**Data-Driven Decision-Making: Rural Public High School Teachers' Perceptions of Data-Driven Instruction**

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This dissertation titled

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**Abstract**

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Data-Driven Decision-Making: Rural Public High School Teachers' Perceptions of Data-Driven Instruction

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Research is well established in urban school districts regarding teachers' engagement in and perceptions of data-driven instruction. However, little research has been conducted on teachers' perceptions of using data to inform instruction in rural school districts. Thus, this quantitative study examined rural public high school teachers' perceptions of data-driven instruction in Indiana. Specifically, this study identified rural public high school teachers' perceptions in terms of what types of data they use to support instruction, their attitudes toward data use, their competence in using data to drive instruction, and the support systems that help or hinder their ability to effectively participate in data-driven instruction. Additionally, this study examined possible relationships among demographic variables of rural public high school teachers and their corresponding perceptions of data-driven instruction. The participants varied in gender, age, years of teaching experience, subject taught, and highest level of education attained.

Overall, the results of this study reveal that while rural public high school teachers had a seemingly positive attitude toward data use and felt it was important to use multiple types of data to inform instruction, they did not feel competent participating in the data-driven decision-making process to inform pedagogical practices. Reported barriers for effectively using data to drive instruction include the lack of professional development regarding data use, lack of collaborative inquiry among educators, lack of support from external sources (i.e., data coach, instructional coach), lack of valuable data management systems, and lack of administrator leadership and support. Consequently, since teachers are required to be able to use a variety of student data with fidelity to improve student learning and

achievement by state and federal education legislation, school districts and educational leaders can begin fostering a culture a data use in their schools and build teacher competence by providing professional development opportunities and time for collaborative inquiry, employing a data expert, training teachers to effectively utilize data management systems, and modeling successful data use.

**Dedication**

*This dissertation is dedicated to my parents who have instilled in me the value of education and love of learning. Thank you for continuously encouraging me to persevere and pursue my dreams.*

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## Chapter 1: A Problem of Practice

Throughout the years, federal educational legislation has been reauthorized from the Elementary and Secondary Education Act to the No Child Left Behind Act to the Every Student Succeeds Act. Through each reauthorization, specific mandates were slightly modified, or new mandates were added. However, the required use of data by educators to improve student learning has remained a fixed and unwavering component (Every Student Succeeds Act [ESSA], 2015; No Child Left Behind Act of 2001 [NCLB], 2002; U.S. Department of Education, 2017). For decades, school systems have been held accountable for increased student academic achievement. Beginning with the Elementary and Secondary Education Act of 1965, educational reform initiatives to support the use of student data have come and gone in a cyclical pattern, and educators have consistently been required to effectively and successfully participate in the data-driven decision-making process to improve student learning (Kerr et al., 2006; Mandinach & Honey, 2008; Marsh et al., 2006; U.S. Department of Education, 2017). Fortunately, such a feat does not have to be an individual endeavor, nor does it need to be completed blindly.

Due to the prevalence of the data-driven decision-making process in the industrial world, schools have access to a multitude of frameworks and how-to guides for implementation (Coburn & Turner, 2011; Ikemoto & Marsh, 2007; Mandinach et al., 2008; Marsh et al., 2006). A prominently used framework in education found throughout a variety of studies is Mandinach et al.'s (2006a) *Conceptual Framework for Data-Driven Decision Making* (Abbott, 2008; Hamilton et al., 2009; Ikemoto & Marsh, 2007; Mandinach, 2012; Marsh et al., 2006; Means et al., 2010). Even though this framework provides guidance on applying the process in practice, educators must first obtain six skills regarding data use for effective implementation: collecting, organizing, analyzing, summarizing, synthesizing, and prioritizing data (Mandinach et al., 2006a). In a holistic view, educators must be data literate.

While being data literate has no clear definition, there are skills teachers must acquire to participate in data-driven instruction effectively. These skills include being able to collect and organize a plethora of numerical and non-numerical student data, analyze and summarize the data for useful information, and synthesize and prioritize the information for useful knowledge (Dunn et al., 2013b; Ikemoto & Marsh, 2007; Mandinach, 2012; Mandinach et al., 2011; Mandinach et al., 2006a; Mandinach et al., 2008; Means et al., 2010). With these abilities, teachers are able to begin identifying student strengths and weaknesses to inform instruction for improved student learning (Ikemoto & Marsh, 2007; Mandinach, 2012; Means et al., 2010). In addition to acquiring such skills, other factors have been found to highly influence teachers' participation in the data-driven decision-making process and, in turn, data-driven instruction.

Commonly found factors influencing teachers' use of data to inform instruction across existing research are teachers' participation in collaborative inquiry, the amount of data-focused professional development received, the number and type of external sources a school uses such as a data coach, the availability of quality data, the access to and ease of use of a data management system, and the amount of time available to participate in the data-driven decision-making process (Datnow et al., 2007; Kerr et al., 2006; Marsh et al., 2006; Means et al., 2011; Wayman, 2010). Additionally, the significance of each factor varies from school to school in relation to both the degree each factor is operational and the school's level of implementation of the data-driven decision-making process. Thus, there are reported advantages and disadvantages of each component influencing teacher's use of data to inform instruction.

For instance, teachers benefit significantly from collaboration as it allows time for sharing best practices for student engagement and learning as well as time to discuss the holistic picture of a student, which includes numerical and non-numerical data for use to increase student learning (Datnow

& Park, 2018; Datnow et al., 2013). On the other hand, the number of educators involved in collaborative inquiry remains questionable. While some research suggests all educators should be present during the collaborative inquiry process (Datnow et al., 2013; Mokhtari et al., 2007), others suggest there should be a secluded team of educators (Coburn & Turner, 2011; Halverson et al., 2007; Long et al., 2008). Regardless of such inconsistencies as well as the factors influencing data use, teachers' perceptions of data-driven instruction are vital to ensuring schools can build teachers' capacity to use data to improve student learning effectively.

Unfortunately, many teachers' attitudes towards data use is alarmingly inharmonious with the data-driven decision-making process. Studies have found a significant number of teachers directly relate data use to accountability policies and partake in data use practices to meet the specified requirements (Datnow & Park, 2014; Mandinach et al., 2006a). In contrast, many teachers have been found to overlook test data and base their decisions on personally created performance metrics (Ingram et al., 2004; Marsh et al., 2006). Furthermore, some teachers believe improving student learning is dependent on student behavior alone (Schildkamp & Kuiper, 2010). While not all teachers have negative attitudes towards data-driven instruction (Datnow & Park, 2014), ensuring teachers develop a positive attitude toward data use is not a feat that can be achieved without focusing on capacity building efforts, which is directly correlated to their beliefs.

