture what has happened in the classroom. These concerns stem from what participants believed about the nature of learning, which is that learning is personal for each student. Learning is personal in the sense that students, with the help of a guide or facilitator, construct their own understanding of experiences and this understanding they construct becomes new knowledge. This view that learning is personal and knowledge is constructed is the basis for all constructivist paradigms (Abdal-Haqq, 1998; Powell & Kalina, 2009; Sirotnik, 2004) and it explains why participants feel data do not tell the whole story. Essentially, participants do not believe that it is possible to tell a story as complex as that of individual learning through the simplistic group measures they associate with data.

Similarly, a number of participants either directly expressed or provided support for the idea that *data limits learning*. Much of the discussion related to this idea was about how the focus on data is narrowing the breadth and depth of the curriculum.

Specifically, tested subject areas and tested concepts within those subject areas are being emphasized to the detriment of non-tested subject areas and even non-tested concepts within tested subject areas. This is philosophically problematic for participants in this study because it does not support the active involvement with the content necessary for students to construct knowledge. Instead, it supports imitation or repetition of the content, which are methods more characteristics of empiricist or reductionist paradigms than constructivist paradigms (Abdal-Haqq, 1998).

Beliefs About How Learning is Measured

As with participant beliefs about how students learn, participant beliefs about how learning is measured are embedded in many of the concepts included in the discussion of the second research question. In fact, their beliefs about how students learn and how learning is measured are inextricably interwoven and, accordingly, the concepts that explain their beliefs about learning also explain their beliefs about the measurement of learning. There was one additional concept in the discussion of the second research question that relates to their beliefs about how learning is measured, which is the concept that *data are for someone else*.

As noted, participant beliefs about how students learn were expressed as four main ideas found in the concepts of *individual students get lost in data*, *data do not tell the whole story*, and *data limits learning*. To summarize, participants believe in the importance of knowing students individually and in the importance of serving as a guide or facilitator in the learning process. In order to know students, they have to understand their prior knowledge and beliefs, their rate of learning, and what they are learning. They

also believe that students learn by constructing knowledge and that this happens as the result of interactions.

Since participants believe individual students learn differently and at different rates, it follows that they do not view the types of assessments associated with data as good measures of student learning. These assessments are aligned with very specific concepts within subjects and focus on single interpretations of these concepts. In other words, there is only one correct answer and student growth around a concept is not recognized unless they select the one correct answer. In fact, participants in this study would argue that these assessments are equally poor measures of learning for students who do well on them. Participants noted that these assessments do not reveal student thinking on a concept or the process for arriving at correct or incorrect answers. They also noted that these assessments allow for lucky or unlucky guesses.

While it is fairly easy to identify what participants feel is a poor measure of learning, it is not as easy to identify what they feel is a good measure of learning. They generally said that they recognize when students are learning because they *know* the students. The interactions that they see as important for helping students construct knowledge are equally important for helping them understand what they are learning. As with their beliefs about how students learn, their beliefs about how learning is measured also align with constructivist models (Powell & Kalina, 2009).

Finally, as mentioned at the beginning of this section, there was one additional concept included in the discussion of the second research question that relates to what participants believe about how learning is measured. Participants in this study widely

expressed that they *collected and analyzed data for someone else*. This was directly related to the fact that they defined data primarily as the summarized results of the multiple choice common assessments that they were required to administer. This idea that *data are for someone else* is related to what they believe about how learning is measured because, as noted earlier, they do not view the types of assessments they associate with data as good measures of learning. Accordingly, since they do not believe that these required assessments are good measures of learning, they see them strictly as something they do for someone else.

The Substantive Theory

As noted in chapter one, the ideas that accountability is demonstrated through data and that data should be used to inform instructional decision making are central to the accountability movement (Jacobs et al., 2009; Young & Kim, 2010). These ideas were adapted from data driven decision making, which is the central premise of the total quality management (TQM) movement that started in the United States in the 1980s as a way to demonstrate and improve quality in the manufacturing sector (J. A. Marsh et al., 2006; Young & Kim, 2010). Further borrowing from the TQM movement, the accountability movement assumes that legislated external mandates will have the same impact on schools that external monitoring by customers and clients has on business (Newmann et al., 1997). This assumption presumes that schools can and should run like manufacturers or other businesses (Derthick & Dunn, 2009; Young & Kim, 2010), that there is a link between accountability and performance (Newmann et al., 1997), and that external mandates will funnel down and be internalized by classroom-level educators (Katz et al., 2005; Newmann et al., 1997).

