RURAL SCHOOL PRINCIPALS’ PERCEIVED USE OF DATA IN DATA-DRIVEN DECISION-MAKING AND THE IMPACT ON STUDENT ACHIEVEMENT

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This study examined the impact of principals’ data-driven decision-making practices on student achievement using the theoretical frame of Dervin’s sense-making theory. This study is a quantitative cross-sectional research design where principals’ perceptions about data were quantitatively captured at a single point in time. The participants for this study were 253 rural school principals currently serving in schools across Texas, and included both males and females across all ethnic groups, including white, African American, Hispanic, Asian, Native American and other.

A developed survey instrument was administered to principals. The findings from the quantitative SEM analyses indicated that the Principal Uses Data to Improve Student Achievement latent variable (Factor 1) and the Principal and Staff Ability to Analyze Data to Improve Student Achievement latent variable (Factor 2) were significantly and positively associated with student achievement. Higher scores on these two latent variables were associated with better student achievement. There was no statistical association between the Principal Uses Data to Design Teacher Professional Development latent variable (Factor 3) and this target outcome. In total, the three latent variables accounted for 6% of the variance in student achievement (TAKS). When the campus level outcome was considered, no statistically significant associations between any of the latent variables and this outcome were evident. In total, the three latent variables accounted for less than 2% of the variance in campus level.
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CHAPTER 1
INTRODUCTION

The passage and implementation of the No Child Left Behind Act (NCLB, 2001) ushered in a new era of educational accountability and school improvement. Accountability demands are increasingly forcing school leaders to explore student-level data and to complete more sophisticated analyses. Schools are now held accountable to meet adequate yearly progress (AYP) that requires educators to closely monitor student performance on high-stake assessments. Further, NCLB significantly increased the pressure on states, districts and schools to collect analyze and report data. According to the Teaching and Learning Team of the National Education Association (2000) there is need for better decision making in our nation’s schools and this need has grown in tandem with the rise of standards-based reform and performance accountability systems. After years of exhorting and cajoling schools to improve, policy makers have decided to get tough. To that end, data-driven decision-making (DDDM) has become an emerging field of practice for school leadership (Streifer, 2002) and a central focus of education policy and practice (Mandinach, Honey, & Light, 2006). Nationwide standards-based control and outcome-based funding have brought data-driven decision-making to the top of every principal’s agenda (Leithwood, Aitken, & Jantzi, 2001).

One consequence of the standards and accountability movement is that district and school administrators are mandated to think very differently about educational decision-making, and must use data to collect information ranging from resource allocation to instructional practice (Mandinach, Honey & Light, 2006). O’Day (2002)
notes the complexity of the mechanisms by which accountability is used in school improvement. Researchers note that “data-based decision-making and use of data for continuous improvement are the operating concepts of the day. School leaders are expected to chart the effectiveness of their strategies and use complex and often conflicting state, district and local assessments to monitor and assess progress” (Mitchell, Lee and Herman, 2000, p.22). Herman & Gribbons (2001) noted that despite both the mandates and the rhetoric, schools are woefully underprepared to engage in such inquiry. The practice of applying large-scale data to classroom practice is virtually nonexistent. NCLB emphasizes the importance of using rigorous scientifically based research to guide education decision making. In this respect, rural schools are at a disadvantage because relatively little-high quality research has been conducted about rural education issues (Arnold, 2000). In addition, there are difficulties in conducting research on rural education due to the lack of consensus on operational definitions for “rural.” The lack of a clear definition obscures important views about the needs and issues of rural schools. Therefore, the purpose of the current study was to determine the perceptions of how rural school principals’ use of data improve student achievement.

For the purpose of this study, rural was defined as school districts that do not partially or wholly reside in a metropolitan statistical area in Texas and maintain a school student enrollment of less than 1500. This study included rural independent school districts. This study is significant as three-fourths of Texas public schools are rural, which greatly affects the state of education in Texas. Additionally, this study is important to better understand the skills, knowledge and needs of rural school principals
in data-driven decision-making in order to address principal preparation programs and continued training for the rural school principal.

Background of the Study

Educational researchers have long decried education as a field in which practitioners make decisions based on intuition, gut instinct or fads (Slaven, 2002, 2003). Supporters of data-driven decision-making practices argue that effective data use enables school systems to learn more about their schools, pinpoint successes and challenges, identify areas of improvement, and help evaluate the effectiveness of programs and practices (Mason, 2002). In fact, the theory of action underlying NCLB requires that educators have the will and know-how to analyze, interpret, and use data so that they can make informed decisions in all areas of education, ranging from professional development to student learning (Wohlstetter, Datnow & Park, 2008).

Previous research, though largely without comparison groups, suggests that data-driven decision-making has the potential to increase student performance (Peterson, 2007). When school-level educators become knowledgeable about data use, they can more effectively review their existing capacities, identify weaknesses, and better chart plans for improvement (Earl & Katz, 2006). A recent national study of the impact of NCLB found that districts indeed allocate resources to increase the use of student achievement data as a way to inform instruction in schools identified as needing improvement (Center on Education Policy, 2004). Student achievement data can be used for various purposes, including evaluating progress toward state and district standards, monitoring student performance and improvement, determining where
assessments converge and diverge, and judging the efficacy of local curriculum and instructional practices (Crommey, 2000). In short, data must be actively used to improve instruction in schools, and individual schools often lack the capacity and knowledge to implement what the research suggests (Spillane, Halverson & Diamond, 2004).

Statement of the Problem

Minimal educational research has been conducted on principal’s perceptions regarding data analysis in rural school settings. Arnold, Newman and Bailey (2003) suggested that there is almost no rural education research that is rigorous enough to guide important decision making with any degree of certainty. O’Conner (2001) and Byrd and Eddy (2010) examined principals use of data in an urban setting to discover principals perceptions about data use and its impact on student achievement. Although Byrd and Eddy contributed greatly to the body of research on this topic the findings cannot necessarily be generalized to rural school principals. Therefore the purpose of this study is to bridge the gap in literature by investigating the relationship between rural school principal perceptions about data use and the impact on student achievement.

Research Question

The following research question was derived from theory and forms the basis of this study: What is the relationship between principals’ perception of data use and the impact on student achievement among rural school principals in Texas?
Purpose of the Study

The purpose of the current study was to determine the perceptions of rural school principals’ use of data and impact student achievement.

Theoretical Framework

Decision-making is the process of identifying problems, generating potential alternative solutions, assessing the probabilities that a given alternative will result in a given outcome and developing a preference ordering among outcomes (O’Reilly, 1983; Simon 1960). Data-driven decision-making in this study is defined as the purposeful process of selecting, collecting and analyzing relevant data to define school problems, develop alternatives, compare outcomes of the alternatives, and choose the preferred alternative (O’Reilly, 1983; Streifer, 2002).

Data-driven decision-making has been practiced for decades in most businesses and industries. Data-driven decision-making originated from business management models and contributes to the foundational activity that underlies NCLB (2001). The business management approaches embracing data use for organizational decision-making includes total quality management (TQM) (Deming, 1986), knowledge management (KM) (Davenport & Prusak, 1998) and organizational learning (OL) (Argyris & Schon, 1996). These three approaches can influence school leadership and stimulate changes in the practices of school leaders’ decision-making.

The fundamental values of TQM (Deming, 1986) are to satisfy customer requirements, encourage employee innovation, improve quality, serve the customer, provide for free flow of information, instill pride and teamwork and create an atmosphere
of innovation and continuous improvement. TQM’s philosophy has been applied to educational leadership such as commitment to aims and purpose, a shared common vision, accountability and testing designed to improve education quality, and continuous improvement of schools.

Using data in decision-making is one of the important strategies in TQM. Deming (1986; 1991) provided several statistical models or tools related to the notion of data-driven decision-making for quality improvement. Examples are cause and effect analysis; customer needs analysis, customer data gathering, benchmarking, and establishing targets and goals. Sagor and Barnett (1994) suggested that TQM leadership in schools develops the cultural norms such as specifically focusing on students, holding high expectations, using data for decision-making, and valuing collaborative work.

Knowledge management is a process of people’s transformation of data and intellectual assets into enduring value (Duffy, 2000). Data become information when its creator adds meaning and values by contextualizing, categorizing, calculating, correcting and condensing the data. Information transforms into knowledge with humans’ comparison, consequences, connections and conversations. In the field of education, the knowledge ecological framework can enable schools to examine the plethora of data collected and transform these data into information and knowledge (Petrides & Guiney, 2002).

Organizational learning (OL) is a business model that has been adopted by schools in order to implement data-driven decision-making. Organizational learning is a process that enhances an organization’s ability for creativity (Argyris & Schon, 1996).
The key goal of organization learning is to clarify what is important by continually learning how to see the current reality more clearly and developing abilities to move beyond the set goals. Petrides and Nodine (2001) maintain that within a culture of Organizational learning, shared vision provides the focus for learning. A shared vision grows out of an opportunity to communicate, learn, experiment, be held accountable for results, and most of all shape the future. Organizational Learning is seen as an influential process for accomplishing goals of school improvement and a strategy that is particularly useful toward long-term changes (Marsh et al., 2006; Petrides & Nodine, 2005).

Dervin’s (1983; 1992) sense-making theory provides a useful theoretical framework for this study. Dervin’s model views information behavior in terms of a situation, a gap and an outcome, with information being used to bridge the gap and achieve the outcome. This framework, which overarches KM, TQM and OL, recognizes the importance of understanding how the information helps the user “make sense” of a situation, and highlights the role of information use. However, in subsequent discussions of Dervin’s work (e.g., Choo 1993; Wilson 1999), it is often the classification and articulation of information needs (i.e., the nature of the gap) that is emphasized. While need and use are clearly linked since information is needed to fulfill a use, there is a shift in perspective and emphasis depending on whether the focus is on needs or uses. Discussion of need tends to highlight the purpose for which the information is sought – the goal or objective – but does not usually extend to including exactly how the information is applied to achieving the goal. Shifting the focus to use can highlight the latter.
Sense-making theorists argue that the meaning of information is not self-evident; rather, individuals need to construct their understanding of the meaning and implications of the evidence at hand. Theorists do this by fitting new information into their pre-existing understandings or cognitive frameworks (Porac, Thomas, & Baden-Fuller, 1989; Weick, 1995). Kennedy (1982) calls these frameworks working knowledge, or, “the organized body of knowledge that [school] administrators and policymakers use spontaneously and routinely in the context of their work. This includes the entire array of beliefs, assumptions, interests, and experiences that influence the behavior of individuals at work” (pp. 1-2). Thus, interpretation of evidence is mediated by an individual’s beliefs and experiences.

The extensive use of data-driven decision-making in policy and practice at schools reveals a strong need for research on the current realities of data-driven decision-making practices and how those practices impact student achievement. Data-driven decision-making is a critical issue in both practice and research, yet surprisingly little empirical research has actually been conducted on these issues, especially from the principal’s perspective (Luo, 2008). In addition, university preparation programs are facing increased scrutiny as principals are facing new roles and heightened expectations, requiring new forms of training. In particular, the demand that principals have a positive impact on student achievement challenges traditional assumptions, practices, and structures in leadership preparation programs (Lashway, 2003). Principals themselves are among the first to agree that they need to be more effectively prepared for their jobs. In fact, 67% of principals reported that “typical leadership programs in graduate schools of education are out of touch with the realities of what it
takes to lead today’s school districts” (Farkas et al., 2003). Earl and Katz (2006) note, data use is suddenly not a choice for school leaders, but a must. However, there is little evidence that current coursework in traditional preparation programs directly connects practices to principals’ on-the-job performance or to student achievement (Browne-Ferrigno & Muth, 2004; Byrd & Eddy, 2010).

Principals of today’s schools must be able to lead instruction, shape an organization that demands and supports excellent instruction and dedicated learning by students and staff to connect the outside world and its resources to the school and its work (Hale & Moorman, 2003, pp. 7-8). Gerald Tirozzi (2001), the executive director of the national association of secondary school principals, adds that principals in the 21st century will be recognized as 1) leaders of curricular change, 2) innovative and diversified instructional strategies, 3) data-driven decision-making and 4) the implementation of accountability models for students and staff.

The general consensus in most quarters is that principal preparation programs are too theoretical and totally unrelated to the daily demands on contemporary principals. The course work is poorly sequenced and organized, making it impossible to scaffold learning. Because clinical experiences are inadequate or non-existent, students do not have mentored opportunities to develop practical understanding or real-world job competence (Department of Education, 2005, p 4-5). The recruitment and retention of administrators who is adequately prepared to create and sustain high-performing learning systems are difficult to maintain. Rural principal gaps in data-driven decision-making skills and knowledge begins in university administrator preparation programs that are geared primarily for training urban and suburban school leaders. Mid-continent
Research for Education and Learning (McREL) review of rural education literature points to a shortage of information about regarding data use among professional development of rural administrators (Arnold et al., 2003).