In terms of data-driven decision-making, a teacher's sense of efficacy is comprised of his/her beliefs that they have the skill set and capacity to participate in the data-driven decision-making process to improve student academic achievement regardless of a student's skill level (Bandura, 1977; Dunn et al., 2013a; Dunn et al., 2013b; Tschannen-Moran & Hoy, 2001). Existing research has indicated teachers with a strong sense of self-efficacy in terms of teaching are more likely to embrace data-driven decision-making practices (Dunn et al., 2013b). However, increasingly more evidence exists that suggests teachers' low levels of confidence and self-efficacy have become a prominent obstacle for schools when integrating data-driven decision-making practices (Dunn et al., 2013b; U.S. Department of Education, 2008; Wayman, 2005). Overall, while there is an abundance of knowledge regarding teachers' perceptions of data-driven instruction across literature, it is important to note the knowledge was obtained by studies conducted in an urban school setting (e.g., Datnow & Park, 2014; Feldman & Tung, 2001; Kerr et al., 2006). Research conducted in rural educational settings is exceptionally limited (Arnold et al., 2005; DeYoung, 1987; Sherwood, 2000). Correspondingly, what is known regarding teachers' perceptions of data-driven instruction is not necessarily applicable in rural education since urban-based research does not address the needs and culture of a rural school (DeYoung, 1987; Sherwood, 2000).

Due to the limited amount of research regarding rural education, educational leaders do not have sufficient information when making informed decisions (Arnold et al., 2005). In light of this fact, rural schools will continue to face existing challenges such as retaining highly qualified teachers, having significantly limited resources for internal support, and having limited financial support (AASA, The School Superintendents Association, 2017; Arnold et al., 2005). Additionally, existing urban-based research regarding data-driven decision-making is of little aid in building rural teachers' data literacy skills. Therefore, there is a need to address rural teachers' perceptions of data-driven instruction since using student data for informed decision-making is and will seemingly always be a vital component within federal education legislation.

**Statement of the Problem**

Research is well established on how teachers engage in data-driven instruction regarding the various types of data being used by educators, factors that influence educators' use of data, and the growing need for support systems in schools for data-literacy development (Abrams et al., 2016;

Datnow & Hubbard, 2016; Dunlap & Piro, 2016; Mandinach & Gummer, 2013; Marsh et al., 2006; Militello et al., 2013). However, little research has been conducted on rural public high school teachers' perceptions of data-driven instruction (Arnold et al., 2005; Harmon et al., 1996). The National Rural Education Association (2020) developed a research agenda for the years 2016-2021 that depicts teachers' participation in data-driven decision-making as a top priority for future research. Overall, rural public school districts have limited knowledge regarding how to support high school teachers in becoming data literate and effectively participating in the data-driven decision-making process, which ultimately impacts teachers' use of data-driven instruction to improve student learning.

**Purpose of the Study**

The purpose of this quantitative study is to examine rural public high school teachers' perceptions of data-driven instruction in Indiana. Specifically, this study will identify rural public high school teachers' perceptions in terms of what types of data they use to support instruction, their attitudes toward data use, their competence in using data to drive instruction, and support systems that help or hinder their ability to participate in data-driven instruction effectively. Additionally, this study will examine possible relationships among demographic variables of rural public high school teachers and their corresponding perceptions of data-driven instruction.

**Research Questions**

The research questions that follow will guide this study and aid in examining rural public high school teachers' perceptions in using student data to drive instruction.

1. What types of data do rural public high school teachers use to drive their instruction?
2. What are rural public high school teachers' perceptions of their attitude toward using data to drive instruction?

3. What are rural public high school teachers’ perceptions of their competence in using data to drive instruction?
4. What are rural public high school teachers’ perceptions regarding supports or barriers to using data to drive their instruction?
5. To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict state data is used to drive instruction?
6. To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict periodic data is used to drive instruction?
7. To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict local data is used to drive instruction?
8. To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict personal data is used to drive instruction?
9. To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict attitude toward using data to drive instruction?
10. To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict competence in using data to drive instruction?

**Significance of the Study**

The results of this study will not only contribute to existing research regarding data-driven decision-making in education but will also create a foundation of knowledge in terms of teachers' participation in data-driven decision-making in a rural educational setting. Furthermore, the study will have an impact on both teachers and educational leaders. Through participating in the survey, teachers will have the opportunity to increase their knowledge regarding student data that are available for use and existing support systems that could be implemented to aid successful data-driven instruction. Teachers will also have the opportunity gain a better understanding of their use of student data to drive instruction. On a larger scale, educational leaders will benefit from this study as the results could drive allocation of funding towards items such as tangible resources, professional development, data management systems, and external sources to support building teacher's data literacy skills, which could increase continuous school improvement and student learning.

**Definition of Terms**

***State Data.*** Data from standardized state assessments such as ISTEP+ 10, ILEARN – Biology, ILEARN – U.S. Government, and WIDA (Wayman et al., 2016b).

***Periodic Data.*** Data from commercially available periodically administered assessments such as NWEA, Acuity, and Achieve 3000 (Wayman et al., 2016b).

***Local Data.*** Data from district-developed assessments such as common formative assessments and end-of-course exams (Wayman et al., 2016b).

***Personal Data.*** Data from classroom-based assessments, such as quizzes, homework, portfolios, end-of-unit tests, and writing assignments (Wayman et al., 2016b).

***Data-Driven Instruction.*** Collecting, organizing, analyzing, summarizing, synthesizing, and prioritizing student data to make instructional decisions (Mandinach, 2012; Mandinach et al., 2006a).

# Chapter 2: A Review of Relevant Literature

Federal education legislature in the United States has held K-12 school systems under stringent accountability measures, which remain a common obstacle for all educators. For this reason, schools have adopted numerous educational reform initiatives in order to satisfy accountability demands; a noteworthy requirement within these demands is using student data to show growth in student achievement (Gamble-Risley 2006; Ikemoto & Marsh, 2007; Kerr et al., 2006; Mandinach & Honey, 2008; Mandinach et al., 2006a; Marsh et al., 2006). Thus, since schools have been forced to use student data under government policy, data-driven decision-making has become a key component in educational reform agendas to ensure continuous school improvement and student academic achievement (Datnow & Park, 2014; Gamble-Risley, 2006; Marsh et al., 2006). Data-driven decision-making is a nonlinear, complex process comprised of numerous limitations, which may pose as an obstacle for improved student achievement (Ikemoto & Marsh, 2007; Mandinach, 2012; Mandinach et al., 2006a; Marsh et al., 2006; Means et al., 2009; Wayman, 2005). Therefore, educators must have the capacity to effectively and successfully participate in the data-driven decision-making process.

To address these issues, this review of literature examines the influence of federal and state legislation on data-driven decision-making in schools, the components of the data-driven decision-making process, factors that help or hinder effective implementation of data-driven decision-making in school systems, and emerging themes regarding teachers' capacity to participate in the data-driven decision-making process. Additionally, this review of literature guides the conceptual framework, research design, and research questions of the study and concludes with supporting evidence for the need to examine rural public high school teachers' sense of efficacy in using student data to drive instruction and support systems that help or hinder their ability for effective data-driven instruction.

## Era of Accountability

For over a century, federal and state educational legislation has been a prominent force in driving the need for reform in school systems across the nation for advancement in student learning and, thus, the economy (Mackenzie, 1894; National Commission on Excellence in Education, 1983; The President's Committee on Education Beyond High School, 1957). The initial proclamation of improving school systems for increased student learning is found in the *Report of the Committee of Ten* enacted in 1894. This report stressed the desire for a common education among all students to ensure that the American youth was receiving a strong academic preparation regardless of their future endeavors (Mackenzie, 1894; Peterson, 2013). Despite this strong fervor of needed improvement in education across the nation, the goal was ultimately unattainable due to the lack of equal access to education and educational resources.