This study found that the way this school district implemented data driven decision making was in direct support of the philosophy of the accountability movement as borrowed from TQM. This study also found that at least two of the presumptions associated with implementing TQM-style accountability in education were not true in this district. These presumptions were that schools can and should run like manufacturers or other businesses (Derthick & Dunn, 2009; Young & Kim, 2010) and that external mandates will funnel down and be internalized by classroom-level educators (Katz et al., 2005; Newmann et al., 1997). The reason these presumptions were not true is attributed to a conflict conceptually between the way data driven decision making is adapted for education and improving standardized test scores.

Data driven decision making as adapted for education.

Although the idea of using data to inform instructional decision making is adapted from data driven decision making in TQM (J. A. Marsh et al., 2006; Young & Kim, 2010), it is conceptually different. The reason for this is because improving student achievement is not the same thing as improving the quality of a manufactured product and, as such, is not accomplished through the same methods. The primary method used in educational data driven decision making involves changing instruction or curriculum based on data, which is also referred to as classroom-level curriculum development (Shawer, Gilmore, & Banks-Joseph, 2008). Conceptually, this idea of classroom-level curriculum development has constructivist underpinnings because it encourages change based not just on test data, but also on observations and interactions (Shawer et al., 2008). In other words, it supports the active learning that is characteristic of a constructivist pedagogy (Abdal-Haqq, 1998; Powell & Kalina, 2009; Sirotnik, 2004).

Improving standardized test scores.

While data driven decision making in education has been defined in a way that supports constructivist pedagogies, the same is not true for the standardized measures it is meant to affect. Whereas data driven decision making requires classroom-level educators to be curriculum developers, standardized testing encourages them to be curriculum transmitters. Curriculum development is left up to experts with knowledge of the content and structure of the relevant standardized tests (Shawer et al., 2008). Pedagogically, standardized testing supports an empirical or reductionist approach to teaching and learning where the educator transmits or delivers knowledge to the students, the students store it intact, and then the students access it when they are asked for the one correct answer on a standardized test (Abdal-Haqq, 1998).

Summary

What participants in this study believe about how students learn and how learning is measured has strong constructivist underpinnings. Further, data driven decision making as adapted for education supports constructivist paradigms. From an organizational theory perspective, these constructivist beliefs align with a cultural or symbolic frame. Paradoxically, the standardized testing that data driven decision making is supposed to affect supports empiricist or reductionist paradigms or, from an organizational theory perspective, a structural frame. What participants associate with data for data driven decision making is largely indistinguishable from standardized test data and, as such, there was not any real connection between this data and teaching and learning. Quite simply, participants do not view this data as a good measurement of

learning or a good input to support instructional change and, since they see this data as the only data, they reject the idea of using data to inform instructional decision making.

Contributions to the Empirical Knowledge Base

This study, which sought to develop theory rather than test theory, was not guided by the current empirical knowledge base but, instead, the literature in this knowledge base was used to shape the discussion of the findings. Although the empirical knowledge base did not guide the inquiry for this study, it was an aim of this study to contribute to the knowledge base. In this section, I will discuss how this study's findings relate to what is already known about educator perspectives on using data and what this study's findings may add to this knowledge base.

Data Equals Test Scores

There is literature in the empirical knowledge base to indicate that standardized test scores have become the primary source of data for continuous improvement for most schools (Flowers & Carpenter, 2009; Pritz & Kelley, 2009; Schmoker, 2003) and have even become synonymous with the term data (Jacobs et al., 2009; Young & Kim, 2010). This study's findings generally support the idea that standardized test scores are synonymous with data as the majority of participants referred to these scores as data. However, this study found that specific data from a new category of data were even more synonymous with the term data for these participants and, in fact, even served to define the term data for these participants.