A recent survey of principals supports this notion. Butler (2008) found that two-thirds of 500 principals surveyed believed that typical graduate leadership programs “are out of touch” with today’s realities. Butler’s finding is alarming as we are in an era of high-stakes exams where principals are required to use data analysis in data-driven decision-making, yet many have to learn these skills on the job. To exacerbate the dilemma, data analysis skills are not taught to future principals in many pre-service preparation programs even at this late date (Byrd and Eddy, 2010).

In addressing the areas of principals’ data-driven decision-making practice, the Educational Leadership Constituent Council (ELCC, 2002) standards were used as the framework for this study, through which principals’ data-driven decision-making was examined in the context of improving student achievement. The National Policy Board for Educational Administration published the revised Standards for Advanced Programs in Educational Leadership in 2002, which were developed and revised by the ELCC (2002) and adopted by the National Council for the Accreditation of Teacher Education (NCATE, 2002). ELCC standards serve as school leadership preparation program standards and can be used as a cornerstone for the professional development of existing school administrators (Murphy & Shipman, 1998; Murphy, Yff, & Shipman, 2000). Compared to the old standards, the revised standards have more emphasis placed on school administrators’ ability and knowledge in using data where data-driven decision-making is integral to school administrators’ skills in all the area standards (Lou,
2008). While state and national standards recommend principals practice data-driven decision-making, it is not clear how rural school principals use data to improve student achievement. Therefore, the purpose of this study was to determine how the perceptions of rural school principals’ use of data in the data-driven decision-making process and the impact on student achievement.

Definition of Terms

The definitions of terms are provided for a clearer understanding of the issues underlying the current study.

- Data-driven decision-making (DDDM): the purposeful process of selecting, gathering, and analyzing relevant data to address school improvement or student achievement issues and acting on those findings (Bernhardt, 2004a; Streifer, 2002).

- Data: a variety of information collecting to determine if learning has taken place (Picciano, 2006).

- Student achievement: For the purpose of this study, the Texas Assessment of Knowledge and Skills (TAKS) test is used as an indicator of student achievement.

- Rural Schools: The Texas Education Code does not articulately define rural schools, however for the purpose of this study the researcher defined a rural school district was operationally defined as a school district that does not partially or wholly reside in a metropolitan statistical area in Texas and school enrollment is less than 1500.
Summary

Data-driven decision-making is a relatively new and complex process impacting American education today. In response to the development and enactment of federal and state mandated accountability systems, school and district officials face unprecedented demands to use evidence in their decision making (Bernhardt, 1998, 2004b; Darling-Hammond, 2004; Doyle, 2003; Honic & Coburn, 2005; Massell, 2000). Under this new environment of state and federal accountability requirements, the use of data-driven decision-making has begun to move beyond accountability purposes and evolve as a process. Systematically, it now aims to measure student progress, set school improvement goals, and increase the quality of curriculum and instruction to focus on increasing student achievement (Ainsworth & Viegut, 2006; Bernhardt, 2004b; Datnow, Park & Wohlstetter, 2007; Mandinach, Honey, Light, Heinze & Rivas, 2006; Massell, 2000; Supovitz & Klein, 2003).

Utilizing business models of effective data use, many researchers work to identify and translate the efficiency of collecting, analyzing and acting on data within the context of educational environments (Bernhardt, 1998, 2004b; Picciano, 2006; Streifer, 2002). Yet even with reports of success, systematic and strategic use of data is at the beginning stages in many districts. Challenges exist such as defining, establishing, and sustaining the fundamental structures and processes to utilize data unique to each school. Additional challenges exist as many rural school principals and administrators lack the education, skills and leadership to drive data-driven decision-making effectively at the campus and district level which is critical to improving student and school needs.
CHAPTER 2

REVIEW OF LITERATURE

The concept of data-driven decision-making is not a new concept in the educational community (Bernhardt, 1998, 2004b; Love, 2002; Wayman & Stringfield, 2006). Gordon and Bridglall (2003) conclude that historically the use of data to inform decisions about educational practice has been present as early as the 1950s. They report results from tests and assessments were used to make decisions about instruction as early as 1949. In 1967, Flanagan and Glaser (as cited in Gordon & Bridglall, 2003) discuss their use of data to differentiate instruction to address the individual educational needs of students.

More recently, the concept of data-driven decision-making in education can be traced to the debates about measurement-driven instruction in the late 1970s (Popham, 2003); state requirements to use outcome data in school improvement planning and site-based decision-making process dating back to 1980s (Massell, 2000); and school system efforts to engage in strategic planning in the 1990s (Schmoker, 1999). With the reauthorization of the Elementary and Secondary Education Act (ESEA), the No Child Left Behind Act (NCLB) legislation requires schools to use student data for federal accountability purposed directly linked to reporting levels of student achievement within each district (NCLB, 2002).

Data-driven decision-making is a relatively complex process impacting American education today. In response to the development and enactment of federal and state-mandated accountability systems, school and district officials
face unprecedented demands to use evidence in their decision-making (Bernhardt, 1998, 2004b; Darling-Hammond, 2004; Doyle, 2003; Honig & Coburn, 2005; Massell, 2000). The No Child Left Behind Act (NCLB) and state-mandated accountability policies have accelerated efforts already underway by schools to employ data-driven decision-making when implementing school-based decisions (Bernhardt, 2003; Lashaway, 2002; Streifer, 2002). Under this new environment of state and federal accountability requirements, the use of data-driven decision-making has begun to move beyond the purposes and evolve as a process. It now aims to systematically measure student progress, set school improvement goals and to increase the quality of curriculum and instruction to focus on increasing student achievement (Ainsworth & Viegut, 2006; Bernhardt, 2004a, 2004b; Datnow et al., 2007; Mandinach et al., 2006; Massell, 2000; Supovitz & Klein, 2003).

Several states such as California, Colorado, Iowa, Maryland, Wisconsin and Wyoming, require the use of data-driven decision-making as a part of state policy (Armstrong & Anthes, 2001). Additionally, many educational professional associations and agencies such as the American Association of School Administrators (AASA), the Educational Commission of the States (ECS), the National School Board Association (NSBA), the National Staff Development Council (NSDC), and the North Central Regional Educational Laboratory (NCREL) have made data-driven decision-making a priority.

The Education Commission of the States (ECS, 2000) investigated the state conditions and policies that support the use of data for decision-making and school improvement. Case studies were conducted in thirteen schools within six school districts
in five states (California, Colorado, Iowa, Maryland and Texas). Researchers found that moderate to high-stakes accountability systems mandated districts to formulate comprehensive data-driven school improvement plans, measure progress toward those plans and report back to the state. However, there is no mention that principals were trained or able to make effective data-driven decisions.

In an effort to address the needs of an ever increasing diverse student population, school leaders are compelled “to have enough information at hand to know where problems exist and how to best solve them” (E-lead, 2009, p. 4). Data-driven decision-making in the context of schools involves a process of collecting, disaggregating and analyzing student data. This collection of student data, according to Cradler (2009), serves “to inform decisions related to planning and implementing instructional strategies at the district, school, classroom, and individual student levels” (p. 1). This process is “more than an accountability tool; it is a diagnostic tool (Doyle, 2003, p. 1) that requires school leaders to be data and data analysis literate. This is critical to Dervin’s sense making theory. There must be enough data and information accessible in order to make decisions. However there is a lack of decision-making knowledge and experience in the principalship to bridge this gap of effective data-driven decision-making (Dervin, 1992).

Recognizing the difficulty of this process for rural educators, McREL undertook an effort to discern the extent of the rural education knowledge base through discussion with experts in the field (Arnold, Newman, & Bailey, 2003). The review suggests that there is almost no education research that is rigorous enough to guide important decision making with the necessary level of certainty.
Data-Driven Decision-Making Leadership

Data analysis skills related to principals’ educational background and training seem to be a critical element influencing principals’ information behaviors related to data-driven decision-making (Choppin, 2002; Mason, 2002). Processing of information is a vital aspect of human behavior and is a critical input to the decision making process (Taylor, 1986). Dervin (1992) posited that making sense of the data (sense-making) is an active two-way process of fitting data into a frame (mental model) and fitting a frame around the data. Neither data nor frame comes first; data evoke frames and frames select and connect data. If principals are to “incorporate the information into their cognitive maps or repertoire of strategies they must attend to it and have sufficient knowledge and ability to interpret it” (O’Day, 2002, p. 299). While school leaders may fear or even loathe quantitative or qualitative analysis, data-driven decision-making based on rigorous statistical measures requires an understanding of the statistical principles that underlie the decisions being made (Earl & Katz, 2006). Thus, it is the priority of data-driven decision-making for principals to have a basic understanding of applied statistics, data analysis skills, and other necessary computer skills (Thornton & Perreault, 2002). The importance of principals’ having these skills is further underscored by Hoyle, English, and Steffy (1994) who submitted that successful school leaders are skillful at interpreting and conducting research, evaluating programs, and planning for the future. However these skills are not being taught in pre-service classes in such a manner that all school leaders have these necessary skills (Byrd and Eddy, 2010).

Data-driven decision-making is an interactive, multifaceted, and contextual practice within the school organization. Decision making, the uses of data, and the context within
which decision makers make choices are interrelated. The situational context of information acquisition and use through which decisions are made are critical in understanding organizational decision-making (Dervin, 1992).

Creating a Culture of Inquiry

In order for data-driven decision-making to be successful, rural school leadership must establish a culture of inquiry which promotes a continuous cycle of improvement based on student data. Earl and Katz (2005) affirm that educators need – to develop an inquiry habit of mind, become data literate, and create a culture of inquiry (p. 18). Togneri and Anderson (2003) further specify that three elements are documented in the literature as critical to creating a culture of data-informed decision-making: fostering a spirit of inquiry, valuing openness and transparency of data, and ensuring trust.

Young (2006) states that to construct a foundation for systematic data within a culture of inquiry, successful school systems create explicit norms and expectations regarding data use at the district and school levels. To ensure effectiveness, specific measurable goals must be aligned to standards at the district, school and classroom levels (Datnow et al., 2007). Once these goals are established, a system-wide curriculum must be developed which adheres to these standards. Taylor expresses the importance of processing information. Goals are critical for the human processing and desired results are gained through effective data-driven decision-making.

Datnow et al. (2007) maintains that an integral component within the foundation of a culture of inquiry is the leadership used to maintain and sustain data-driven decision-making. Non-threatening leaders foster data use through modeling. School
leaders that build a culture which values the regular, consistent use of data are also essential for supporting performance driven systems (Ackley, 2002; Ezarik, 2002, 2001; Kerr et al., 2006; Mandinach et al., 2006; Petersen, 2007; Supovitz & Klein, 2003). Several studies further stress the importance of creating protocols to establish norms and rules for discussion about student data (Datnow et al., 2007; Petersen, 2007; Young, 2006).

Strong leadership is a central factor that builds organizational capacity to use data. In districts classified as exemplary data users, Armstrong and Anthes (2001) and Datnow et al. (2007) report that the superintendent, central office, and school board members set the expectations for data use by committing to data use in the district vision, district data collection plan and district resources.

Although superintendents set the tone for a district’s philosophy, Mandinach et al. (2006) explain that strong leadership on the school level appears to be more important in facilitating or impeding the use of data. Wayman and Stringfield (2006) found that educators in their study explicitly singled out their principals as a major factor in the success of data initiatives. Principals tend to have more direct contact with faculty and therefore, more substantial influence on faculty in communicating the importance and stimulation of teacher data use. Bernhardt (2004a), Love (2002) and Supovitz and Klein (2003) further emphasize that principal leadership is responsible for providing the appropriate professional conditions to maintain a respectful, trusting and collaborative culture. Principals create the right conditions for data-driven decision-making when they provide time for assessment, train teachers to use assessment data when planning instruction and state clear expectations for student performance.
Building Data-Driven Leadership

Principals who have a strong conceptual background in data-driven decision-making are better able to guide their staff in the use of data (Lashway, 2002). Kerr et al. (2006) report that school leaders who effectively use data for inquiry and decision-making are knowledgeable, committed, and build strong vision for data use in their schools. O’Day (2002) asserts that schools which study data seriously generally have a strong administrator who assists staff with the analysis and interpretation of data. In a study of five America’s Choice schools which surveyed 68 school principals, Supovitz and Klein (2003) maintain that strong school leadership is critical in the successful implementation of data use in schools. Further findings suggest that the principal’s consistent emphasis on data turns data into action in classrooms. Similarly, Choppin (2002) reports findings in a study of six Milwaukee Public Schools that identifies strong leadership in schools successfully implements data use as they model effective data use to inform decisions.