Equality in education was first addressed at the onset of the civil rights movement in the landmark case of *Brown v. Board of Education* (1954), where programs, lessons, and teachings in segregated educational settings were found to be insufficient. While this was a revolutionary decision on behalf of education in the United States, the decision was only a piece of the solution. The Soviet Union's success in both launching Sputnik and producing the scientists, engineers, and technicians that had the academic capacity to do so prompted the United States to convene the President's Committee on Education Beyond High School to address its seemingly lack of nation-wide academic achievement (Gamsen et al., 2015; Johanningmeier, 2010; The President's Committee on Education Beyond High School, 1957). As a result of the assembly, the United States introduced the 1958 National Defense Act to provide federal assistance to schools to ensure an increase in nation-wide academic achievement and an increase in intellectual rigor to produce more mathematicians, scientists, and individuals fluent in a foreign language in order to become the leading nation in conducting superior technological advancements (Gamson et al., 2015; Johanningmeier, 2010; Krejsler, 2018). Meanwhile, the civil rights movement progressed and spurred a second landmark decision – the Elementary and Secondary Education Act of 1965 (ESEA).

***The Elementary and Secondary Education Act***

While the purpose of ESEA was to ensure equal opportunity for all students by closing the achievement gap economically and socially, the increasingly distressing signs regarding the lack of academic advancement in K-12 schools across the United States compared to other nations spurred the composition of *A Nation at Risk* (Gamson et al., 2015; Johanningmeier, 2010; Krejsler, 2018; Mehta, 2015; National Commission on Excellence in Education, 1983; Rhodes, 2012). With the looming growth of global competition and decrease in academic achievement across the nation, *A Nation at Risk* identified the need for uniformity and consistency of academic standards among school systems to address the United States' longstanding desire to increase academic achievement among all students (Johanningmeier, 2010; Mehta, 2015; National Commission on Excellence in Education, 1983; Peterson, 2013; Swanson & Stevenson, 2002). *A Nation at Risk* was not the first document produced in the United States that declared the decline in education and academic standards as well as the desperate need for improvement. However, it was seemingly a prominent piece of literature regarding a change in education and, more specifically, the revolutionary introduction of standards-based reform and data-driven decision-making in education.

The standards-based education movement is found throughout the multiple revisions of ESEA, which were made by the United States in response to *A Nation at Risk* and the need for academic standards for increased student proficiency so that students nation-wide had the capacity to contribute to their economy (Johanningmeier, 2010; McDermott, 2011; Rhodes, 2012). The initial revision in 1994 included the Improving America's Schools Act (IASA), which significantly altered the initial purpose of ESEA and focused on equality in education regarding high expectations and standards for all rather than merely equal access to education (Rhodes, 2012). Schools across the nation were required to adopt similar academic standards, implement common assessments, and ensure all students were being held at the same level of high expectations in order to receive federal funding (Gameson et al., 2015; Rhodes, 2012). In response to this phenomenon, there are conflicting views regarding the adoption of academic standards. Supporters of the standards-based reform movement suggested uniformity is of the utmost importance, and all students should be held at the same level of high expectations regarding learning (Hamilton et al., 2008). In contrast, those who opposed the movement felt standards should be developed and tailored according to students' needs rather than providing a common education for all (McDermott, 2011). Regardless, the conditions under IASA were not enough to satisfy the demands of increased educational achievement across the nation.

***No Child Left Behind***

An additional and notable revision was made to ESEA in 2001 with the introduction of No Child Left Behind (NCLB), which was enacted in 2002 and provided a more strict and formidable standards-based education movement as federal funding in education rested on the imposed demands of student academic achievement and whether schools were able to satisfy those demands (Gamson et al., 2015; Krejsler, 2018; Rhodes, 2012; U.S. Department of Education, 2017). Although many components comprise NCLB, they have a consistent theme: closing the achievement gap by improving student learning (NCLB, 2002). Consequently, in assuming schools were adhering to the mandates of NCLB, all students were expected to be assessed in science where respective states were to measure each student's growth by the year 2007 (Marx & Harris, 2006). Additionally, by the school year 2013-2014, NCLB expected all students to be proficient in mathematics and English. (Gamble-Risley, 2006; Rhodes, 2012). While this was a daunting task for all educators, it came with support from the United States

Department of Education in the form of educational accountability and, in particular, the use of data-driven decision-making.

In an effort to continue providing both federal education aid and a fair and equal education to all students, NCLB required each state to adopt a test-based accountability system. Since the overarching goal was to ensure all students had the opportunity to achieve proficiency and outperform their peers in other nations, this newly created accountability system required common standards-based assessments for all students and, thus, a common education among school systems – a theme reintroduced once again that was first found in the *Report of the Committee of Ten* (Hamilton et al., 2008; Krejsler, 2018; Mackenzie, 1894; Marsh et al., 2006; NCLB, 2002; Rhodes, 2012; Swanson & Stevenson, 2002). As a result, schools across the United States combined school-wide reform and state-standard instructional alignment to create a more profound version of standards-based reform. In light of standards-based reform, multiple studies have stated concerns that assessment should not drive instruction as this method can lead to extraneous results regarding actual student achievement (Hamilton, 2003; Mokhtari et al., 2007; Pella, 2012). Conversely, others have argued that if a concept is important enough to test, then the concept should be equivalently important enough to teach (William, 2007).

Nonetheless, through these state-mandated assessments, schools were required to participate in the data-driven decision-making process, which consisted of collecting, analyzing, and synthesizing student achievement data to determine student performance outcomes. These results were reported to the U.S. Department of Education to undergo federal assessment for adequate yearly progress (AYP) – a method of evaluation that determined whether schools would receive federal education aid (Hamilton et al., 2008; Marsh et al., 2006; Mokhtari et al., 2007; Rhodes, 2012). Ultimately, NCLB determined whether schools achieved AYP by assessing the percentage of students meeting or exceeding targeted proficiency levels in mathematics and English – science was not included; hence, the need for schools to be data literate is ever apparent (Marsh et al., 2006; Marx & Harris, 2006). While the goal of all students being proficient in mathematics and English by 2014 did not come to fruition under NCLB, the overall requirement of increased student proficiency continued for school systems.

***Every Student Succeeds Act***

Since the federal government felt NCLB had unrealistic and unworkable goals for school systems across the United States, it altered the existing requirements and constructed a new law known as the Every Student Succeeds Act (ESSA) (ESSA, 2015). To create ESSA, the U.S. Department of Education revised ESEA, once again, by integrating language from NCLB such as closing the achievement gap and affording students a high-quality education as well as including additional provisions for increased accountability measures for schools (U.S. Department of Education, 2017). As a result, not only are schools required to continue to use student data to show student growth in reading, mathematics, and science but now they must also use student data to show growth in English-language proficiency scores, graduation rates, and growth in a school quality academic measure of the schools choosing (ESSA, 2015). While ESSA does not have a timeline in which all students are required to be proficient in any selected area, the accountability measures given are equally challenging.