The new category of data this study identified was referred to as *standardized test preparation data* and included both tools and assessments intended to support improving

standardized test scores. The specific data from this category that defined the term data for these participants were data from *local common assessments*. These assessments, which were supposed to connect classroom instruction with improving standardized test scores, shared many similarities with standardized tests. As such, the data from these assessments were also very similar to data obtained from standardized testing. Although for study participants data from local common assessments were even more synonymous with the term data than were data from standardized tests, this generally supports the idea that standardized tests have become synonymous with data as the real purpose of local common assessments is simply to help participants internalize goals related to improving standardized test scores.

Reasons Educators May Not Use Data

While there is not a lot known about how educators use data to inform instruction or their perspectives on using data to inform instruction (Young & Kim, 2010), the literature does identify some potential reasons why educators may not use data to inform instruction. These potential reasons, which are grouped into three primary categories in the literature review, will be discussed similarly in this section.

Technical skills to analyze and use data.

Several authors note that educators report feeling ill equipped or ill prepared to analyze and use data (Earl & Katz, 2006; Flowers & Carpenter, 2009; Jacobs et al., 2009; Ronka et al., 2008; Williamson & Blackburn, 2009), suggesting that they may feel that they do not possess the requisite technical skills. This study found that this was generally not the case as most participants characterized their own skills as good. It is important to note, however, that most participants only associated the term *skills* with *analysis*, and

they considered analysis to be a mathematical process. While participants were not necessarily able to articulate how the results of analysis inform instruction, they also did not view knowing how to use results as a skill. Interestingly, what this study found contradicts the literature only because participants did not *perceive* that they lacked the skills necessary to analyze and use data, not because this is patently accurate. In other words, regardless as to their skills, *feelings* about their skills do not explain why they may not use data.

Also included in this category is the idea that educators may feel that the process of analyzing and using data is “overwhelming” (Flowers & Carpenter, 2009; Mokhtari et al., 2007/2008; Schmoker, 2003; Williamson & Blackburn, 2009); however, there is not strict agreement in the literature regarding what this means. At least one author suggests that this feeling is related to a tendency by experts to overcomplicate data analysis and use (Schmoker, 2003), while others attribute it to the sheer amount of data available to educators (Williamson & Blackburn, 2009). Several authors, however, posit that educators feel this process is “overwhelming” because it is time consuming (Flowers & Carpenter, 2009; Mokhtari et al., 2007/2008). This study did not find much evidence that participants feel experts overcomplicate data or that they are inundated with data, but this study did find that they felt it is very time consuming to analyze and use data. On the surface, time might be considered a contributing factor in explaining why participants may not use data. However, while participants clearly see analyzing and using data as time consuming activities, time is a factor relative to their *perceived value* of these activities.

Mistrust of data.

Earl and Katz (2006) suggest that one of the reasons educators may not use data to inform instructional decision making is because they mistrust data. They believe that educators may mistrust data either because they are more confident in their own tacit knowledge or because they feel data can be skewed and used against them. Participants in this study generally did not express feelings that could be construed as mistrust of data. There was some support in the findings for the idea that data can be skewed, but there was not any evidence to suggest that they feel data are intentionally skewed or used against them. What participants referred to that supports this notion that data can be skewed were measurement problems associated with differences in teaching styles, student motivation, and the structure and nature of the assessments. Similarly, there was a lot of evidence to suggest that participants valued their own tacit knowledge over data, but there was not an element of mistrust associated with this evidence either. Instead, the value they place on their own tacit knowledge can be directly attributed to their constructivist views on teaching and learning, which, ultimately, shape their views on how learning is measured. They simply do not feel that what they associate with data reflect learning.

Fear of data.

A final reason found in the empirical knowledge base for why educators may not use data is that they may fear data. Although fear of data may stem from mistrust of data, authors identify at least two other potential factors that may contribute to fear of data. First, educators may fear data because data have become synonymous with standardized test scores (Jacobs et al., 2009; Young & Kim, 2010) and, due to the high-stakes nature of

standardized testing, serve as alarms or red flags (Earl & Katz, 2006; Jacobs et al., 2009). These alarms or red flags highlight problems, but often do not provide constructive inputs to drive instructional decision making. Second, educators may fear data because they may fear the prospect of their performance being evaluated based on student performance (Earl & Katz, 2006).