Sutherland (2004) found that principals who were not enthusiastic about using data themselves were found to impact the enthusiasm among teachers and even prevent good analyses from having positive impact on practice. Further Murnane, Sharkey, and Boudett (2005) found that when a data team embraced data analysis and promoted data-driven decision instruction, a lack of support from school leadership meant that the team’s work was not likely to make a difference with school practices. These studies emphasize the importance of a strong data-driven decision-making program to be in place so that school leaders may effectively lead and use data successfully on the campus.
To develop schools organizationally, effective leadership requires local educators to use data effectively to influence decisions based on particular sets of needs and circumstances (Leithwood, Begley, & Cousins, 1994). Without such local discretion, school improvement would likely be frustrated, and school performance would suffer (Hallinger & Heck, 1998; Leithwood, 1994; Marks & Printy, 2003; Mohrman, Wohlstetter, & Associates, 1994). Because data abound, all principals, specifically rural school principals must become data savvy in using student-level data in making informed decisions. Maxwell (2004) submits that collecting data and analyzing the data is the linchpin of both district and campus improvement initiatives, and part of the reason that exemplars of “best practices” are using data to manage a wide range of school functions, especially those directly related to student achievement. This adds to the difficulty facing rural schools as there has been a steady migration of the most successful graduates away from rural areas (Jischke, 2000).

The Western States Benchmarking Consortium (Schachter, 2006) found that high performing districts implement data-driven decision-making in collaborative atmospheres. In a group of seven high performing school districts, one innovation that they emphasized is their collective work on interim assessments and real time feedback to make adjustments in instruction. The Western States Benchmark Consortium developed 16 benchmarks covering four strategic areas for school improvement. One of these four strategic areas is data-driven decision-making. Four benchmarks of data-driven decision-making were defined as: 1) using a variety of data effectively; 2) using information to improve instructional practice; 3) using data to affect student
performance; and, 4) relating investments, outcomes and improvement strategies (Schachter, 2006).

A study of the New York City’s public school system, Light, Honey, Heinze, Brunner, Wexter, and Mandinach (2005) report on the Center for Children and Technology. The report focuses on the examination of educators’ use of data to make decisions about teaching, learning and educational practice from data made available through the Grow Reports (reports which aligned standards, testing results and instructional strategies for educators). Their findings indicate teachers rely on multiple sources of data to make instructional decisions and report they triangulate assessment data in a variety of ways to provide a fuller picture of student understanding. Teachers were found to use Grow Report data to target instruction; differentiate instruction to meet the needs of all learners; support conversations with parents, administrators, and teachers about student learning; shape teachers’ professional development; and encourage student self-learning.

The results of these studies indicate that school use of data-driven decision-making is an intricate and multilayered process. While positive benefits exist, the complex nature of the implementation of sustainable data-driven decision-making at the school level still remains daunting but is a critical task that must be shared and mastered by educators today.

Shared Vision

The quest for quality education during the past five years has resulted in a number of initiatives, which have made significant demands on principals in public
sector schools, amongst which is the practice of accountability. Hence, school leadership in the context of accountability requires a paradigm shift, moving from the traditional concentration on maintenance and hierarchy, to change, collegiality, teamwork, and instructional improvement at the classroom level. More succinctly, principals must understand how to establish a shared vision and design professional development opportunities that involves everyone to ensure that decisions are aligned with the shared vision and all decisions are indeed data-driven.

Across mainstream educational leadership literature, the term vision has had two primary definitions: (a) a leader’s image of the future and (b) change goals. Translating vision into practice has become increasingly difficult (Ylimaki, 2006). An important aspect of vision is the notion of "shared vision." Studies have shown that it is the presence of personal vision on the part of a leader, shared with members of the organization that may differentiate true leaders from mere managers (Manasse, 1986). Therefore, a leader's vision needs to be shared by those who will be involved in the realization of the vision.

Across studies, researchers report a relationship between collaboration and data use (Datnow et al., 2007; Supovitz & Klein, 2003; Wayman et al., 2005; Young, 2006). Wayman et al. (2005) states that this relationship between data use and collaboration is reciprocal suggesting that data initiatives are more likely to be successful if teachers are allowed to learn and work collaboratively in a constructive manner. Using data within a collaborative framework affords educators more opportunities to interact, share ideas, and support colleagues’ understanding of data use (Wayman et al., 2005; Wayman & Stringfield, 2006).
Regarding teachers’ use of data for instructional planning and feedback, Young (2006) found that school leadership interacts with the normative work arrangements within teachers’ grade-level teams. Young demonstrated how shared leadership focused on data use affected teachers’ motivation for using data and “correspondingly loosens or tightens the connections between data-driven rhetoric and teachers’ data practices” (p. 532). Young defined leadership as agenda setting, a term she chooses to mean articulating general reasons for using data and specific expectations for particular data, modeling data use, scaffolding teachers’ learning about data use, and structuring collaborative time for data use. Young also suggested that both depth of activity and breadth of collaboration are important developmental considerations that school leaders can influence. Particularly in the important early stages of any new implementation, leaders of schools can “structure team interactions with instructionally relevant activities” (Young, 2006, p. 543) so that teachers practice new strategies even as they forge new collaborative norms to attain the shared vision.

Professional Development

Researchers maintain that building organizational capacity for data use is a complex and worthy process which holds the potential to help schools better meet the needs of students today (Bernhardt, 2003; Boudett, Murnane, City & Moody, 2005; Datnow et al., 2007; Holcomb, 2004; Love, 2002; Supovitz & Klein, 2003; Wayman & Stringfield, 2006; Young, 2006). Through establishment of a culture of inquiry, strong leadership, professional development and a data collection process, schools will begin to develop an infrastructure in which data-driven decision-making is possible. By
supplying the provision of quality of time for data use and collaboration, districts will allow schools to build solid foundations for effective system-wide data use (Datnow et al., 2007). Professional development is essential in the rural school setting as there is not the opportunity to collaborate with multiple peers and schools as may be afforded urban or suburban schools.

The quality of the data use in schools is dependent upon the professional capacity of the individuals engaging the data (Datnow et al., 2007). Even with supports and resources, effective and efficient data use is dependent on educator capacity to analyze and act on data accurately (Ainsworth & Viegut, 2006; Datnow et al., 2007; Mandinach et al., 2006). The literature reveals an emergent discussion by researchers of the new skill sets or literacies required in order to efficiently and effectively utilize data for decision-making in schools (Ainsworth & Viegut, 2006; Datnow et al., 2007; Love, 2002; Maninach et al., 2006; NEA, 2003; Streifer, 2004; Supovitz & Klein, 2003; Young, 2006). Assessment literacy, technology literacy and pedagogical literacy are cited in the literature as three essential professional competencies teachers must develop in order to effectively employ the tenets of data-driven decision-making. With the emphasis on utilizing data to inform instruction, districts acknowledge the urgency for educators to acquire these skills and are being challenged to provide training and professional development for both new and experienced teachers (Ainsworth & Viegut, 2006; Bernhardt, 2005; Datnow et al., 2007; Depka, 2006; Love, 2002; Mandinach et al., 2006; NEA, 2003; Popham, 2003; Supovitz & Klein, 2003; Wayman, 2005b; Young, 2006).
Student achievement data point out professional development needs for individual schools and teachers. However, if data are to provide meaningful guidance in the process of continuous improvement, teachers and administrators require professional development regarding data analysis, designing assessment instruments, implementing various forms of assessment, and understanding which assessment to use to provide the desired information. It takes time for teachers and principals to learn new skills and behaviors. One-shot workshops will not accomplish the goal, no matter how good the workshops are. People need to focus their efforts over time until new behaviors become internalized. Individual teacher growth can improve student learning, but whole school professional development holds promise for raising the achievement levels of all students (Walker, 2007). Because the pre-service preparation of principals in assessment and data analysis has been weak or nonexistent, educators must have generous opportunities to acquire knowledge and skills related to formative classroom assessment, data collection, data analysis, and data-driven planning and evaluation (NSDC, 2009). According to Dervin’s sense-making theory, data-driven decision-making requires information and the proper interpretation of the results to bridge the gap and achieve the intended outcome. While on-the-job internships offer pre-service administrators a glimpse of the requirements for the position, they do not offer ample time to learn everything about the job prior to practicing, including how to use data to design professional development opportunities around the use of data (Peterson, 2002). In a comparison of three urban school systems, Firestone, Mangin, Martinez, and Polovsky (2005) suggested that district offices can influence teaching through professional development. District and campus leaders can structure their programs to
provide coherent and content-focused professional development. However, given the many demands placed on the principal, it is not clear how principals use data to determine professional development opportunities for teachers to improve student achievement.

Effects of High Stakes Environment

As states have grown more influential by developing standards for curriculum, student performance and assessment, school districts and schools have had to yield considerable autonomy, becoming accountable to the state for a range of student outcomes (Conley, 2003; Fuhrman & Elmore, 2004). Failure to meet state and national academic assessments can subject districts to takeover and schools to reconstitution. Intensifying the pressures of this high-stakes environment, local stakeholders, such as parents and businesses, have also demanded improved student performance. In response, community and school boards often establish their own sets of goals for schools (Firestone & Shipps, 2003).

Principals’ Use of Data

Creighton (2001) maintains that data-driven decision-making is the hallmark of good instructional leadership. Principals and teachers can learn to maneuver through the statistical data to help create goals and strategies for change and improvement. Creighton also states that meaningful information can be gained only from a proper analysis of data and good decisions based in a thoughtful process of inquiry and
analysis. Dervin’s sense making theory pairs with this showing the importance of gathering all possible data to build sustainable data-driven decisions.

Matthews (2002) addressed the issues of the principal’s responses to data of high-stakes tests and their assessment of data-based decisions by interviewing six Virginian middle school principals. Findings indicated that principals responded to the call to use data as a guide for decision-making by devising systematic processes and implementing changes based on data. They used data as a basis for decision-making and did not rely on their own expertise alone in making decisions. LaFee (2002) insisted that data-driven decision-making is rapidly spread, but is progressing slowly in schools. There is increased interest and efforts by schools in data-driven decision-making. The benefits and values of data-driven decision-making are commonly recognized by school leaders. Data-driven decision-making is the buzz phrase of choice for educators including principals for the new decade (Salpeter, 2004).

At the building level, utilizing data to inform organizational and instructional decisions is complex (Wayman, 2005a). As a result, the potential of school-level data use is under-utilized (Supovitz & Klein, 2003). Furthermore, much of school data goes unexamined.

In an examination of four exemplary school systems, (Datnow et al., 2007) found five common characteristics in establishing effective data-driven decision-making in schools: (a) establishing a culture of data use and continuous improvement; (b) building a foundation for data-driven decision-making; (c) investing in an information management system; (d) building school capacity for data-driven decision-making; and, (e) analyzing and acting on data to improve performance. Although the schools they
examined made great strides in the area of data-driven decision-making, in many cases the researchers found that sustaining a culture of continuous improvement through the use of data-driven decision-making requires a continual investment in data management resources which may be difficult for some schools to maintain. The researchers found that the investment in both human and technical resources is integral to the effective sustainable use of data-driven decision-making in schools.

Supovitz and Klein (2003) examined five schools. The researchers noted teachers collected data from three primary sources, state and district level, school level and classroom level. Their results indicated that state testing data provide some useful, but very limited information and lacked adequate detail to provide guidance in decision-making. However, on the classroom level, teachers used multiple sources of data to differentiate instruction effectively. In addition to the utility of various data, these researchers concluded that systematically using data in schools takes commitment on many levels. They also reported seven major ways in which teachers and administrators in their sample used data for instructional or organizational improvements: (a) to inform instruction, (b) to identify low-performing students and inform assistance plans, (c) to plan professional development, (d) to set targets and goals, (e) to celebrate both faculty and student accomplishments, (f) to offer supporting evidence in conversations with parents (Supovitz & Klein, 2003). Time, leadership, training, technology and discipline are found necessary in order to use data effectively.

Peterson (2007) examined data-driven decision-making practices at three different schools: a traditional public school, a district-turned charter school, and a relatively new charter school. Collectively, the experiences of these schools illustrated
the benefits from using both internal assessments and standardized test results in combination with strong professional development. Among the positive benefits associated with the effective use of this type of data-driven decision-making implementation, Petersen reported a change in the teacher perception of data. Teachers no longer saw data as additional, but part of instruction and as part of instruction and as a professional responsibility encouraging them to set high expectations for student learning. In addition the collaborative culture created within the schools fostered an inclusive climate in the manner in which teachers were recruited, prepared and supported.

According to Bernhardt (2004b), the factor that separates successful schools in their reform efforts is the use of one, often neglected element – data. Researchers suggest that a key element in determining high-performance in schools is their systematic use of data-driven decision-making (Armstrong & Anthes, 2001; Bernhardt, 2004b; Datnow et al., 2007; Supovitz & Klein, 2003; Togneri & Anderson, 2003).