***Standards***

In addition to measured standards provided by ESSA and AYP, literature within federal and state policies such as the Interstate Teacher Assessment and Support Consortium (InTASC) and the Professional Standards for Educational Leaders (PSEL) – formerly known as Interstate School Leaders Licensure Consortium (ISLLC) – contains strong statements about using data for both school improvement and student achievement (Council of Chief State School Officers, Interstate Teaching Assessment and Support Consortium [InTASC], 2013; Mandinach & Gummer, 2013; Mandinach et al., 2011; National Policy Board for Educational Administration [NPBEA], 2015). According to NPBEA, the former ISLLC standards were revised in 2015 in order to provide educational leaders more fruitful direction for successful student outcomes. For example, within the standards, there are multiple instances in which school leaders are held accountable in using assessment data for purposeful planning in improving student achievement. While these standards were written for all educational leaders, there is an emphasis within the literature that they are geared more toward school-level leadership (NPBEA, 2015). Hence, principals must be able to use student data effectively for school achievement purposes.

On the other end of the spectrum, InTASC (2013) contains standards focused on the need for teachers to use a variety of data to improve student achievement. To accomplish such a feat, the standards hold teachers accountable in using assessment data to guide, modify, and differentiate instruction to accommodate students of all capacity levels (InTASC, 2013). The standards also require teachers to collaborate with colleagues in determining meaningful data to improve learner outcomes (InTASC, 2013). Consequently, the InTASC and NPBEA policies, which respectively hold teachers and administrators accountable for student learning, converge to support school accreditation processes that require educational leaders and teachers to be data literate (InTASC, 2013; Mandinach & Gummer, 2013; Mandinach et al., 2011; NPBEA, 2015).

**Data-Driven Decision-Making**

Accountability measures at all levels governing education have influenced the need for educators to be efficient in using student data to drive instruction for improved student achievement. Therefore, it is of utmost importance that teachers build their capacity to be data literate. This necessity is also reflected in the growing literature regarding the nuances of data-driven decision-making in schools such as the data-driven decision-making process, supports and barriers to using data, and the role of faculty at differing levels within a school regarding the use of data (Coburn & Turner, 2011; Mandinach & Honey, 2008; Mandinach et al., 2006a; Marsh, 2012; Means et al., 2009). While there is no clear definition of data-driven decision-making or data literacy due to the variety of data collected by educators at differing levels in the school systems, which has a different meaning depending on the role of the educator, the intricate process has become a seemingly vital component within education (Datnow et al., 2013; Mandinach, 2012; Mandinach et al., 2011; Mandinach et al., 2008). In light of this essential component in education, it is important to note this process is not newly innovated as the industrial world has been participating in data-driven decision-making for decades.

***History of Data-Driven Decision-Making***

Data-driven decision-making in education has not only been in practice for decades but has also been modeled on industry and manufacturing frameworks, which were implemented to improve leadership, quality, and production – a similar feat schools are currently attempting to accomplish (Breiter & Light, 2006; Datnow & Park, 2018; Marsh et al., 2006). Despite the fact there is no clear definition of data-driven decision-making, there is a consensus the modeled process involves the collection, organization, analyzation, summarization, synthetization, and prioritization of data (Mandinach, 2012; Mandinach et al., 2006a; Marsh et al., 2006). In terms of the collection and organization of data, research has been conducted on data management systems beginning as early as the 1970s (Breiter & Light, 2006). Thus, while accessing data may seem new to educators, there is considerable support available to aid school systems in easing the process of understanding data management systems.

In light of this support, Datnow and Park (2018) suggested the use of data to inform decisions in the educational setting is not a novel task. The seemingly new undertaking is due to the federal and state accountability measures that are inextricably tied to specific data and specific decisions. These measures require educators to be more intentional in using data to improve student achievement. Also, due to the prevalence of the data-driven decision-making process in the industrial setting, many researchers have reported a multitude of existing frameworks and how-to-guides available for use to aid in implementing data-driven decision-making in schools (Coburn & Turner, 2011; Ebbeler et al., 2017; Ikemoto & Marsh, 2007; Mandinach et al., 2008; Marsh et al., 2006; Schildkamp & Poortman, 2015; William, 2007).

***Conceptual Framework***

Numerous versions of conceptual frameworks and theoretical frameworks exist regarding data-driven decision-making. While Datnow and Park (2014) suggested schools merge multiple frameworks to take into account how different factors influence data use, a common framework found throughout numerous studies that guide educators through the data-driven decision-making process at the classroom, building, and district level is Mandinach et al.'s (2006a) *Conceptual Framework for Data-Driven Decision Making* (Abbott, 2008; Hamilton et al., 2009; Ikemoto & Marsh, 2007; Mandinach, 2012; Mandinach et al., 2008; Marsh et al., 2006; Means et al., 2010). However, despite the framework guidance on applying the process in practice, educators must obtain six skills regarding data use for effective implementation: collecting, organizing, analyzing, summarizing, synthetizing, and prioritizing data (Mandinach et al., 2006a). Once those skills have been developed, the cyclical nature of the conceptual model provides educators with a continuous progression beginning with collecting and organizing data, analyzing and summarizing the data for useful information, and synthesizing and prioritizing the information for useful knowledge (Dunn et al., 2013b; Ikemoto & Marsh, 2007; Mandinach, 2012; Mandinach et al., 2011; Mandinach et al., 2006a; Mandinach et al., 2008; Means et al., 2010). At the classroom level, teachers would complete the cycle of the framework by identifying student strengths and weaknesses to make an informed decision for instructional modification that would have a positive impact on improving student learning (Mandinach, 2012; Mandinach et al., 2006a). To begin applying this conceptual model, data must be collected in all forms and organized for logical sense-making.

***Types of Data***

The amount of student data available to educators is seemingly proliferating; therefore, teachers must be able to navigate the various forms of data and utilize them at their full potential to make informed decisions regarding instruction (Datnow & Hubbard, 2016; Lachat & Smith, 2005; Mandinach, 2012; Mandinach et al., 2011). Such data comes in the form of student test data (state, periodic, local, and classroom), student demographic data, Individualized Education Plans, Individualized Learning Plans, and school performance data, to name a few (Datnow & Park, 2018; Hamilton et al., 2009; InTASC, 2013; Mandinach et al., 2006a; Marsh et al., 2006; Mokhtari, 2007; Wayman, 2010). While there is considerable debate on the usefulness of test data as well as how much data should be used to make informed decisions, the end goal is for teachers to knowledgably utilize the appropriate data to answer their data-driven inquiries regarding instructional modifications to improve student learning (Abbott, 2008; Feldman & Tung, 2001; Hamilton et al., 2009; Kerr et al., 2006; Long et al., 2008; Mandinach et al., 2008; Means et al., 2009; Supovitz & Klein, 2003). To begin, a prominent form of data available to teachers is student test data.