This study found that participants would agree with the view that data are alarms or red flags that highlight problems, but that often do not provide constructive inputs to drive instructional decision making. Some participants directly expressed concerns about this, while others provided evidence of this in that they were able to articulate how to analyze and interpret data, but not how to use the results to inform instruction. Interestingly, while participants would agree with this view, they would not associate it with feelings of fear. Participants who directly expressed concerns about this related these concerns with feelings of frustration. This study did, however, find that participants fear the prospect of being evaluated based on student performance. At least one participant referred to being judged based on student performance and described it as inaccurate, while others alluded to worries or concerns about how they might be viewed professionally based on student performance.

Summary

Findings from this study affirm, contradict, and contribute to the empirical knowledge base primarily in areas related to how educators define data and reasons why educators may not use data. While there were findings in this study linked to other areas of the empirical knowledge base, these findings were less definitive and, and as such, they serve more to highlight the need for future research than to contribute to the

empirical knowledge base itself. Discussion related to these findings will be included in the discussion regarding the implications of this study for practice and future research.

Implications for Practice and Future Research

This study found that there is a theoretical mismatch between what participants believe about teaching and learning and standardized measures of learning. This conflict between the conceptual underpinnings of their pedagogical beliefs and mandated assessment, coupled with a narrow definition of data, explains why these participants generally do not value data and do not embrace data driven decision making. This theory and other study findings highlight some important implications for practice and future research.

What Data Are Good Measures of Learning?

This district emphasized local common assessments to the degree that participants defined all data the same way they defined common assessment data. Common assessment data were the only data participants were required to collect and analyze, and they were given substantial calendar time for the purpose of analyzing these data collaboratively within their grade-level or department-level PLCs. Participants were clearly expected to use these data as the basis for instructional decision making. They do not, however, view these data as useful because they believe learning is both personal and individual and that these data do not reflect individual growth or learning.

Although these participants did not view data as very useful, there is evidence that there is real value in using data to inform instruction (Bernhardt, 2009; Jacobs et al., 2009; Ronka et al., 2008; Schmoker, 2003; Williamson & Blackburn, 2009). Further,

there is evidence that the accountability movement as we know it today and the body of policy that defines it are here to stay for a while (Goertz & Duffy, 2003), and that the ideas that accountability is demonstrated through data and that data should be used to inform instructional decision making are central to this movement (Jacobs et al., 2009; Young & Kim, 2010). As such, there is a need for further research toward understanding what data are good measures of learning. Since educators do not view summarized data from the standardized multiple choice assessments that are so characteristic of reforms related to this movement as good measures of learning, it will be important to figure out what data they would view as good measures of learning. Along these same lines, it will be perhaps even more important to figure out what data educators and policymakers would *both* agree are good measures of learning (Sirotnik, 2004). This research may present some interesting challenges since there are complex networks that bridge the divides between researchers, practitioners, and policymakers (Thomas & Pring, 2004).

What is the Theory of Causation?

There not only needs to be research about what data are good measures of learning, there also needs to be research about the implications of these data for instruction. There was evidence in the empirical knowledge base to suggest that data do more to identify problems than to provide solutions (Jacobs et al., 2009), which is a notion this study supports. While most participants in this study provided at least one example of how they used data to inform instruction, they were not able to explain how the data had actually informed instruction. Essentially, if how they taught something the first time did not produce the desired results, they simply tried something else. Some participants even directly expressed concerns that data only identified problems, not

solutions. Just as educators need data they believe are good measures of learning, they also need data that provide them with a theory of causation.

What Conditions Support the Development of Data Capacity?

There is support in the literature for the idea that effective data use will not occur until schools address data capacity (Ronka et al., 2008). While data capacity is not clearly defined in the literature, the term seems to refer to how data literate a school is collectively (Newmann et al., 1997; Ronka et al., 2008; Young & Kim, 2010). There are three organizational conditions identified in the literature that are thought to support the development of data capacity. First, educational leaders in a school or school district have to be technical experts in data analysis techniques and serve as data coaches (Ronka et al., 2008; Young & Kim, 2010). Not only do they have to be experts in analysis, they also have to be able to help classroom-level educators identify the instructional implications of analysis (Young & Kim, 2010). Second, there has to be structured time for collaborative data analysis built into the school calendar (J. A. Marsh et al., 2006; Newmann et al., 1997; Ronka et al., 2008; Young & Kim, 2010). Finally, there has to be technology in place that facilitates using data (J. A. Marsh et al., 2006; Newmann et al., 1997; Young & Kim, 2010).