An emerging body of descriptive research reveals that exemplary districts and schools all approach and operationalize data-driven decision-making differently (Datnow et al., 2007). However, at the same time, this research reveals that exemplary districts also utilize many common processes and resources that support the effective use of data (Bernhardt, 2003, 2004b; Breiter & Light, 2006; Datnow et al., 2007; Herman & Gibbons, 2001; Ingram, Louis & Schroeder, 2004; Kerr et al., 2006; Mandinach et al., 2006; Massell, 2000; Supovitz & Klein, 2003; Togneri and Anderson, 2003; Wayman & Stringfield, 2006; Young, 2006).
Anderson (2003) summarizes findings across several recent studies of the use of data: Successful districts in the current era of standards, standardized testing and demands for evidence of the quality of performance, invest considerable human, financial and technical resources in developing their capacity to assess the performance of students, teachers and schools, and to utilize these assessments to inform decision-making about the needs and strategies for improvement, and progress toward goals at the classroom, school and district levels (p. 9).

Common Norms of Data-Driven Decision-Making

Compared to the limited number of studies indicating the good practices of data-driven decision-making, more research informs us that data-driven decision practices are not satisfactory and even missing from many schools (Lou & Childress, 2009). Data are not frequently used systematically or are not used well at the school level (Bernhardt, 1998). Many school leaders struggle to incorporate data-driven decision-making into their schools (McLeod & Creighton, 2001). Although data-driven decision-making has many vocal proponents, it is equally clear that the message has not yet gotten to the front lines of principals (Doyle, 2003).

The majority of principals use intuition to guide them through their most important decisions (Davis & Davis, 2003). Intuition or gut feelings play a primary role in principals’ decision-making. Many school leaders make decisions “by using intuition and shooting from the hip, rather than considering data collection and data analysis” (Creighton, 2001, p.52). Traditionally, data have not been the important factors in the way schools make decisions. The intuition of principals’ advocacy by parents and
political interests often has guided decision-making (American Association of School Administrators, 2002). Therefore they minimize the effortful, analytic processing of information to solve problems (Hoy & Hiskel, 1996).

Jamentz (2001) concluded that principals seldom uncover the silver bullets in their data reports. The schools of his experiences were characterized with ongoing, messy, and ambiguous processes of framing questions, examining and weighing evidence, taking actions and discerning new questions. Similar results are shown in Reeves’ (2002) analysis of school examples. He concluded that an astonishing number of principals make critical decisions about curriculum, instruction, assessment and placement on the basis of information that is inadequate, misunderstood, misrepresented or simply absent. A limited number of principals use data to influence their decisions although school systems have devoted enormous resources to developing data. School principals commonly underutilize available data (Noyce, Perda & Traver, 2000).

Although NCLB requirements involve the use of data to make decisions to assist teachers to impact behavioral change to ensure students graduate college and workforce ready and reach intended goals, studies have shown that principals lack the knowledge to properly analyze data. Reeves and Burt (2006) found that principals were concerned about the use of data analysis due to lack of training among both principals and teachers. In addition to the frustrations of principals that are not sure exactly what data to use or how to use it, the frustrations of teachers’ abilities to use the data abound as well. Many principals that are inadequate at collecting, analyzing and using data themselves have even more difficulty in leading their teachers through the data-driven
decision-making processes necessary to affect behavioral change in the schools (Reeves & Burt, 2006).

**Movement of Data-Driven Decision-Making**

Data use essentially sets a course of action and keeps a staff on that course to school improvement and student success. Further, the wealth of data from assessments of student achievement, as well as information available from other evaluations of student and school performance, can create a divide or gap between what is currently being done and what needs to be practiced to improve student performance. While the elements of Dervin’s theory are common place in schools (a situation, a gap and an outcome, with information being used to bridge the gap and achieve the outcome), the interpretation and use of data among principals to improve student achievement is uncertain. This is further exacerbated by the fact that most university principal preparation programs do not place a strong emphasis on ensuring that principals have data analysis skills. The expanding nature of information accessibility requires school and district leaders and teachers to analyze and interpret multiple forms of data that theoretically result in substantive changes.

Creighton (2001) states that educators’ fears of statistics likely relate to a variety of factors, but principal and teacher preparation programs must accept the fact that the presentation of statistics in education probably lacks four important components. First, it does not emphasize the relevance of statistics to the day-to-day lives of principals and teachers. Second, it does not fully integrate current technology into the teaching and learning of statistics. Third, few (if any) statistics courses are designed for students
enrolled in education leadership or teacher education programs. Fourth, many statistics courses taught in colleges of education focus on inferential statistics as a tool for conducting research projects and dissertations. Far less time is spent on statistical strategies that might help principals improve their skills in problem analysis, program and student evaluation, data based decision-making and report preparation.

According to McNamara and Thompson (1996), applied educational statistics instruction must move away from the traditional conception of statistics as mathematical theory and approximate administrator and teacher preparation programs. Bracey (1997) states that many university professors who create and use statistics are more comfortable using statistics than they are teaching other human beings what they mean. In all too many instances, statistics are taught in a theoretically rarefied atmosphere replete with hard to understand formulas and too few examples to the daily life of education practitioners.

While there has been much rhetoric surrounding the quality of principal preparation programs (Browne-Ferrigno et al., 2002; Levine, 2005; Maxwell, 2008; Tirozzi, 2001), and given the increasing demands placed on school leaders by NCLB to improve student achievement, the question of how principals use data to improve student achievement once they are in the field has taken on heightened significance (Browne-Ferrigno & Muth, 2004; Butler, 2008).

Summary

Data-driven decision-making is a relatively complex process impacting American education today. Data-driven decision-making in the context of schools involves a
process of collecting, disaggregating and analyzing student data. Neither data nor frame comes first; data evoke frames and frames select and connect data. Data-driven decision-making is an interactive, multifaceted, and contextual practice within the school organization.

Kerr et al. (2006) report that school leaders who effectively use data for inquiry and decision-making are knowledgeable, committed, and build strong vision for data use in their schools. Because data abound, principals must become data savvy in using student-level data in making informed decisions.

Young demonstrated how shared leadership focused on data use affected teachers’ motivation for using data and “correspondingly loosens or tightens the connections between data-driven rhetoric and teachers’ data practices” (p. 532). Student achievement data point out professional development needs for individual schools and teachers.

Creighton (2001) maintains that data-driven decision-making is the hallmark of good instructional leadership. LaFee (2002) insisted that data-driven decision-making is rapidly spread, but is progressing slowly in schools. There is increased interest and efforts by schools in data-driven decision-making. The benefits and values of data-driven decision-making are commonly recognized by school leaders. However, much of school data goes unexamined.

Many school leaders struggle to incorporate data-driven decision-making into their schools (McLeod & Creighton, 2001). Many school leaders make decisions “by using intuition and shooting from the hip, rather than considering data collection and data analysis” (Creighton, 2001, p.52). Traditionally, data have not been the important
factors in the way schools make decisions. A limited number of principals use data to influence their decisions although school systems have devoted enormous resources to developing data. School principals commonly underutilize available data (Noyce, Perda & Traver, 2000).

Approximately one out of every six students attends school in a rural community (Arnold, 2004). Thus, rural students represent a significant population that is affected by decisions made by educators. Like all education leaders, rural educators need sound guidance and training in data-driven decision-making in order to improve education outcomes for all of their students. However, relatively little high-quality research has been conducted about rural education issues over the past two decades. Therefore, the purpose of the current study is to determine how the perceptions of rural school principals use of data impact student achievement.
CHAPTER 3.

METHODOLOGY

Introduction

This chapter describes the research methodology that was used to accomplish the purpose of the study, which was to determine the perceptions of rural school principals’ use of data and impact on student achievement. Specifically, this chapter describes the target population, data collection procedures, instrumentation, model development, and data analyses.

Research Design

The current study utilized a quantitative cross-sectional research design where principals’ perceptions regarding the use of data were examined at a single point in time. A quantitative approach was utilized to collect data from a purposeful sample of rural school principals and generalized to principals as a whole across the State of Texas. Findings from this study can inform educational leadership programs, add to the literature related to training and preparing rural school principals.

Target Population and Sampling Strategy

The targeted population for this study was all rural school principals currently serving in rural schools across Texas. This population included principals serving students in kindergarten through 12th grade in rural school districts which maintained a total student enrollment of less than 1500.

A total of 1442 school principals were initially contacted to participate in the
study. Of the 1442 potential participants, 253 principals from 204 rural school districts responded, which yielded a 17.5% response rate. Among the 253 participants, 106 (41.87%) were female while 146 (57.7%) were male. Regarding race, 11 (4.3%) were African American, 225 (88.9%) were Anglo, 1 (0.04%) was Asian, 13 (5.1%) were Latino, 1 (0.4%) were Native American, while 2 participants (0.7%) were classified as other. Individuals who claimed more than one race were defined as other.

The majority of participants \( n = 90, 35.6\% \) were employed in elementary, 78 (30.8%) were employed as high school principals, 44 (17.4%) were principals in middle schools, 22 (8.7%) were principals of K-12 schools, while 19 (7.5%) were principals of schools classified as other.

As displayed in Table 1, the average tenure among participants in the current position ranged from 8.02 years \( (SD = 7.45) \) among middle school principals to 10.80 years \( (SD = 7.45) \) among elementary principals. In addition, the average experience as a principal among the total participants was 9.63 \( (SD = 6.59) \), while average length of tenure at the current campus was 5.31 \( (SD = 4.85) \).

Table 1

<table>
<thead>
<tr>
<th>Campus Type</th>
<th>( n )</th>
<th>Tenure as Principal at Current Campus</th>
<th>Mean (Years)</th>
<th>Std. Deviation</th>
<th>Years as Certified Principal</th>
<th>Mean (Years)</th>
<th>Std. Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elementary School</td>
<td>90</td>
<td></td>
<td>6.23</td>
<td>5.95</td>
<td></td>
<td>10.8</td>
<td>7.45</td>
</tr>
<tr>
<td>Middle School</td>
<td>44</td>
<td></td>
<td>6.07</td>
<td>4.86</td>
<td></td>
<td>8.02</td>
<td>4.74</td>
</tr>
<tr>
<td>High School</td>
<td>78</td>
<td></td>
<td>4.55</td>
<td>4.57</td>
<td></td>
<td>9.55</td>
<td>6.17</td>
</tr>
<tr>
<td>K-12</td>
<td>22</td>
<td></td>
<td>3.77</td>
<td>2.86</td>
<td></td>
<td>7.91</td>
<td>6.44</td>
</tr>
<tr>
<td>Other</td>
<td>19</td>
<td></td>
<td>4.05</td>
<td>2.44</td>
<td></td>
<td>10.16</td>
<td>7.31</td>
</tr>
<tr>
<td>Total</td>
<td>253</td>
<td></td>
<td>5.31</td>
<td>4.85</td>
<td></td>
<td>9.63</td>
<td>6.59</td>
</tr>
</tbody>
</table>
Regarding the highest degree obtained, 235 respondents (92.9%) held a Master's degree while 18 (7.1%) held a doctorate degree. The majority of participants were trained in traditional university certification programs \( (n = 232, 91.7\%) \), 19 participants (7.5\%) were trained through alternative certification programs, while 2 (0.8\%) did not have principal certification. Note, alternative certification programs included both private providers and regional educational service centers throughout Texas.

Data for this study was derived from an online survey, the Principal Data Use Instrument. The survey was designed to determine principals’ perceptions regarding the use of data. The survey consisted of 50 questions that included 13 demographic items, 34 items on data-driven decision-making as it relates to the perceptions of principals use of data and the impact on student achievement and two open ended items.

Instrumentation/Variables

The Principal Data Use Instrument was designed to determine principals’ perception of data use and the impact on student achievement at the campus-level. This 50-item Principal Data Use instrument, utilized in the current study was based on a prior study by Byrd and Eddy (2010) and altered for the current study based on a thorough review of the literature and ELCC/NCATE (2002) leadership program standards. The instrument asked participants to rate their agreement or disagreement in areas that included: 1) How they use data to improve student achievement, 2) how they use data to shape the vision, and 3) how they use data to design professional development for teachers. It was assumed that all participants defined data similarly in
their responses. Participants rated their agreement or disagreement with each question based on a corresponding 4 choice scale that included 1 = strongly disagree, 2 = disagree, 3 = agree, and 4 = strongly agree.

In Byrd and Eddy’s (2010) study 15 items of the instrument were utilized and were found to measure three constructs. The constructs included Principal uses of data to improve student achievement, Principal Uses of Data to Shape Vision and Principal Uses of Data to Design Professional Development. The intention of this study was to utilize all 34 questions of the Principal Data Use Instrument, conduct exploratory factor analysis on all questions and determine the underlying constructs and the impact of the constructs related to the perceptions of principals data use and the impact on student achievement.