**Test Data.** Federal and state educational mandates have stringent accountability measures attached to student test scores; thus, teachers often reported using these scores to inform their instruction (Breiter & Light, 2006; Marsh et al., 2006). Despite this fact, teachers have questioned the accuracy of state test data (Kerr et al., 2006; Pella 2012), which results in a lack of buy-in regarding data use – a vital component for meaningful and effective data-driven decision-making (Ingram et al., 2004). This seemingly negative perception regarding the reliability of state test data can be attributed to its scant usefulness. For instance, existing research has suggested state assessment data is not provided in a timely manner for effective use, and the information provided is too broad of knowledge regarding student learning as one can only observe how a student performs on a limited number of categories within a specific topic and at a certain grade level (Kerr et al., 2006; Means et al., 2009; Suppovitz & Klein, 2003). On the contrary, other research has supported the use of state test data due to the opportunity for teachers to gain insight on the strengths and weakness of students in terms of general topics, which can then be used to differentiate learning for particular groups of students (Lachat & Smith, 2005; Suppovitz & Klein, 2003). In consideration of this controversy, there are other avenues of assessment that can aid educators in using data for improved student learning.

To make informed decisions regarding instructional modifications, teachers should not rely on a single assessment; rather, they should be analyzing state, periodic, local, and classroom assessments (Hamilton et al., 2009; Marsh et al., 2006). For this reason, using multiple forms of test data has become a common practice due to teachers' lack of desire to rely on state assessment data. In response to this phenomenon, school districts across the nation have begun implementing periodic assessments to gain more reliable data in addition to the already practiced local and classroom assessments (Datnow & Hubbard, 2015; Datnow & Park, 2014; Marsh et al., 2006). As can be surmised, there are advantages and disadvantages of implementing additional testing throughout the school year.

The advantages of using data from periodic assessments – also referred to as benchmark assessments or interim assessments – is that they are tied to state standards and can be synthesized across classes and grade levels, which provides the opportunity for informed instruction to improve student learning throughout the academic school year (Datnow & Park, 2014; Hamilton et al., 2009; Wayman et al., 2006). In comparison to state assessments, periodic assessments provide more regular feedback to teachers regarding student growth and are not as wide-ranging in topic (Datnow & Park, 2014; Marsh et al., 2006). On the other hand, there are disadvantages of using periodic assessments as they are only valuable for any given year as they inform instruction for a single cohort of students (Hamilton et al., 2009; Marsh et al., 2006). Periodic assessments also take time away from teaching, and they assess the same material as local formative assessments and classroom assessments (Marsh et al., 2006). With this in mind, there has been great debate on the benefits and usefulness of data from local formative and classroom assessments.

To enumerate, local formative assessments and classroom assessments such as projects and homework are popular among teachers regarding data use as the increased frequency of the information and daily feedback is highly attractive (Marsh et al., 2006). For instance, Marsh et al. (2006) found where local test data was commonly used to drive instruction such as modifying curriculum to align with state assessments and differentiating instruction to tailor to whole class needs, small group needs, and individual student needs, classroom data was often used to provide guidance on the progression of student learning. In contrast, classroom data has also been found to be limited in its usefulness as the data is restricted to one setting and cannot be used to influence instruction across all classes (Hamilton et al., 2009). While assessment data is valuable in its own right, educators must close the gap between using data for accountability measures and using data for instructional modification (Mandinach, 2012). In order to achieve such a feat, there are alternate data that can and should be used to inform instruction.

**Other Data.** Examining data across multiple sources is vital to ensure equitable learning opportunities, improved student academic achievement, and, ultimately, continuous improvement (Datnow & Hubbard, 2016; Datnow & Park, 2014; Datnow & Park, 2018; Halverson et al., 2007; Hamilton et al., 2009; Mandinach, 2012; Suppovitz & Klein, 2003). Moreover, observing a wide range of data allows for discrepancies to be located, which not only provides the opportunity to target strengths and weaknesses of students for tailored instruction but also informs equitable instructional practices for those students who have historically been identified as disadvantaged (Datnow & Park 2018; Mandinach, 2012; Marsh et al., 2006). Even though data is commonly perceived as numerical values, this is not the case when participating in the data-driven decision-making process. Along with numerical data such as school performance data and student performance data, non-numerical data such as student demographic data, behavior charts, Individualized Education Plans, and records of parent communication should be collected and analyzed to provide a perspective for educators to frame their lessons and plan for differentiated instruction (Datnow & Park, 2018; Hamilton et al., 2009; InTASC, 2013; Marsh et al., 2006). Just as with student growth, educators should be cognizant of their own professional growth and continuous improvement.

Mokhtari et al. (2007) suggested data should not be limited to strictly student data; instead, teacher data should also be collected and analyzed, such as professional development data, observational data, and instructional practices. Since educators have a direct impact on student achievement, their performance is relevant to the data-driven decision-making process as it has the potential to influence learner outcomes. As can be seen, analyzing data across a variety of sources provides a cohesive picture of student progress and allows for more evidence to be utilized to inform instruction and increase student growth (Datnow & Park, 2018; Hamilton et al., 2009; Kerr et al., 2006). In light of this fact, to ensure data is effectively and successfully used for instructional improvement, teachers must be data literate.

### ***Data Literacy***

To apply the conceptual model for data-driven decision-making, teachers must have the capacity to use data for informed decision-making, also known as data literacy, which is a key component of the data-driven decision-making process (Mandinach, 2012; Means et al., 2011).

However, existing literature has suggestedb educators lack data literacy skills in terms of collecting and organizing data, analyzing and summarizing information gleaned from the data, and synthesizing and prioritizing the knowledge found from the information to make informed, reliable decisions (Choppin, 2002; Feldman & Tung, 2001; Hamilton et al., 2009; Ikemoto & Marsh, 2007; Mandinach et al., 2008; Mason, 2002; Wayman & Stringfield, 2006). Thus, data literacy is an area of much-needed improvement. While the specified tasks may sound daunting, guidance is provided to increase an individual's capacity for data literacy.

To begin, even though the ideal time to ensure teachers are gaining data literacy skills is during their years of schooling to become an educator, which studies have shown is effective in warranting some level of capacity regarding successful data-driven instruction (Dunlap & Piro, 2016; Mandinach & Gummer, 2013; Mandinach & Gummer, 2016), there is a progression of skills educators must attain to become data literate. First, teachers must be able to collect and organize the data; once those skills have been mastered, teachers can begin analyzing and summarizing the data to gather meaningful information (Coburn & Turner, 2011; InTASC, 2013; Mandinach & Gummer, 2013; Marsh et al., 2006). Even though these skills are seemingly simple, there are hidden obstacles. For instance, since there is a plethora of student data for educators to sift through, they must be able to ask meaningful questions that will narrow the type of data needed to contribute to improved student learning (Hamilton et al., 2009; Marsh et al., 2006; Means et al., 2011). While this is a key ingredient to data-driven decision-making, existing research has found both teachers and administrators are unable to effectively participate in data-driven inquiry (Choppin, 2002; Feldman & Tung, 2001; Ikemoto & Marsh, 2007; Kerr et al., 2006; Means et al., 2009; Suppovitz & Klein, 2003). Of course, asking the right questions to effectively inform instruction does not have to be an autonomous task.