This study found that two of the three conditions that are thought to support the development of data capacity were present in this district. First, there was clearly a great deal of structured time built into the school calendar for the purpose of collaborative data analysis. Participants said there was time scheduled for this at least once a week throughout the school year. Second, there was a lot of technology in place to facilitate using data. The district's instructional technology facilitator developed Excel

spreadsheets to assist participants with tracking and analyzing common assessment data, and the district purchased or licensed several test preparation programs that included data tools. The condition that did not seem to be present was leadership serving as data coaches. There was simply no indication that leadership guided analysis or helped participants identify the instructional implications of analysis. That is not to say that the leadership in this district were not technical experts, only that there was not any evidence that they were active data coaches.

Although two of the three conditions thought to encourage the development of data capacity were present in this district, there was evidence that participants were not using data effectively. However, since this study found that participant perspectives on using data were shaped largely by the way they defined data and how useful they regarded data, it is unclear what role any of these conditions, whether present or missing, played in this district. Further research in the area of developing data capacity is necessary in order to understand things such as how much benefit each condition has alone, whether there are other conditions not yet identified, and if these conditions together can change educator perspectives about using data.

Organization Theory as a Conceptual Framework for Future Studies?

The conceptual framework for this study was developed around the structural and cultural frames (Bolman & Deal, 2003; Morgan, 1997), which are widely recognized tools in organizational theory. These frames proved to be good lenses for viewing the problem through as this study found that the empirical or reductionist approach to teaching and learning supported by the way these participants felt they were expected to use data could be explained through the structural frame, while the constructivist

approach to teaching and learning the participants internalized was better understood through the cultural frame.

While this study did find a conflict between structure and culture, there were implications that other frames from organizational theory might be useful in future studies for addressing the gap between how policymakers and educational leaders expect data to be used to inform instruction and how classroom-level educators internalize and implement these expectations. For example, since several of the participants indicated that they had little or no involvement in developing the common assessments used to collect data, this might indicate that they feel disconnected from the data. These participants seemed to feel that data do not align with their curriculum and expressed that data are more a measure of preparation for standardized testing than a measure of classroom learning, which are issues that might be understood through the political frame (Bolman & Deal, 2003).

Further, another example from this study supports the idea that the human resource frame might be relevant for understanding this issue (Bolman & Deal, 2003). Although most participants felt expectations to use data that they characterized as pressure, none of them expressed feeling rewarded or recognized by administration for meeting these expectations. In fact, some of them expressed dissatisfaction over a lack of feedback from administration. Moreover, none of the participants expressed feeling any internal or intrinsic reward for using data. The fact that these participants did not feel that using data resulted in any external or intrinsic reward is an issue that might be understood through the human resource frame (Bolman & Deal).

Developing Professional Development

From the outset of this study, it was my hope that this research might inform future professional development around the topic of using data to improve instruction as the need for such programs is widely acknowledged (Katz et al., 2005; Pritz & Kelley, 2009; Ronka et al., 2008). There are some professional development frameworks identified in the literature, but they fail to address how to actually analyze data and how to use the results of analysis to improve instruction. In addition to these professional development frameworks, there is also evidence that schools have implemented initiatives such as Professional Learning Communities (PLCs) and Response to Intervention (RtI) to provide structured support for using data to inform instruction.

Although none of the professional development frameworks identified in the literature were used in this district, PLCs and RtI had both been successfully implemented. Interestingly, in spite of clear evidence that these structures provided support for using data, participants did not generally view participation in PLCs or RtI as professional development. In fact, they associated professional development strictly with formal workshops. Further, complicating the issue of professional development is the idea that participants did not associate using data to inform instruction with a skill.

While this study contributes to the empirical knowledge base and will, to some degree, inform professional development, there is still much research to be done on this topic. For the development of effective professional development, research should be done to identify good measures of learning and the implications of those measures for instruction. While these measures will have to satisfy policymakers, they will also have to account for what educators believe about teaching and learning.