Content Validity

A review panel consisting of 25 practicing principals, 3 university professors in educational leadership, and 2 professors in educational psychology reviewed the instrument. All questions were found to measure the intended constructs and thus, were utilized in the current study.

Construct Validity

Construct validity was determined using principal component analysis in conjunction with parallel analysis. Specifically, to determine the underlying structure of the instrument, principal component analysis was conducted utilizing a Varimax orthogonal rotation. Based on the principal component analysis and the results of the
parallel analysis (O’Connor, 2001), it was determined that the instrument measured three underlying constructs. Construct 1 included 11 items measuring principals’ use of data to improve student achievement (ELCC, 2002; Standard 2 and 4), Construct 2 included 8 items measuring principals’ use of data to determine principal and staff use of data to improve student achievement (ELCC, 2002; Standard 4 and 6), and Construct 3 included 2 items measuring principals’ use of data to design teacher professional development (ELCC, 2002; Standard 2 and 3). Reliability for the total instrument based on the 21 retained items, (as measured by Cronbach’s alpha) was .908. Regarding reliability of each construct, reliability for Construct 1 = .85, Construct 2 = .80, and Construct 3 = .75.

Factor Analysis Results

An initial exploratory factor analysis of the 34 items suggested that an eight-factor solution best explained the data. However, the overall variance explained by factors 4 through 8 of this and subsequent solutions was less than 5% per factor. Typically, a factor must account for 5% of overall variance for the factor to be deemed plausible. Moreover, many items had low primary factor loadings and/or high secondary factor loadings. The multivocality (term utilized to describe when an item loaded on multiple factors) of these items was consistent across factor models tested. Based on these preliminary models, 15 items were thus removed from the item pool (Q1, Q2, Q6, Q8, Q16, Q17, Q18, Q19, Q20, Q27, Q28, Q31, Q32). The remaining 21 items were subject to additional EFA-MLs.
Based on the variance accounted for each factor and the simple structure achieved for the factor loadings, a 3-factor model was identified as a plausible factor structure. As shown in Table 2, all factor loadings were large and positive, and relatively pure markers of the respective factors; communality estimates were reasonably large (all values greater than .20), and each factor accounted for more than 5% of the variance in the solution. Moreover, a modified version of parallel analysis (Glorfeld, 1995) supported the 3-factor solution: the eigenvalues from the factors from this model were compared to the eigenvalues for factors from randomly-generated data: (a) Factor 1: 6.50 vs. 0.64; (b) Factor 2: 1.11 vs. 0.54; and (c) Factor 3: 0.73 vs. 0.46. Although factor 3 does not meet the desired 1.0 value, it is greater than the randomly-generated data making it a reasonable third factor. Therefore, this solidifies the validity of the 3-factor solution in this study, due to the significantly greater value from factors from this model compared to randomly-generated data.
Table 2

Factor Loadings, Communality Values, and Percentage of Variance Accounted for by Each Factor in the 3-Factor Solution

<table>
<thead>
<tr>
<th>Item</th>
<th>Factor 1</th>
<th>Factor 2</th>
<th>Factor 3</th>
<th>$h^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Q3</td>
<td>0.65</td>
<td></td>
<td></td>
<td>0.37</td>
</tr>
<tr>
<td>Q4</td>
<td>0.45</td>
<td></td>
<td></td>
<td>0.22</td>
</tr>
<tr>
<td>Q5</td>
<td>0.50</td>
<td></td>
<td></td>
<td>0.25</td>
</tr>
<tr>
<td>Q7</td>
<td></td>
<td>0.43</td>
<td></td>
<td>0.22</td>
</tr>
<tr>
<td>Q9</td>
<td>0.51</td>
<td></td>
<td></td>
<td>0.33</td>
</tr>
<tr>
<td>Q10</td>
<td>0.61</td>
<td></td>
<td></td>
<td>0.41</td>
</tr>
<tr>
<td>Q11</td>
<td>0.55</td>
<td></td>
<td></td>
<td>0.46</td>
</tr>
<tr>
<td>Q12</td>
<td>0.75</td>
<td></td>
<td></td>
<td>0.53</td>
</tr>
<tr>
<td>Q13</td>
<td>0.51</td>
<td></td>
<td></td>
<td>0.35</td>
</tr>
<tr>
<td>Q14</td>
<td>0.38</td>
<td></td>
<td></td>
<td>0.21</td>
</tr>
<tr>
<td>Q15</td>
<td>0.84</td>
<td></td>
<td></td>
<td>0.60</td>
</tr>
<tr>
<td>Q21</td>
<td>-0.46</td>
<td></td>
<td></td>
<td>0.29</td>
</tr>
<tr>
<td>Q22</td>
<td>0.45</td>
<td></td>
<td></td>
<td>0.28</td>
</tr>
<tr>
<td>Q23</td>
<td>0.76</td>
<td></td>
<td></td>
<td>0.54</td>
</tr>
<tr>
<td>Q24</td>
<td>0.73</td>
<td></td>
<td></td>
<td>0.47</td>
</tr>
<tr>
<td>Q25</td>
<td>0.50</td>
<td></td>
<td></td>
<td>0.44</td>
</tr>
<tr>
<td>Q26</td>
<td>0.40</td>
<td></td>
<td></td>
<td>0.36</td>
</tr>
<tr>
<td>Q29</td>
<td></td>
<td>0.96</td>
<td></td>
<td>0.99</td>
</tr>
<tr>
<td>Q30</td>
<td></td>
<td>0.46</td>
<td></td>
<td>0.42</td>
</tr>
<tr>
<td>Q33</td>
<td>0.52</td>
<td></td>
<td></td>
<td>0.33</td>
</tr>
<tr>
<td>Q34</td>
<td>0.55</td>
<td></td>
<td></td>
<td>0.39</td>
</tr>
</tbody>
</table>

Percentage of Variance

<table>
<thead>
<tr>
<th></th>
<th>Factor 1</th>
<th>Factor 2</th>
<th>Factor 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage</td>
<td>30.0</td>
<td>23.70</td>
<td>12.20</td>
</tr>
</tbody>
</table>

Note. Percentage of variance accounted for by each factor is postrotation. $h^2$ = communality coefficient. All secondary loadings are less than |.25|.

Variables

The variables examined in this study include principals' perceptions toward data based on constructs derived from an exploratory factor analysis and a single dependent variable defined as student achievement. The data use constructs and student achievement were then assembled and examined in a structural equation model.
Student Achievement

In the current study, student achievement was measured by one indicator which included the percentage of students passing the Texas Assessment of Knowledge and Skills (TAKS) reading and mathematics assessments at the campus level. The TAKS is a comprehensive testing program for public school students in grades 3-11. The TAKS is designed to measure to what extent a student has learned, understood, and is able to apply the concepts and skills expected at each tested grade level. Each test is linked directly to the Texas Essential Knowledge and Skills (TEKS) curriculum. The TEKS is the state-mandated curriculum for Texas public school students (TEA, 2010).

School Level

School level in this study was defined as all school levels between the grades of kindergarten through 12. The following five categories make up school level: 1) Elementary school, which included Grades 3 – 5; 2) middle schools, which included Grades 6 – 8; 3) high school, which included Grades 9 - 12; 4) K-12, 3 – 12; and 5) other. Schools classified as other were schools that were intermediate schools, including Grades 5 and 6 only or district alternative schools.

Procedure

Initially, 1442 rural school principals were invited to participate in the current study. School addresses, phone numbers, email addresses, school demographics, and principal names were downloaded from the Texas Education Agency website. Downloaded information was sorted by region and enrollment. Schools that were in an
urban or suburban area or maintained a student enrollment over 1500 were deleted. A letter describing the study and survey was emailed to each rural school principal (Appendix A and Appendix B). Upon receiving notification that an email address was incorrect or there had not been a response from the principal within a week of the initial email, a personal call was placed to that principal to request their participation in the study. The resulting response rate was 17.5%.

**Data Analysis**

Initially, descriptive analysis, including means and standard deviations and frequencies and percentages, were calculated among the survey items. Further, the distribution and shape of the data were examined to determine if transformation of the data was warranted. Then, TAKS results from each campus were linked to individual principal responses via the district-campus state identification number. Subsequently, structural equation modeling (SEM) was conducted to determine how the principals’ perception of data use affects student achievement.

Exploratory factor analysis via structural equation modeling (SEM) with maximum likelihood (EFA-ML) estimation was used to explore the dimensionality of the total instrument that included 34 items and compared to the initial results of the principal component analysis that identified 3 constructs based on 15 items. The ML estimation procedure was used in this study to allow the researcher to determine the number of factors by examining the output from the principal component analysis. The ML estimation mathematically is identical to the common factor analysis model. Because of the exploratory nature of the analysis, several factor models (a single factor model and
up to a possible 8-factor model) were evaluated. First, factor models were examined with the complete item pool (all 34 items). Based on the Principal Component Analysis, factor models were tested that included examining items that did not load consistently on a single factor or loaded on multiple factors (referred to as multivocality). Analytically, items were removed 1 at a time. Based on the suggestions of Comrey and Lee (1992), items with primary factor loadings (i.e., factor pattern matrix coefficients) greater than .30 with secondary factor loadings less than .25 were kept for further analysis. The goal of the analyses was to derive simple structure (i.e., pure markers for each factor). Direct oblimin rotation was used for all multifactor models, as the derived factors were assumed to be correlated. PASW (version 17) was utilized for all descriptive analysis, while AMOS (version 18) was used for structural equation analysis. PASW, previously SPSS Statistics, is statistical software that analyzes operation data and AMOS is a structural equation modeling program.

Summary

This chapter described this study as a quantitative cross-sectional study that was designed to explore the relationship between perceptions of rural school principals’ use of data and impact on student achievement. The population and participants of this study, the variables used and the instrument utilized were defined and explained. Exploratory factor analysis and structural equation modeling procedures of this study were described to determine latent constructs and their relationships to student achievement.
CHAPTER 4
RESULTS

Chapter 4 includes a summary of the results with regard to the perceptions of which rural principals use of data to make decisions and how those decisions ultimately impact student achievement. Chapter 4 begins with the reporting of the results of the descriptive analyses, followed by the results of the bivariate and univariate results.

Student Achievement

Table 3 displays the results of the percentage of students passing the TAKS assessments at the campus level. The greatest percentage of students passing TAKS was associated with the elementary schools ($M = 80.59$, $SD = 12.83$). In contrast, the lowest percentage of students passing the TAKS assessment was associated with high schools ($M = 72.73$, $SD = 15.11$). The results mirror the state averages where high schools tend to have a lower percentage (70.9%) of students passing each of the TAKS assessments, while elementary campuses (77.7%) continually have a larger percentage of students passing each of the state-mandated assessments.
Table 3

*Means and Standard Deviations of the Percentage of Regular Education Students Passing TAKS*

<table>
<thead>
<tr>
<th>Campus Level</th>
<th>N</th>
<th>M</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elem. School</td>
<td>90</td>
<td>80.59</td>
<td>12.83</td>
</tr>
<tr>
<td>Middle School</td>
<td>44</td>
<td>76.89</td>
<td>11.21</td>
</tr>
<tr>
<td>High School</td>
<td>78</td>
<td>72.73</td>
<td>15.11</td>
</tr>
<tr>
<td>K-12</td>
<td>22</td>
<td>76.14</td>
<td>13.69</td>
</tr>
<tr>
<td>Other</td>
<td>19</td>
<td>75.58</td>
<td>12.5</td>
</tr>
<tr>
<td>Total</td>
<td>253</td>
<td>76.76</td>
<td>13.8</td>
</tr>
</tbody>
</table>

Principal Data Use Constructs

The descriptive results of each item used in the Principals Data Use Instrument are reported in Table 4. The means and standard deviations of each of the 11 items associated with construct 1 (Principal uses of data to improve student achievement) ranged from mean = 2.24 (SD = .807) item 14 to Mean = 3.21 (SD = .712) item 4; regarding construct 2 (Principal and Staff Ability to Analyze Data to Improve Student Achievement) the means among the 8 items ranged from 1.74 (SD = .613) to 3.16 (SD = .487); while the range in means associated with the 2 items comprising construct 3 (Principal Uses Data to Design Teacher Professional Development) ranged from 3.13 (SD = .642) to 3.22 (SD = .553). The reliability of each factor was: Factor 1 (α = .85), Factor 2 (α = .80); Factor 3 (α = .75). The interfactor correlations were as follows: (a) $r = .62$ for F1 and F2, (b) $r = .36$ for F1 and F3, and (c) $r = .37$ for F2 and F3.
Table 4