Educators should be actively and collaboratively participating in data-driven inquiry in which they are considering the problem they are facing and what specific data would be helpful in addressing the defined issue (Lachat & Smith, 2005; Mandinach, 2012; Mandinach et al., 2006a). This also means educators must be mindful that not all data collected will be used as it depends on the problem at hand (Marsh et al., 2006). For example, a teacher might collect performance data over all assignments and assessments within one unit; however, not all collected data may be useful in determining the content students need additional help in comprehending. After educators have narrowed the data needed to make an informed decision, the data should be organized in a logical manner for easier analysis (Mandinach, 2012; Mandinach et al., 2006a). Teachers have reported they prefer this process to be completed for them as they have an easier time making sense of data if it is filtered and displayed in an easy-to-read format (Choppin, 2002; Marsh et al., 2006). While this may be true, Huguet et al. (2015) found that even though data reports are useful to teachers, provision of such reports does not aid in improving teachers' data literacy skills. Regardless, once data has been organized, educators can then extract information pertaining to their posed problem.

The process of transferring data into information is commonly referred to as analyzing, which can be very minimal and take little time, or the process can be in-depth and quite time-consuming (Mandinach et al., 2006a). Either way, educators must be able to take that information and construct a summarization for further use by aggregating and disaggregating the data to determine common trends or patterns (Mandinach, 2012; Mandinach et al., 2006a). Due to the variety of data available to teachers and the numerous sources used to collect the data (Marsh et al., 2006; Wayman et al., 2010), there is a need for a clear and concise summarization to efficiently and successfully synthesize and prioritize the information (Mandinach et al., 2006a). At this point in the conceptual framework, Marsh et al. (2006)

suggested educators may find they must begin anew within the data-driven decision-making framework by collecting more data to ensure they provide enough knowledge to guide their decisions.

Once all data has been synthesized, the next suggested step in the data-driven decision-making process involves educators transforming the data into actionable knowledge to make decisions for increased learner outcomes (Coburn & Turner, 2011; Dunlap & Piro, 2016; Mandinach, 2012; Mandinach et al., 2011; Mandinach et al., 2006a; Marsh et al., 2006). In turn, this knowledge is used by teachers to inform multiple types of decisions. For example, Marsh et al. (2006) found through a five-year study on data use in a dichotomy of educational institutions that such determinations made by educators can be categorized under two themes: using student data to identify and set goals for individual and group needs and using student data to modify and improve curriculum, instruction, and resources. It is important to note that although the common terminology of data-driven decision-making seemingly implies data is driving the decisions, Wayman et al. (2010) advised data is not driving decisions but rather should be seen as a tool being used for continuous improvement.

Nevertheless, implementation of the modified instruction should not be viewed as the final task of the data-driven decision-making conceptual framework. Educators must examine the effectiveness of the implemented strategies and potentially return to a component of the cyclical process to retrieve more data and information for further decision-making (Mandinach, 2012; Mandinach et al., 2011; Marsh et al., 2006). On the other hand, existing research has suggested there is a gap in knowledge pertaining to how to correctly interpret and use data to inform decisions, and such aspects within the data-driven decision-making process should be further investigated (Feldman & Tung, 2001; Kerr et al., 2006; Mandinach et al., 2011; Marsh et al., 2006). In either case, educators do not have to face these decisions independently as a collective action is one of the highly emphasized factors within the data-driven decision-making process.

**Factors Influencing Data-Driven Decision-Making**

Many factors contribute to whether educators participate in the data-driven decision-making process effectively and, in turn, data-driven instruction. However, existing research has suggested there are six common components that influence data-driven practices: collaborative inquiry, professional development, external sources, availability of quality data, technology, and time (Kerr et al., 2006; Marsh et al., 2006; Means et al., 2011; Wayman, 2010). Additionally, even though the significance of each factor varies from school to school regarding the level of implementation of the data-driven decision-making process, there have been reported advantages and disadvantages of each component. To begin, a prominent factor influencing data-driven decision-making is collaborative inquiry.

***Collaborative Inquiry***

Collaboration among educators of all levels as a school-wide practice is an important aspect to ensure effective data-driven decision-making (Coburn & Turner, 2011; Datnow et al., 2013; InTASC, 2013; Lachat & Smith, 2005; Park & Datnow, 2009; Wayman, 2010; Wayman & Stringfield, 2006). When educators work collectively, they create the opportunity for positive interaction, shared beliefs and contrasting views to be expressed, challenging and thoughtful questions to be posed, instructional strategies to be shared, and an overall atmosphere of a shared vision in terms of improving student achievement (Coburn & Turner, 2011; Datnow & Park, 2014; Datnow & Park, 2018; Datnow et al., 2013; Datnow et al., 2007; Halverson et al., 2007; Ingram et al., 2004; InTASC, 2013; Means et al., 2011; Wallace & Louden, 1994; Wayman et al., 2006). Even though the ample amount of characteristics expressed regarding the positive attributes of collaboration have been found across literature, the number of educators involved when working collectively remains to be agreed upon.

For instance, rather than secluding a team of educators to work on the data-driven decision-making process as some research has suggested (Halverson et al., 2007; Long et al., 2008), other studies have urged all educators to partake in the rigorous, complex data-driven decision-making process (Datnow et al., 2013; Mokhtari et al., 2007). In further contrast, Coburn and Turner (2011) found there is a delicate balance between too many stakeholders involved and not enough stakeholders involved – specifically in public schools. When differences of opinion and data interpretation occurred in terms of specific decisions, authoritative figures or educational leaders prevailed more often than teachers (Coburn & Turner, 2011). Conversely, shared decision-making has also been found to mitigate the leverage administrators have within their authoritative role and promote trust across educators (Hargreaves & Braun, 2013). Regardless of the conflicting views on educator involvement, there are positive elements of collaborative efforts.

Through a study of the impact of data-driven decision-making in urban elementary schools and urban high schools, Datnow et al. (2013) found teachers benefited greatly during collaboration as the time allowed for sharing of best practices for student engagement and learning and resulted in increased student achievement. Similarly, in a decade-long study of teachers across all grade levels, Datnow and Park (2018) found during collaborative inquiry that teachers often discussed the holistic picture of a student. This viewpoint includes not only academic data but also a student's home life, behavior, social and emotional skills, and demographics, to name a few. Thus, collaboration among teachers positively influences the effective use of data for informed decision-making to improve academic achievement.

Despite the mentioned positive qualities of collaborative inquiry, schools must be cognizant that not all teachers are accustomed to working collaboratively and may not welcome the practice as they might lack the skills to effectively and successfully participate in the collaborative inquiry process as well as not want to be involved (Friend & Cook, 1992; Jimerson & Wayman, 2015; Wallace & Louden, 1994). Not to mention, there have been recorded instances of collaboration efforts that proved to have a negative impact on effective data use. Halverson et al. (2007) found teacher discussions often focused on data of low-performing students in order to increase the percentage of students reaching proficiency. This practice compromises the purpose of data-driven decision-making in education, which is to increase learning and achievement for all students. For further support, Wallace and Louden (1994) reported from two case studies that not all educators embrace collective inquiry, and not all collaborations produce fruitful outcomes as there are specific qualities needed to promote successful collaborations.