A final thought on developing professional development is that, to be effective, any professional development program will have to be embraced and modeled by educational leaders. Some of the participants in this study expressed frustrations over a lack of feedback from administration. This emerged in the study during inquiry about the organizational culture and was discussed under the same heading; however, it was probably actually a larger issue deserving greater prominence. This lack of feedback, which caused participants to feel that their work with data was meaningless, might actually be linked to the concept of teacher alienation (Brooks, 2006). The implications of this are larger than what could be addressed with this study and point to the need for research related the role teacher alienation plays in educator perspectives on using data.

Summary

The findings from this study could be used by educational leaders to inform current school reform initiatives or professional development programs in their own settings, particularly if these settings share any similarities with the one described in this study. While this study provides some important insights regarding how these participants define, value, and perceive their own use of data, additional research is necessary if future professional development programs are going to *shape* how educators in other settings define, value, and *actually* use data.

Summary

This study found that understanding educator perspectives on using data to inform instruction was important for explaining the gap between how policymakers and educational leaders expect data to be used to inform instruction and how classroom-level educators internalize and implement these expectations. This study also found that in

order to understand these perspectives, it was necessary to understand their beliefs about how students learn and how learning is measured. For participants in this study, these beliefs defined their roles as classroom-level educators and their views on the nature of learning. For the end users of this study, these beliefs point to a theoretical conflict between educators' pedagogies and the practice of using standardized measures to evaluate learning. This theoretical conflict, which is the basis for the substantive theory developed in this study, contributes to the empirical knowledge base and has implications for practice and future research.

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Appendix A

Informed Consent for Participation

Study Title:

A Grounded Theory Approach to Understanding Educator Perspectives on Using Data to Inform Instruction

University of Missouri-Columbia, Department of Educational Leadership and Policy Analysis

You are invited to participate in a qualitative research study of educator perspectives on using data to inform instruction. Specifically, this study will seek to better understand educators' views of their own data analysis skills, how they value and make meaning of data, and what characteristics of their training and/or organizational cultures contribute to these views. The study will address a gap in the research base and may inform future professional development on using data. The potential benefits of participating in this study are the opportunity to make a contribution to the research base and to benefit from future professional development. The risks of participating in this study are minimal and there are no risks to your employability, insurability, or professional reputation. You have been selected as a potential participant based on your employment as a classroom-level educator in the (omitted) public school district.

Upon agreeing to be a part of this study, you will participate in a face-to-face interview that will be digitally recorded and transcribed. The interview should last between 30 and 45 minutes. Some participants will be asked to answer follow-up questions for the purposes of clarification or further exploration of emergent themes. Follow-up questioning may be conducted via email, over the phone, or face-to-face. All participants will be asked to review summarized findings to check for accuracy as research data are analyzed. Your participation is voluntary and you may withdraw from the study at any time. Your personal decision whether or not to participate will in no way jeopardize your future relations with the University of Missouri-Columbia or (omitted) Public Schools. Additionally, your participation in the study will not jeopardize your current or future employment with (omitted) Public Schools or any other school district.

The promise of strict confidentiality is assured both in the collection and reporting of results. Findings from this research will be presented in such a way that no individual will be identifiable. Although the information may be used in a published paper presented to the University of Missouri-Columbia or an educational publication, your name and identity will not be revealed. Additionally, data from this study will be not be labeled with any identifying information and will be stored securely and separately from any data key. No one outside of this study will have access to information regarding your identity.

If you have any questions or comments, you are welcome to contact the researcher or her University of Missouri –Columbia advisor.

Research Student:

Stephanie Broyles
18727 State Route O
Rolla, MO 65401
(573) 202-8671

University of Missouri-Columbia Advisor:

Dr. Peggy Placier, Associate Professor
202 Hill Hall
Columbia, MO 65211
(573) 882-9643

For questions regarding your rights as a research participant, please contact the Institutional Review Board (IRB) office located in 483 McReynolds Hall, University of Missouri-Columbia at (573) 882-9585.

Your signature below indicates that you have decided to participate having read the information provided above. You will receive a copy of this permission form.