Means and Standard Deviations of the Principal Data Use Constructs and Individual Items

<table>
<thead>
<tr>
<th>Item</th>
<th>M</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Principal Uses of Data Analysis (α* = .85)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. I regularly conduct focus groups to dig deeper into data analysis. (Q3)</td>
<td>2.56</td>
<td>.719</td>
</tr>
<tr>
<td>2. Student-level data is analyzed in core subject areas regularly (3-5 times a year) on my campus. (Q4)</td>
<td>3.21</td>
<td>.712</td>
</tr>
<tr>
<td>3. Cohort-Level data is analyzed in core subject areas regularly (3-5 times a year) on my campus. (Q5)</td>
<td>2.81</td>
<td>.770</td>
</tr>
<tr>
<td>4. Principals and campus-level staff have developed campus-wide interim/formative assessments aligned to standards, administered at least 2 times per year in core subjects. (Q9)</td>
<td>3.06</td>
<td>.699</td>
</tr>
<tr>
<td>5. I examine &quot;lagging indicators,&quot; such as results of annual TAKS, to study past instructional practices. (Q10)</td>
<td>3.11</td>
<td>.597</td>
</tr>
<tr>
<td>6. I examine &quot;leading indicators,&quot; such as results of interim/formative assessments to inform immediate instructional decisions. (Q11)</td>
<td>3.12</td>
<td>.572</td>
</tr>
<tr>
<td>7. I gather data in the classroom and hold data-driven meetings to better understand students' progress toward student achievement goals. (Q12)</td>
<td>2.93</td>
<td>.663</td>
</tr>
<tr>
<td>8. I have communicated clear and defined student achievement goals for each subject area. (Q13)</td>
<td>3.11</td>
<td>.576</td>
</tr>
<tr>
<td>9. Data coaches are available to support data analysis campus-wide. (Q14)</td>
<td>2.24</td>
<td>.807</td>
</tr>
<tr>
<td>10. I create explicit expectations and norms by stating explicitly that data use is non-negotiable and models appropriate behavior. (Q15)</td>
<td>2.79</td>
<td>.727</td>
</tr>
<tr>
<td>11. I provide ongoing professional development to teachers on how to use data as a tool to improve instruction. (Q26)</td>
<td>2.76</td>
<td>.592</td>
</tr>
<tr>
<td>Principal and Staff Ability to Analyze Data to Improve Student Achievement (α = .80)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. I do not have the skills to properly analyze data on a regular basis. (Q7)</td>
<td>1.74</td>
<td>.613</td>
</tr>
<tr>
<td>2. I find it difficult to translate the information generated by data analysis into curriculum. (Q21)</td>
<td>2.08</td>
<td>.569</td>
</tr>
<tr>
<td>3. Teachers on my campus compare student achievement results by skill and subject with the results of other teachers in the building to identify and share instructional techniques that increase student achievement. (Q22)</td>
<td>2.87</td>
<td>.604</td>
</tr>
<tr>
<td>4. Teachers on my campus tailor instructional decisions for individual students based on results of both formative and annual student-level assessments. (Q23)</td>
<td>3.16</td>
<td>.487</td>
</tr>
<tr>
<td>5. Teachers on my campus have the necessary skills to analyze and interpret data to improve instructional practices. (Q24)</td>
<td>2.96</td>
<td>.603</td>
</tr>
<tr>
<td>6. I ensure that teachers have regular opportunities to access and use data individually and in teams to review and gauge student learning and alter their instruction accordingly. (Q25)</td>
<td>3.09</td>
<td>.530</td>
</tr>
<tr>
<td>7. I find that the data management system is easy to use. (Q33)</td>
<td>2.76</td>
<td>.543</td>
</tr>
<tr>
<td>8. The data management system allows for longitudinal analysis in core subject areas at the individual student level at least two reporting periods. (Q34)</td>
<td>2.98</td>
<td>.545</td>
</tr>
<tr>
<td>Principal Uses Data to Design Teacher Professional Development (α* = .75)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Data analysis has helped to identify professional development needs in my school. (Q29)</td>
<td>3.22</td>
<td>.553</td>
</tr>
<tr>
<td>2. Data analysis helped me identify areas of teaching/learning that need to be addressed in my school. (Q30)</td>
<td>3.13</td>
<td>.642</td>
</tr>
</tbody>
</table>

*α = Cronbach’s alpha; M = Mean, SD = Standard Deviation
Table 5 displays the correlation between the principals’ perception of data use constructs and student achievement. The desired values of a correlation that would show a positive impact would be values greater than .05. Correlated to factor 1, there is no significant impact on student achievement. Both factors 2 and 3 show a negative correlation to student achievement however, similar to factor one, none of the constructs show a significant impact on student achievement.

Table 5

| Pearson Product-Moment Correlations between Principal’s Perception of Data Use Constructs and Student Achievement |
|-------------------------------------------------|--------|
| Student Achievement (1) | 1.00   |
| Principal Use of Data to Improve Student Achievement (2) | .001   | 1.00 |
| Principal and Staff Ability to Analyze Data to Improve Student Achievement (3) | -.116  | .000 | 1.00 |
| Principal Uses Data to Design Teacher Professional Development (4) | -.003  | .000 | .000 | 1.00 |

Structural Equation Model

After the preliminary EFA-ML identified 3 factors, these factors were modeled as latent variables that predicted observed variables representing student achievement (TAKS) and campus level (see Figure 1). Predictive models with latent variables were referred to as structural equation models (SEM). There were two primary parameters of interest in the target SEM. First, factor loadings represented the strength of the relationship between each observed variable and the latent variable. Importantly, these
latent variables were free of measurement error, as each observed variable had unique variance associated with it that was relegated to an error term. The second set of parameters of interest was referred to as structural coefficients. These coefficients represented associations between the 3 latent variables and the target achievement outcomes; these values were akin to regression coefficients. An additional benefit of SEM is that it allowed the researcher to simultaneously estimate all model parameters.

SEM models were evaluated at two levels: overall model fit and individual parameters subsumed within the model (e.g., factor loadings, structural coefficients). With respect to overall model fit, many researchers have suggested using multiple measures of descriptive model fit to determine whether or not a model fits well at a global level (e.g., Hoyle, 2000). This is because the only available inferential test statistic, the chi-square likelihood ratio test statistic, is heavily influenced by sample size. In the current study, the following two descriptive fit indices were employed: (a) the Standardized Root Mean Residual (SRMR) and (b) the Root Mean Square Error of Approximation (RMSEA; Steiger, 1990). Values less than .08 are indicative of reasonable model fit. These two descriptive fit indices were recently endorsed by Bentler (2007). In evaluating the statistical significance of individual model parameters, a statistical significance level of .05 was employed. For all models, parameters were estimated using the maximum likelihood estimation procedure employed by EQS (Bentler, in press).

The target SEM model displayed in Figure 1 fit reasonably well according to the descriptive indices of model fit, $\chi^2(222) = 469.24, p < .05, \text{SRMR} = .058, \text{RMSEA} = .066$. As shown in Figure 2, all factor loadings loaded were relatively large and statistically
significant, confirming what was found in the EFA-ML. When considering the structural
coefficients, the Principal Uses Data to Improve Student Achievement latent variable
(Factor 1) and the Principal and Staff Ability to Analyze Data to Improve Student
Achievement latent variable (Factor 2) were significantly and positively associated with
student achievement (TAKS). Higher scores on these two latent variables were
associated with better student achievement. There was no statistical association
between the Principal Uses Data to Design Teacher Professional Development latent
variable (Factor 3) and this target outcome. In total, the three latent variables accounted
for 6% of the variance in student achievement (TAKS). When the campus level outcome
was considered, no statistically significant associations between any of the latent
variables and this outcome were evident. In total, the three latent variables accounted
for less than 2% of the variance in campus level.
Figure 1. Observed SEM model. All factor loadings and structural coefficients are standardized values. *p = .05
Data Analysis Summary

Exploratory factor analysis (EFA) was conducted using structural equation modeling (SEM) to examine factor structures and determine whether the observed model fit the theoretical model. An SEM model was utilized to determine principal data use constructs on student achievement when considering the structural coefficients, Factor 1, Principal Uses Data to Improve Student Achievement latent variable and Factor 2, Principal and Staff Ability to Analyze Data to Improve Student Achievement latent variable were significantly and positively associated with student achievement (TAKS). Higher scores on these two latent variables were associated with better student achievement. There was no statistical association between the Factor 3 Principal Uses Data to Design Teacher Professional Development latent variable and this target outcome. In total, the three latent variables accounted for 6% of the variance in student achievement (TAKS). When the campus level outcome was considered, no statistically significant associations between any of the latent variables and this outcome were evident. In total, the three latent variables accounted for less than 2% of the variance in campus level. Additional details of the results may be found below.

Open Ended Results

Each participant in the study had the opportunity to respond to two open-ended questions. The first question asked for the three most important purposes of which data analysis is used in the participants’ school. Although there were unique answers from each participant, the principal responses easily fit into one of four areas. All survey participants did not answer this question, while some gave more than one response. Of
the 253 participants, 49 did not choose to respond to this open ended question, while 67 participants gave more than one response resulting in a total of 271 responses regarding the most important purposes of which data analysis is used in the participant’s school.

One hundred six (39.1%) of the principals wrote that student need was the most important use of data analyses on their campus. In the area of student need, data analyzed were classroom grades, individual student grades, attendance, benchmarks and test scores. This information was utilized to determine student performance goals, interventions, acceleration, tutorials, or remediation. Additionally, data was analyzed to determine student need by sub population (i.e. ethnicity, low socio-economic status, or special needs students).

The use of data for campus improvement goals was a top priority to 48 (17.7%) of the principals. Data included evaluation of the district scope and sequence, monitoring curriculum implementation, identifying program needs, effectiveness of programs and determining professional development needs.

The third area of important uses of data analysis on the campus was to determine teacher effectiveness. This area was significant for 47 (17.3%) of the principals. Principals indicated they analyzed data of students’ progress and grades, of teacher implementation of effective instruction and individual teaching practices to determine if campus teachers were effective. This information was also used on some campuses to determine blame or innocents for classroom or curriculum successes or failures.
Finally, 69 (25.5%) of the respondents felt that data analysis on the campus level was important in order to evaluate test scores. The tests analyzed specifically included chapter tests, benchmarks, reading proficiency tests, TAKS test and Texas English Language Proficiency Assessment System (TELPAS). This data was analyzed to determine needed remediation classes or tutorials for students, and also to project campus accountability ratings. Figure 2 depicts the overall responses from all participants in the current study, expressed in percentage and separated under each of the categories that the principals indicated as uses of data on their campuses.

![Figure 2. Purposes of data use on the rural school campuses in the current study.](image)

Figures 3 though 6 depict the participant responses by campus level. Campus levels include 1) elementary school, 2) middle school, 3) high school, 4) K-12 schools, and 5) other. Schools categorized as other include intermediate schools or district alternative schools. At all campus levels, principal responses indicated that student need was the most important reason for data use on their campus. Responses indicating student need was the most important use of data analysis ranged from 34.4%
($n = 31$) at the elementary campus level to $52.5\%$ ($n = 10$) at the intermediate and alternative campuses. Figure 3 depicts the percentage of principal responses that perceived that data analysis at their campus level was most used to address student need.

![Percentage of Participant Responses by Campus Level](image)

**Figure 3.** Purposes of data use for student need on the campus by campus level.

Figure 4 depicts the use of data to address campus improvement goals, by campus level. The use of data to address campus improvement goals was of highest importance at the high school campuses with $24.4\%$ ($n = 19$), while it was of least priority for the K-12 campuses with $13.6\%$ ($n = 3$). Principals indicated the need for data analysis in order to evaluate programs, align curriculum and ensure that the goals set in place were measurable.
Figure 4. Purposes of data use for achieving campus goals by campus level.

The third area of importance that principals indicated to be significant for uses of data analyses was to determine teacher effectiveness. Figure 5 depicts the principal responses by campus level. Principals stated that they analyzed data to determine if teachers were following the district curriculum, students were progressing successfully and discipline was carried out effectively. Use of data to determine teacher effectiveness was of highest priority at the middle school campuses at 22.7% \( (n = 10) \) and of least priority to the intermediate and alternative campuses at 15.8% \( (n = 3) \).
Figure 5. Purposes of data use to determine teacher effectiveness by campus level.

The final area indicated by the principals as important uses of data analyses was to evaluate student test scores. Principals indicated that analyzing standardized tests such as TAKS, TELPAS and locally developed reading and math tests were important uses of data analyses at their campus. The K-12 campuses, 31.8% \((n = 7)\), indicated that utilizing data to evaluate test scores was of significant importance while the intermediate and alternative campuses with 21.1% \((n = 4)\) indicated the use data analyses to evaluate test scores as least important.
The second open-ended question asked participants to share barriers or challenges to the use of student data to improve learning at the campus. As with the first open-ended question, all participants did not answer the question, however many of the respondents did mention more than one category as a barrier or challenge on their campus.