Through cross-analyzing findings from the case studies, Wallace and Louden (1994) found such qualities include, but are not limited to, educators sharing their similarities and differences as it affords opportunities to grow and reflect on current practices, participating in effective communication, and exhibiting mutual trust and respect. Participants in the study who demonstrated these qualities were able to grow professionally in terms of pedagogical practices, which has a direct effect on student improvement (Wallace & Louden, 1994). In another study, Datnow et al. (2013) found teachers' positive attitude and full participation in collaboration over data use was due to administrators' guidance on setting norms and expectations for data discussions, providing structured time for collaboration, and modeling positive data use. In addition to pedagogical practices, collectively working together is beneficial for improving teacher data literacy.

Many researchers have reported most educators have a lack of knowledge and skills to effectively implement data-driven decision-making (Hamilton et al., 2009; Mandinach et al., 2008; Marsh et al., 2006; Mokhtari et al., 2007). However, evidence has suggested collaboration is a form of professional development as it allows educators to identify areas of content knowledge to strengthen, target, and share effective practices to improve others' instructional methods and allows data-driven decision-making to become a part of how a school system functions for continuous improvement rather than regarded as extra work (Coburn & Turner, 2011; Datnow et al., 2013; Marsh et al., 2006; Means et al., 2011; Means et al., 2009; Wayman et al., 2010). Furthermore, Datnow and Hubbard (2016) found collaboration proves successful in increasing teachers' ability to use data. Thus, collective spaces have been found to be a principal factor schools depend on to increase teachers' data literacy skills (Marsh, 2012; Means et al., 2010).

Collective spaces have also been found to indicate a school's level of improvement and student achievement. For instance, Hall and Ryan (2011) suggested one can identify how a school will perform under current accountability measures in terms of school improvement and student achievement based on the school system's collective capacity. After conducting a year-long study on the impact of external accountability on internal accountability in a middle school setting, Hall and Ryan (2011) found the demands of external accountability measures such as standardized testing and meeting AYP had a direct impact on the collective mindset of the staff. Teachers were found collaborating in terms of best practices, professional development, and effective data use, and the facilitation of such collaboration had a positive impact on the improvement of student learning. As can be seen, collaboration is seemingly a common theme for ensuring successful professional growth and student achievement as well as a major component influencing the data-driven decision-making process.

Along with collaborative inquiry, there is a system readily available for integrating data-driven decision-making in schools to assist in student achievement and school improvement; however, a one-size-fits-all approach is not realistic nor emphasized in any existing data-driven decision-making framework or how-to guide. Decisions will vary among districts, schools, and educators (Ikemoto & Marsh, 2007; Marsh et al., 2006; Pella, 2012). For example, while educational leaders (i.e., superintendent, principal, assistant principal) look at data for whole-district or whole-school analysis for school improvement, teachers look at data to inform instructional decisions or curriculum modifications for student improvement (Dunlap & Piro, 2016; Marsh et al., 2006). Also, the contrasting diversity among school systems will contribute to the types of data prominently used by schools to guide educational decisions (Marsh et al., 2006). Since there is a variety of differences in terms of data use across educators – not to mention schools – professional development is a key player in tailoring data-driven decision-making guidance for increased data literacy skills.

***Professional Development***

The degree to which teachers have been found to participate in data-driven instruction directly correlates to the support and training they receive in collecting, analyzing, and making sense of data as well as effectively participating in data-driven inquiry, which informs instruction for improved student learning (Jimerson & Wayman, 2015; Kerr et al., 2006; Wayman, 2010). Conversely, the professional development often found to be provided to teachers is structured around accessing and utilizing a data warehouse or data management system (Datnow & Hubbard, 2016; Jimerson & Wayman, 2015). There has been little evidence teachers are receiving the professional development they need to be data literate, such as learning how to synthesize and prioritize data to make instructional decisions for improved student learning (Datnow & Hubbard, 2016; Jimerson & Wayman, 2015; Kerr et al., 2006; Means et al., 2011). For instance, Jimerson and Wayman (2015) found teachers were not trained in the data-driven inquiry process or how to use data to drive instructional practices. Similarly, in a nation-wide survey of school districts, Means et al. (2010) found that although professional development was being provided to both teachers and administrators, it was fragmented information and did not provide well-rounded training to effectively participate in the data-driven decision-making process. Additionally, while professional development may come in the form of support regarding guidance on successful collaboration as well as how to navigate time management for successful integration of data-driven instruction on a daily basis (Wayman et al., 2010), these supports are merely assumed to mitigate the gap among teachers' capacity for data literacy as their worth depends on the expertise of the participating teachers (Datnow & Hubbard, 2016; Young, 2006). Nevertheless, teachers need more guidance for successful data use rather than the tedious and less informative routine of simply collecting, organizing, analyzing, and summarizing data.

The heart of the problem within data-driven decision-making is applying the knowledge within data-driven inquiry to make informed decisions – a component of the data-driven decision-making process that is rarely found within professional development conferences (Datnow & Hubbard, 2016; Mandinach & Gummer, 2013; Marsh et al., 2006). Even though workshops and training have been found to be a common form of support for teachers regarding data-driven decision-making, the value of these professional development activities leaves much to be desired (Marsh et al., 2006; Means et al., 2010). Despite these circumstances, professional development is a vital support for teachers to effectively participate in the data-driven decision-making process (Choppin, 2002; Feldman & Tung, 2001; Ikemoto & Marsh, 2007; Mandinach, 2012; Mandinach & Honey, 2008; Mason, 2002; Means et al., 2009; Suppovitz & Klein, 2003). By all means, however, there are also external support systems available for school use to begin improving teachers' data literacy skills.

### *External Sources*

For instance, teachers who felt competent in participating in data-driven instruction reported support from their administrators in the form of outside sources such as data-focused professional development, access to a data coach, access to faculty with outstanding data analysis skills, and prepared reports of student data that were easily readable and could be interpreted with ease (Datnow et al., 2007; Feldman & Tung, 2001; Kerr et al., 2006; Marsh et al., 2006). Providing outside support such as a data coach is also a strategy that can build teacher capacity in effectively engaging in data use and should be considered a worthwhile investment by administrators (Datnow et al., 2007; Feldman &

Tung, 2001; Kerr et al., 2006; Suppovitz & Klein, 2003). For instance, in an experimental study, Gleason et al. (2019) found schools in the treatment group who were assigned a data coach were able to build a culture of data use as part of everyday pedagogical practices compared to schools in the control group who did not receive support. On the other hand, specific guidelines must be adhered to in order for a data coach to have a successful impact on improving teachers' use of data.