Researcher

Participant

Date _____

Appendix B

Recruitment eMail

Subject: Educational Research Project

Dear (Name):

I work in the district at (omitted) and am a student at the University of Missouri – Columbia, completing a doctorate in education. In fulfillment of my doctoral degree program requirements, I am conducting interview-based research in our district. The research is related to using data to inform instructional decision making. I have identified you as a potential research participant based on one or more of the following factors: your years of experience teaching, your level of education, the subject matter and/or grade level you teach, and your building assignment. Participation in the research is both voluntary and confidential and requires only a small time commitment. If you are interested in learning more about my research and how you can help, I would like to schedule a brief meeting with you to further discuss your potential participation. Please feel free to call or email me to schedule a time for a brief meeting or to decline this invitation.

Sincerely,

Stephanie Broyles

Appendix C

Recruitment Script

Thank you for taking time to meet with me today. The purpose of this meeting is for me to invite you to participate in a qualitative research study investigating educator perspectives on using data to inform instructional decision making. Specifically, my study will seek to better understand educators' views of their own data analysis skills, how they value and make meaning of data, and what characteristics of their training and/or organizational cultures contribute to these views. This study is important because educators are increasingly being expected to use data to inform instruction and there is not much known about how educators are using data or what influences how they use data. I am conducting this study for the University of Missouri-Columbia in partial fulfillment of the degree of doctorate of education.

I am attempting to recruit a cross-section of educators in our district, characteristic of the various building assignments, grade-levels or content areas, years of experience teaching, and educational backgrounds present in the district. You were selected as a potential participant based on your employment as a classroom-level educator in the (omitted) public school district representing one or more of the salient characteristics of my desired cross-sample.

Your participation in this research study is both voluntary and confidential and you have the right to withdraw at any time. Your decision whether or not to participate will in no way affect your relationship with the University of Missouri-Columbia or (omitted) Public Schools, nor will it affect your current or future employment with (omitted) or any other school district. At no time will anyone outside this study know your identity. I will report all results using pseudonyms and with identifying information removed. I will label data as to not identify participants and I will store data securely and separately from any data key.

Your participation would require one face-to-face interview that will be digitally recorded and transcribed. The interview should last between 30 and 45 minutes. I will ask some participants to answer follow-up questions at a later date for the purposes of clarification or further exploration. Follow-up questions may be asked via email, over the telephone, or face-to-face. I will ask all participants to review a summary of the major findings to check for accuracy.

The benefits to you of participating in this study are the potential to make a contribution to the research base and to benefit from future professional development informed by the findings of this study. The risks to you are very minimal and there are not any associated with your employability, insurability, or professional reputation.

Do you have any questions regarding my study, this request, or what would be required of you?

Would you be willing to participate in this study?

If yes:

This is the informed consent form advising you of your rights as a participant in this study. Please read it and sign it. You will be provided with a copy.

If no:

Thank you for meeting with me today. Could you recommend another educator in our district that might be interested in participating in this study?

Appendix D

Semi-Structured Interview Questions

All participants:

1. What kinds of data related to student learning do you have available to you?
2. Do you use data to inform instructional decision making?

If yes:

3. Explain how you use data to inform instruction. What types of data do you use, how frequently do you use data, and what exactly do you do with data?
4. Provide examples of instructional changes you've made for an individual student or group of students based on data. What prompted the analyses and subsequent changes?

If no:

5. Explain how you decide to make changes to instruction.

All participants:

6. How would you characterize your own data analysis skills? Do you feel you possess the skills necessary to analyze data and use it to inform instruction?
7. Describe any professional development you've participated in or formal coursework you've taken related to using data to support instructional decision making.
8. Talk about any expectations your district or building leadership has that you use data to inform instruction.
9. Describe any supports that are in place in your building to improve data analysis skills or to facilitate data analysis and use.
10. Is there anything you would like to add that you feel may help me better understand educator perspectives on using data to inform instructional decision making?

Appendix E

Example from Matrix Comparing Summarized Participant Responses by Question

Participant	What are Data?	Use Data?	How?
4	Common Assessments (All Tests Common), Homework	Yes. Grades homework every night in order to know whether to move forward. All tests are common assessments, which are discussed at PLC meetings or through emails. Data are used to know whether to re-teach or move on.	Does item analysis on tests. Looks for a 70-80% success rate on each question. Grades homework every night. Looks not only for a certain success rate, but also looks for why students are missing certain questions. Uses homework formatively even though there is a grade attached (grade is for motivation). Uses information to decide whether or not to re-teach.
5	Common Assessments, EOCs	Yes.	Common assessment data is tracked in Excel spreadsheets and analyzed collaboratively. Does item analysis on tests. Looks for 67% success rate on each question. Utilizes same process when EOC scores come out in the fall. Through a professional conversation they decide if questions were good or not and whether to re-teach or not. Knowing how they should teach it differently is a big question.