Lack of resources was a strong barrier or challenge for 128 (56.0%) of the respondents. Time was the overarching challenge with money and technology also issues of concern. Additionally, there were district program changes that challenged the campuses abilities to analyze data. With the magnitude of issues and needs at the campus level, analyzing data took significant time that was not available. Money was at a shortage and technology access, current programs or internet access caused challenges for the campuses.

A lack of knowledge on how to interpret data or what to do with the data was a barrier for 78 (34.1%) of those who responded. Principals felt that many of them did not
have the comfort or skills to understand how to analyze data and tell a story with data. Additionally, principals felt teachers did not know how to analyze the data available to them. Professional development was necessary to assist staff in utilizing and analyzing data. There was no mention of where the professional development was obtained, however some mentioned that this was a challenge also because it connected back to lack of resources and inability to receive assistance in data analysis training.

The final challenge or barrier of the principals was to create a data-driven culture. Twenty-three (10%) of the respondents felt it a challenge to create this culture and get teacher buy-in on data analyses, monitoring of the teachers to ensure implementation of agreed upon changes and the ability to change the mind set of “I’ve done it this way and it worked, therefore I don’t intend to change…” philosophy. Figure 7 displays the overall barriers present at all of the principal campuses.

![Figure 7. Barriers or challenges of data use to improve student achievement at all campuses in the current study.](image-url)
Figure 8 displays the principal responses to the second open-ended question by campus level. Overall, the overshadowing barrier that principals stated most impacted the campus level was the lack of resources. Resources included, but were not limited to, access to computers, access to internet, district support, money, time or data management system. The campus level with the highest concern of this barrier was the intermediate and alternative campuses with 68.4% \((n = 13)\) while the K-12 campuses had the lowest concern for lack of resources at 45.5% \((n = 10)\).

Figure 8. Lack of resources as a barrier or challenge of data use to improve student achievement by campus level.

The second barrier addressed by the principal responses at the campus level was the lack of data analysis knowledge and ability. Although this barrier could also be considered a lack of resources, enough principals specifically stated that there was a
lack of knowledge, training, and ability to analyze data that it was determined to be a separate barrier. The school level with the highest concern for this barrier was high school campuses at 33.3% ($n = 26$) and the lowest concerned campus levels were intermediate and alternative campuses at 26.4% ($n = 5$). Lack of data analyses knowledge as a barrier is depicted in Figure 9.

![Figure 9. Data analyses knowledge as a barriers or challenges of data use to improve student achievement by campus level.](image)

Finally, the third campus barrier addressed by the principals was the lack in ability to create a campus data-driven culture or vision. Principals indicated with all the other barriers, indentified in this section, it was difficult to create a collaborative data-driven culture or vision at the campus level. Over 22% ($n = 5$) of the K-12 campus
principals shared that building a campus data-driven culture or vision was a barrier, while only 5.3% ($n = 1$) of the intermediate and alternative school campuses considered creating a campus-driven culture as a barrier. Figure 10 displays data-driven campus culture or vision as a barrier at each campus level.

![Figure 10](image)

*Figure 10.* Lack of data-driven campus culture/vision as barriers or challenges of data use to improve student achievement by campus level.

The open ended responses of the participants of this study made it clear that there is a definite gap in knowledge of data analysis and ability to lead a data-driven decision-making campus. The open-ended responses were significantly different than the responses to the survey questions. The survey answers indicated that there was a strong understanding of data and there were data-driven systems in place on the campuses of these rural school campuses. However, the open-ended responses
indicated a gap in data analyses knowledge, ability and resources. The factor analysis indicated there was no overall statistical significance that the rural school principals’ use of data impacted student achievement at the campuses. Therefore, a gap is clearly present in the principals’ perception of use of data to improve student achievement. There is a discrepancy between what the principals indicated on the survey that they are doing at their campuses versus the responses they gave on the open ended questions. The responses given were more accurate indicator of the rural school principals’ knowledge and ability in leading a data-driven campus that may impact student achievement. Although the majority of the principals stated on the survey that they had a strong data-driven system in place on their campuses, it was clear that was a discrepancy between perception and reality as there was a lack of knowledge and ability to analyze data and implement changes necessary to impact student achievement.

**Summary**

Exploratory factor analysis via structural equation modeling (SEM) with maximum likelihood (EFA-ML) estimation was used to explore the dimensionality of the 34 survey items. The ML estimation procedure is mathematically identical to the common factor analysis model used in the analyses reported below. Because of the exploratory nature of the analysis, a number of factor models (1-factor through 8-factors) were evaluated. The goal of the analyses was to derive simple pure markers for each factor. Direct oblimin rotation was used for all multifactor models, as the derived factors were assumed to be correlated.
The analysis employed a fully recursive SEM model, which tested principal data use constructs (latent variables of the three subscales of the Principal Data Use instrument) on student achievement. By estimating the most likely relationships between variables, the model was also modified by adding paths of statistical significance between the variables that made theoretical sense in order to improve the fit until a final best model was obtained.

Chapter 5 details the overview of the study, interpretations of findings, and implications of this quantitative cross-sectional research study. The chapter concludes with limitations of the study, recommendations for further research and practice, and provides a final summary of the study.
The purpose of the current study was to determine the perceptions of rural school principals’ use of data and the impact on student achievement. A quantitative cross-sectional research design was utilized where Texas rural school principals’ perceptions regarding the use of data were examined at a single point in time.

This chapter summarizes the findings of the study with regard to the research question posed in Chapter 1. Relevant implications and conclusions are drawn based on these findings in terms of potential influence on research and practice. Finally, this chapter presents recommendations for future research. The discussion is organized around the original research question:

What is the relationship between principals’ perception of data use and the impact on student achievement among rural school principals in Texas?

The findings from this study reveal that the three constructs, principal uses of data to improve student achievement, principal and staff ability to analyze data to improve student achievement, and principal uses of data to design teacher professional development were reliable predictors of the outcome variable, student achievement (TAKS). The three constructs accounted for 6% of the variance in overall student achievement; however, there was no significance in student achievement by the campus level. Therefore, no statistically significant associations between any of the constructs and the outcome of student achievement were evident.

The results of the final structural equation model analysis revealed a path from principals use of data to improve student achievement had a positive impact on student achievement (.26 \( p < .05 \)) as did principal and staff ability to analyze data (.32 \( p < .05 \)).
In contrast the path from principal uses of data to design professional development (-.06) had no impact on student achievement. The pathways from each of the constructs to the campus level were all similar and with no statistical significance. In total the three constructs, principal use of data to improve student achievement, principal and staff ability to analyze data to improve student achievement, and principal uses of data to design teacher professional development accounted for less than 2% of the variance at the campus level. While statistical significance was achieved in the present model it was found that sample size explained 2% of variance in the outcome variable, TAKS scores. As only 2% of student achievement (TAKS) results were contributed to principal uses of data, this is evidence that principal perceptions of their data use are not aligned with their actions and implementation of their data analysis. Consequently, although principals perceive they use data to improve student achievement on their campus, 98% of the variance of student achievement results is unaccounted for.

The structural equation model analysis results suggest that principals do not have the requisite skills to properly analyze data and apply the results to the classroom. As O'Day (2002) submits, “If principals are to incorporate the information into their cognitive maps or repertoire of strategies, they must attend to it to ensure quality data and must have sufficient knowledge and ability to interpret it”. It is apparent, based on the findings from the current study, that principals do not have the data analysis skills and knowledge or do not collaborate in the data analysis process in order to impact student achievement.

These results align with the previous study by Byrd and Eddy (2010) who investigated the urban principals’ perceived use of data and the impact on student
achievement. The results of the previous study and the current study are similar and together they offer a statewide perspective of Texas principals’ difficulty in data analysis based on perceptions.

Both studies align with Dervin’s sense making theory. There must be enough data and information accessible in order to make decisions. However it appears to be a lack of decision-making knowledge and experience in the principalship to bridge this gap of effective data-driven decision-making (Dervin, 1992).

It could be concluded that whether a principal is in the rural or the urban setting in Texas, there is a definite perception gap regarding campus data-driven decision-making. This perception gap is supported by the findings in both the current and previous studies. Although principals from both rural and urban schools indicate that quality data analysis is being conducted at the campus level, principal perceptions are not valid as there is no significant statistical impact on student achievement. It could be concluded that principals’ perception gap is based on their lack of training, knowledge and ability to analyze data, collaborate in the decision making process and effectively implement instructional changes into the classroom.

Additional results in the current study were obtained from two open-ended questions incorporated into the survey 1) principal uses of data analysis at the campus level and 2) determine barriers of data use on the campuses. Eighty-one percent of the principals responded to the first open ended question related to principal uses of data analysis at the campus level. Each indicated that they analyze data to address student need, evaluate the campus improvement plan, determine teacher effectiveness and evaluate student test scores. By supplying specific examples of data use at the campus
level, the principal answers to this question gave insight to the survey responses regarding data analysis. Overall, principals indicated that they perceived themselves to have a strong data driven system in place at their campuses, as they gave examples of the purposes of data use on their campuses. However, as evidenced by the structural equation model, it could be concluded that although the principals indicated examples of data use on their campus, that data analysis was not occurring or not effectively occurring (in other words, there is a lack of proper skills to analyze data).

In the second open-ended question, related to barriers of data use on their campus, the rural school principals indicated that there were significant barriers that inhibited quality data analysis at the campus level. Fifty-six percent of the principals indicated that time, money or technology were barriers to data analysis at their campuses while 34% of the principals stated that there was a lack in data analysis knowledge that hindered data-driven decisions on their campuses.

The findings from the survey questions indicated that the principals perceived they utilize data on their campuses, have data-driven systems in place, and make curricular changes to address student need based on data analyses. However, the principal open-ended responses regarding barriers indicated that quality use of data was not taking place at the campus level. This aligns with the results of the structural equation model of the current study and supports the conclusion that principal perceptions of data use is not a valid indicator of actual data-driven decision-making on the campus.

Overall, rural school principals perceived they used data to improve student achievement, to design professional development, and to determine the ability of the
staff to analyze data to improve student achievement. However, as revealed in the results of the structure equation model analysis and review of the open-ended questions, principal perceptions are not a reliable indicator of data use and the impact on student achievement at the campus level.

Conclusion

One in six students attends school in a rural community (Arnold, 2006). Thus, rural students represent a significant population that is affected by decisions made by educators. All principals, but specifically rural school principals create the right conditions for data-driven decision-making when they provide time for assessment, train teachers to use assessment data for planning instruction and state clear expectations for student performance. The quality of data use in schools is dependent upon the professional capacity of the individuals engaging the data (Datnow et al., 2007).

In the current study principals perceived they were data-driven decision-makers, however there was a misalignment in their ability to analyze data, implement instructional changes supported in the data, and positively impact student achievement at the campus level. To correct this alignment need, rural school principals must have adequate data-driven decision-making education in their principal certification course work and receive ongoing training that will allow them to continue to become exemplary data-driven leaders of their campuses.

The accountability movement has encouraged district and school administrators to think differently about educational decision-making, and to use data to collect information on everything from resource allocation to instructional methods (Mandinach,
As evidenced by the current study, rural school principals may not have the data analysis skills to effectively and efficiently utilize the data to make decisions that impact student achievement. In order for rural school principals to be able to analyze data effectively, they must have data analysis training.

Unfortunately, the demands for data-based decision-making have not been paired with adequate training or support to educate school leaders on these practices (Herman & Gibbons, 2001). This is evidenced in the current study, as principals responded to the survey items agreeing or strongly agreeing that they have a data-driven culture at their campuses and they responded to data in order to impact student achievement. Among the responses of the first open-ended question, related to data uses on the campus, the principals gave examples of the data analysis on their campuses. However, on the second open-ended question, related to the barriers of data analysis on their campuses, the principals indicated that there was a significant lack in knowledge on data analysis and there were significant barriers that hindered data-driven decision-making from occurring on their campuses. There appears to be a disconnect in perception between the principal responses on the survey items compared to the principal responses on the open-ended question. Overall, the findings of the structural equation model were more clearly understood as it became apparent through analysis of the open-ended questions that there was a misalignment in the principals’ ability to analyze data effectively in order to impact student achievement.

Young (2006) states that to construct a foundation for systematic data within a culture of inquiry, successful school systems create explicit norms and expectations regarding data use at the district and school levels. To ensure effectiveness, specific
measurable goals must be aligned to standards at the district, school and classroom levels (Datnow et al., 2007).