Appendix F

Example from Analysis Comparing Direct Participant Responses by Concept

Concept: “Data do not tell the whole story”

P1: It is easy to get lost in the numbers and the data and this is what it says and to lose what is being done in the classroom... umm... the impacts. Umm... actually even local and state governments and even federal government, they see the numbers, which doesn't tell the story, the whole story. It gives you a small window and, umm, of what's actually going on, what is the impact.

P2: Yeah, right, right, well, I know as an educator I get frustrated with, with numbers sometimes. Even though I am a (subject omitted) teacher and numbers are supposed to be my thing, sometimes a number doesn't reflect exactly what you did in your classroom. You know, I have students that have test anxiety – can't take a test no matter how hard you try to get them prepared – and so their number may show they know this when in actuality they know this.

P3: It's because we can't, I can't give you a spreadsheet that shows, uh, the improvement that happened, the learning that happened in my classroom. It's not a numbers kind of thing.

P4: So I think sometimes you have to be really careful that we're not simply analyzing a test question or a question, as opposed to can the students really do this?

P7: Well, I don't... not really. I mean, you have to use it, but you also have to use common sense and you also have to use your classroom observations... I mean, what data get's put on paper doesn't... it's kind of nonspecific.

Appendix G

COMMON ASSESSMENT DATA 2011-2012				COMMON ASSESSMENT DATA 2011-2012			
TEACHER:				TEACHER:			
DATE & NAME OF ASSESSMENT:				DATE & NAME OF ASSESSMENT:			
TOTAL STUDENTS:				TOTAL STUDENTS:			
PERCENT TO BE FLAGGED:		60%		PERCENT TO BE FLAGGED:		60%	
Quest. #	CLE	Incorrect Responses	Percent Incorrect	Quest. #	CLE	Incorrect Responses	Percent Incorrect
1			#DIV/0!	1			#DIV/0!
2			#DIV/0!	2			#DIV/0!
3			#DIV/0!	3			#DIV/0!
4			#DIV/0!	4			#DIV/0!
5			#DIV/0!	5			#DIV/0!
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GOAL				GOAL			

Appendix H

Common Assessment Evaluation Form

Test Name: _____ TOTAL NUMBER OF STUDENTS TESTED: ____

Course Name: _____ Average % (by teacher) on Test: ____

School Year: _____

1. Questions that require editing changes (list by item number):

2. Questions that need to be modified for clarity (list by item number):

3. High frequency missed items (list by item number):

4. Low frequency missed items (list by item number):

5. Concepts that require more instruction time:

Please attach a plan for interventions.

Plan should include specifics of the concept(s) and corresponding activities.

VITA

Stephanie Rena (La Lumondière) Broyles was born on April 26, 1970 in Phoenix, Arizona to Joseph and Virginia La Lumondière. She grew up in a military family and attended elementary schools in Arizona, Arkansas, California, and Missouri, and secondary schools in Germany and Turkey. After graduating from high school in Turkey, she earned a Bachelor of Science degree in Business Administration from Columbia College in Missouri and a Master's of Business Administration from the University of South Alabama.

Mrs. Broyles has a diverse professional background that includes finance, human resource, and retail management as well as education. Since transitioning from business management, she has taught business both at a career and technical school and at a community college. She is currently the Director of Student Services at a career and technical school.

Mrs. Broyles' interest in the issue of data driven decision making as explored in this study stems from her educational background in business, her experiences as a finance and human resource manager for a manufacturer, and her current responsibilities as the Director of Student Services for a career and technical school. Her current responsibilities, which include school accreditation and school improvement, require her to not only use data but to also consider the way her organization uses data.

Mrs. Broyles and her husband live in Rolla, Missouri, with her son, Michael Wacker, and their daughter, Emily Broyles. Additionally, she has a step-daughter, Jerralynn Broyles, who is a professionally trained chef and another son, Garrett Wacker, who is currently in college majoring in Petroleum Engineering.