Based on the findings from the current study, it could be concluded that although principals’ indicated that they use data to improve student achievement, use data to design teacher professional development and that data is used to analyze the principal and staff ability to improve student achievement through data analysis, they do not have the necessary data analysis skills and knowledge to impact student achievement.

These findings support the notion that principals must have adequate knowledge and understanding of data-driven decision-making. In order to effectively and efficiently impact student achievement, individuals involved in the decision making and implementation process must have the training and education to know how to analyze current data in a collaborative manner and understand how to implement instructional changes to improve student achievement.

Recommendations

There is a need for reform in the field of education administration, specifically regarding principals, data management, and university preparation programs, to include skills associated with data collection, data analysis and assessment. First, it is recommended that principals must take action. Principals should own the issue of their lack in data analysis skills and be vocal for the need of adequate preparation to be effective data-driven campus leaders. The job description of the principal today continues to morph as high stakes testing continues to determine the success of schools and as we strive to produce students that are college and workforce ready.
Principals must be prepared for this position and equipped with the necessary tools and ongoing support. The responsibility of gaining this knowledge is two-fold. Principals need to receive the appropriate training, which will be addressed further in this section, and principals must own the responsibility to obtain the needed data-driven decision-making skills necessary for today’s principal. Principals must not passively stand by and expect change to occur without their voice and action. Data-driven decision-making is a required skill set for today’s principal and individual action is necessary to gain the needed skills and knowledge to become data-driven leaders.

Second, it is recommended that the establishment of a statewide student data warehouse be considered. High stakes mandates affect the schools, discussions should occur to determine how principals may accomplish effective and efficient data-driven decision-making to positively impact student achievement. A data warehouse would provide administrators and teachers access to student data in a reliable and easy to understand system, allowing school staff to address students struggling academically. The data warehouse would contain state assessment information in addition to locally administered assessments and benchmarks given throughout the current semester. The data would be in real-time and transferable with the student throughout the state. This tool would offer principals the opportunity to improve academic instruction by having a usable and accessible resource of current data to align instruction necessary to impact each student’s academic achievement.

Finally, principal preparation programs must rethink the traditional courses and course methods in order to address the needs of today’s principal in ways that reflect an expectation for skilled analysis of multiple data sources. The leadership courses are not
adequate to prepare individuals for effective data-driven leadership in today’s schools. Although many of these leadership courses are valuable, an overhaul of the traditional principal certification programs should be considered and integrate data-driven decision-making with leadership in order to impact student achievement.

Suggestions for Further Research

Several recommendations for future research in this area can be suggested. Specifically, there are four recommendations that might be considered as a natural extension to this study, and hold the potential to further advance findings in this area. Given the rapidly-changing nature of education and educational policy, it is first recommended that this study be repeated in the future to capture changes in educational leadership training, accountability measures and principal perceptions. To create a longitudinal perspective over time, it is further recommended to repeat this study every five years to track changes, growth and gaps.

Secondly, because this study focused only in Texas, it would be advantageous to explore any possible differences in other states. Though public education is governed at the federal level, differing applications of educational law and policy may create differences in the factor analysis by state. In addition, the emphasis of the current study was on rural schools. Conducting this study in other states with an emphasis on both rural and urban school districts may provide additional insight into commonalities and differences in the decision making process according to district location, size, and geographic region which may also improve the ability to generalize the results.

Third, this study provides a foundation for additional, targeted inquiry into
principal preparation and continued professional development in the area of data-driven decision-making. Further inquiry should be done on exactly what courses principals take in the principal preparation programs and what skills are learned in these courses. Also, what continued data-driven decision-making training is received once principals are in their current role and who is teaching these sessions. Results of this study and future factor analysis studies can allow researchers to use these results as a foundation for investigating how principals at schools with high levels of data-driven decision-making were trained and how they continue to be trained. By examining successful schools and then further studying the academic and professional training of their leaders, recommendations may be created for principal preparation and continued development in data-driven decision-making.

Finally it is recommended based on the current study and further research, that a data-driven decision-making competency exam be considered for all school principals in Texas. It is recommended that the exam be a component of the current state certification exam or an additional required exam. This exam must be passed by the principal prior to receipt of a Texas principal certification and be required for certification renewal. Individuals unable to pass the data-driven decision-making exam would be required to attend a specified data analysis course in order to obtain or retain the Texas principal certification.
APPENDIX A

SURVEY LETTER
Dear Fellow Administrator,

   My name is Kaye Rogers and I am working on my dissertation for completion of my PhD from the University of North Texas. My dissertation is on the effectiveness of Principals’ use of Data in Data-Driven Decision-Making and the Impact on Student Achievement in rural and mid-sized school districts.

   Great demand is placed on principals today to understand and actively read and interpret data, then take this data to create a more positive learning experience and environment for students. However the question arises whether the principal preparation programs are preparing school leaders to be prepared with the necessary instruction to be able to skillfully transform academic programs using data analysis.

   I would greatly appreciate your help by completing a survey to determine how principals use data in schools throughout Texas. The results of this survey will be used to improve preparation programs to best prepare principals to effectively use data to improve student learning in Texas.

   Your response to the survey is voluntary and should only take approximately 10 minutes to complete. If you choose to participate, please answer each question of the survey, as each response provides valuable information. The results will not be publicly identified by individual, campus, or district.

   Please click on the following link to begin the survey.
   http://www.surveymonkey.com/s/8V76PH6

   Thank you very much for your time and your help so that I may gather data to complete this important study. A complete report will be available to you upon completion of the study.

   THANKS!
APPENDIX B

PRINCIPAL SURVEY
Principal's Data Driven Decision Making

1. Data Driven Decisions of the Principals

Thank you very much for taking the time to complete the following survey. The information you provide is strictly confidential and will be used only to document the current state of data use and practice in your district.

Your participation in this survey is strictly voluntary. The results of the survey will be used in my dissertation to improve data collection and use of data to improve student learning in Texas. The results will not be publicly identified by individual, campus or district.

Please answer each question in the survey, as each response provides valuable information. At the completion of the research, a link to my dissertation will be sent to you.

The survey should take approximately 10 minutes.

Thank You!
Kaye Rogers
University of North Texas Doctoral Student

2. Default Section

1. In which district do you work?

2. In which school do you work?
3. Type of campus:
- High School
- Middle School
- Elementary School
- K-12
- Other

4. Gender
- Female
- Male

5. Race:
- Anglo
- African-American
- Latino
- Native American
- Asian/Pacific Islander
- Other

6. How many years have you been a certified Principal?

7. What is the length of your tenure as a principal at your current campus(years)?

What was your primary teaching field prior to becoming a certified principal?
9. How many years of did you teach prior to becoming a principal?

10. Type of principal certification:
   - Alternative
   - Traditional
   - None

11. What is your highest degree conferred?
   - PhD/EdD
   - Master's Degree
   - Bachelor's Degree

12. My school has an established protocol for the collection, analysis, and dissemination of data.
   - Strongly Disagree
   - Disagree
   - Agree
   - Strongly Agree

13. Data analysis for student academic data for my district is provided by:
   - Regional Education Service Center
   - District personnel
   - Outside consultant
   - Other
   - No analysis provided
### Data Driven Decisions of the Principals

14. I involve school staff, students, and school community to determine how differing audiences interpret the data.

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<th>Strongly Disagree</th>
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15. I regularly conduct focus groups to dig deeper into data analysis.

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<th>Strongly Disagree</th>
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16. Student-level data is analyzed in core subject areas regularly (3-5 times a year) on my campus.

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<th>Strongly Disagree</th>
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17. Cohort-level data is analyzed in core subject areas regularly (3 - 5 times a year) on my campus.

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Data Driven Decisions of the Principals

18. I do not have time to analyze data on a regular basis.

- Strongly Disagree
- Disagree
- Agree
- Strongly Agree

19. I do not have the skills to properly analyze data on a regular basis.

- Strongly Disagree
- Disagree
- Agree
- Strongly Agree

20. How many professional development sessions (e.g. Regional Educational Services Center, District-provided) have you attended related to student data analysis?

- 0
- 1
- 2
- 3
- 3+

21. I examine academic achievement at different grade levels over multiple time points when analyzing data.

- Strongly Disagree
- Disagree
- Agree
- Strongly
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<td>22. As principal, I and campus-level staff have developed campus-wide interim/formative assessments aligned to standards, administered at least two times per year in core subjects.</td>
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<td>23. I examine &quot;lagging indicators&quot; such as results of annual TAKS to study past instructional practices.</td>
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<td>24. I examine &quot;leading indicators,&quot; such as results of interim/formative assessments to inform immediate instructional decisions.</td>
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<td>25. I gather data in the classroom and hold data-driven meetings to better understand students' progress toward student achievement goals.</td>
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<td>26.</td>
<td>I have communicated clear and defined student achievement goals for each subject area.</td>
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<td>27.</td>
<td>Data coaches are available to support data analysis campus-wide.</td>
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<td>28.</td>
<td>I create explicit expectations and norms by stating explicitly that data use is non-negotiable and models appropriate behavior.</td>
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<tr>
<td>29.</td>
<td>I find it challenging to apply data to classroom situations.</td>
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30. I find the lack of time, particularly time to update and analyze data to be challenging.

- Strongly Disagree
- Disagree
- Agree
- Strongly Agree

31. I find that the data analysis provided by central office produces outcomes that are easy to interpret.

- Strongly Disagree
- Disagree
- Agree
- Strongly Agree

32. Data analysis has had a positive impact on student learning in my school.

- Strongly Disagree
- Disagree
- Agree
- Strongly Agree

33. Data management tools simplify the process of setting my school targets.

- Strongly Disagree
- Disagree
- Agree
- Strongly Agree
Data Driven Decisions of the Principals

34. I find it difficult to translate the information generated by data analysis into curriculum.

- Strongly Disagree
- Disagree
- Agree
- Strongly Agree

35. Teachers on my campus compare student achievement results by skill and subject with the results of other teachers in the building to identify and share instructional techniques that increase student achievement.

- Strongly Disagree
- Disagree
- Agree
- Strongly Agree

36. Teachers on my campus tailor instructional decisions for individual students based on results of both formative and annual student-level assessments.

- Strongly Disagree
- Disagree
- Agree
- Strongly Agree
37. Teachers on my campus have the necessary skills to analyze and interpret data to improve instructional practices.

- Strongly Disagree
- Disagree
- Agree
- Strongly Agree

38. I ensure that teachers have regular opportunities to access and use data individually and in teams to review and gauge student learning and alter their instruction accordingly.

- Strongly Disagree
- Disagree
- Agree
- Strongly Agree

39. I provide ongoing professional development to teachers on how to use data as a tool to improve instruction.

- Strongly Disagree
- Disagree
- Agree
- Strongly Agree

40. I use data and make comparisons with other schools to identify the school's strengths and weaknesses.

- Strongly Disagree
- Disagree
- Agree
- Strongly Agree
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<td><strong>41. The analysis of data does not improve teaching and learning in my school.</strong></td>
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<td><strong>42. Data analysis has helped to identify professional development needs in my school.</strong></td>
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<td><strong>43. Data analysis helped me identify areas of teaching/learning that need to be addressed in my school.</strong></td>
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<td>Agree</td>
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<td></td>
<td>Strongly Agree</td>
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<td><strong>44. More training is needed to help teachers interpret and use the information generated by our data management system.</strong></td>
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<td></td>
<td>Strongly Disagree</td>
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<td>Disagree</td>
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<td>Strongly Agree</td>
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### Data Driven Decisions of the Principals

<table>
<thead>
<tr>
<th>Question</th>
<th>Strongly Disagree</th>
<th>Disagree</th>
<th>Agree</th>
<th>Strongly Agree</th>
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<tbody>
<tr>
<td>45. Data analysis tells us nothing that we don't already know.</td>
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<td>46. I find that the data management system is easy to use.</td>
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<td>47. The data management system allows for longitudinal analysis in core subject areas at the individual student level over at least two reporting periods.</td>
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</table>
48. In your school, how do you assess the effectiveness of your data management tool(s) in improving student learning? Please check all that apply.

- We collect anecdotal evidence of student progress in learning from teachers in the school.
- We collect relevant examples of students' work to demonstrate progress in learning.
- We review summative teacher assessment outcomes over time.
- We review student test/examination results by reporting period over time.
- We record student's progress in learning each reporting period.
- We review each student's achievements in comparison with targets set.
- We compare achievements in particular year groups with those of previous cohorts in the school.
- We compare student achievement with that in similar local schools.
- We compare student achievement with that in similar schools nationally.

49. Please indicate the three most purposes for which data analysis are used in your school.

50. What are the barriers or challenges to the use of student data to improve learning?
REFERENCES


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Doyle, P. (2003). Data-driven decision-making: Is it the mantra of the month or does it have staying power? TH E Journal (Technological Horizons In Education), 30, 1-2.


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