For example, while data coaches are found to be beneficial in facilitating teachers' use of data and developing data literacy skills (Lachat & Smith, 2005), they must be able to model data use, provide training on data management systems, exhibit interpersonal skills, and demonstrate knowledge in not only pedagogical practices but also in content areas such as math, English, and science, to name a few (Huguet et al., 2015; Marsh et al., 2015). Moreover, schools should be weary of becoming dependent on a data coach as this often leads to teachers not developing data literacy skills for independent use, and data coaches tend to be made unavailable to teachers when their skills are needed elsewhere for school improvement purposes (Datnow & Hubbard, 2016; Hamilton et al., 2009). Another important guideline is ensuring the data coach is frequently interacting with teachers and providing learning opportunities. Huguet et al. (2015) found teachers who were not able to use the data to inform their instruction were under the tutelage of a data coach who did not provide a wide range of instruction on a regular basis. Given these circumstances, the worth of a data coach is also inextricably tied to the availability of quality data for teacher use.

***Availability of Quality Data***

To begin, as previously discussed, federal and state educational policies have included within their literature that schools must show student growth by using student data to meet accountability requirements (ESSA, 2015; NCLB, 2002). However, educators have expressed their concerns regarding the difficulty of using student test scores from state-mandated assessments to inform and differentiate instruction to close the achievement gap and improve student learning because test score results are not delivered in a timely manner (Coburn & Turner, 2011; Hamilton et al., 2009; Hargreaves & Braun, 2013; Ikemoto & Marsh, 2007; Kerr et al., 2006; Mandinach et al., 2011; Marsh et al., 2006). Additionally, educators suggest state test scores are not aligned to content standards, which drive daily instruction (Kerr et al., 2006; Mandinach et al., 2011; Suppovitz & Klein, 2003). Although there is a plethora of other student data teachers can use to inform instruction, the data must be easily accessible for teacher use. With this in mind, through examination of a multitude of diverse educational institutions, Marsh et al. (2006) found that the timeliness of receiving quality data had a tremendous influence on the data-driven decision-making process as well as the accessibility of quality data.

Similarly, after a two-year study of language arts middle school teachers participating in an intense lesson study, which involved data-driven decision-making, Pella (2012) found test score data was rarely used to inform instruction. The data provided little insight to how instruction could be modified to improve learner outcomes and gave broad information in terms of student skills, which was not helpful in differentiating instruction for individual needs (Pella, 2012). Moreover, the participants expressed valuable and quality data correlated with observations made in the classroom, examination of student completed formative assessments that were created collectively by the teachers, and qualitative data in terms of the culture of the families and the community (Pella, 2012). Although this may be true, lack of access to quality data for educator use had been reported by multiple studies (Choppin, 2002; Coburn & Turner, 2011; Ikemoto & Marsh, 2007; Kerr et al., 2006; Marsh et al., 2006; Pella, 2012; Suppovitz & Klein, 2003). However, this perceived lack of quality does not obstruct teachers' use of the data as they are still trying to meet the demands of federal and state accountability (Marsh et al., 2006). With this in mind, systems must be in place to aid educators in accessing student data for informed decision-making.

***Technology***

In response to this phenomenon, technology has increased its role in education by creating data management systems to support the data-driven decision-making process and alleviate a portion of the burden from teachers in terms of collecting and organizing a plethora of quantitative and qualitative student-based data (Coburn & Turner, 2011; Gamble-Risley, 2006; Long et al., 2008; Mandinach et al, 2012; Marsh et al., 2006; Means et al., 2009). Additionally, data management systems have been found to support collaborative efforts and effective instructional decision-making as they provide access to multiple data points to support the data-driven inquiry process and guide informed decision-making (Halverson et al., 2007; Hamilton et al., 2009; Lachat & Smith, 2005; Wayman, 2005; Wayman et al., 2006; Young, 2006). Data management systems are also a key component in developing a data-driven decision-making culture within a school (Hamilton et al., 2009; Wayman & Stringfield, 2006). Since data use has different appearances at all levels within education as the decisions vary at each level, data management systems have also presented the opportunity for all educators to create and organize data reports to analyze information they deem valuable to make informed decisions.

In contrast to the expressed benefits, teachers have reported data management systems as a hindrance toward their use of data for multiple reasons. Such obstacles include not having the proper training to efficiently navigate the systems (Mandinach et al., 2006b; Means et al., 2009); having difficulty accessing and manipulating useful data (Kerr et al., 2006; Marsh et al., 2006; Means et al., 2009; Wayman, 2010); having to access multiple data management systems for useful data regarding any individual student, which is a cumbersome process (Dunn et al., 2013b; Marsh et al., 2006; Wayman et al., 2010); and when data is easily accessible, it is outdated and often strictly test related (Means et al., 2009). Therefore, a data management system is needed that will not only provide numerous forms of data – numerical and non-numerical – for a holistic picture of any given student but will also organize, analyze, and summarize the information for teacher use to inform instruction for improved student learning (Hamilton et al., 2009; Mandinach et al., 2006b; Wayman, 2005). This leads to a point often overlooked: educators must be provided the time to not only effectively utilize the available data for instructional decision-making but also time to implement the established instructional modifications for improved student learning.

***Time***

Multiple studies have suggested lack of instructional time is a key factor in teachers refraining from participating in the data-driven decision-making process (Coburn & Turner, 2011; Marsh et al., 2006, Means et al., 2009). Teachers need to be given flexibility to modify curriculum in accordance with findings from data rather than being forced to follow a pacing guide (Datnow et al., 2013; Gamble-Risley, 2007; Kerr et al., 2006). For further support, InTASC (2013) requires teachers to assess student performance data in all aspects and adjust instruction in accordance to weaknesses and strengths found to improve overall learner outcomes. Hence, enforcing a mandatory pacing guide with no regard to student learning is detrimental to not only effective data use but also student achievement.

Additionally, teachers have reported needing time to simply engage in data use as well as make sense of the data to have the opportunity to make informed decisions regarding their instructional practices (Ikemoto & Marsh, 2007; Ingram et al., 2004; Mandinach, 2012; Means et al., 2009; U.S. Department of Education, 2008). Thus, administrators should consider either implementing time within the school day for educators to use data to inform instruction or adopting an educational reform that weaves data use and instructional pacing to provide the means for data-driven instruction (Feldman & Tung, 2001; Ingram et al., 2004; Kerr et al., 2006). However, these are only a couple suggested strategies administrators should consider integrating in their school. The administrators' role in facilitating successful data use among teachers is much more complex.

**Administrator Role in Data-Driven Decision-Making**

Administrators are key players in promoting the data-driven decision-making process as they set the tone for data use and should be actively fostering a culture of data-driven decision-making in their schools, which has been reported as an effective strategy in increasing staff buy-in – an important factor for successful implementation of any school improvement plan (Datnow & Hubbard, 2016; Datnow & Park, 2014; Datnow et al., 2007; Halverson et al., 2007; Ingram et al., 2004; Long et al., 2008; Mandinach & Honey, 2008; Mandinach et al., 2006b; Marsh, 2012; Marsh et al., 2006; Schildkamp & Poortman, 2015; Wayman et al., 2010). Creating such a culture results in teachers being more open to reflecting on their practice, participating in productive dialogue and collaborative inquiry, embracing a method of instruction that will enhance their pedagogical practices, and having a shared understanding of expectations for data use to mitigates false assumptions (Datnow & Hubbard, 2016; Datnow et al., 2007; Feldman & Tung, 2001; Wayman et al., 2006). For instance, Ikemoto and Marsh (2007) found administrators who projected a strong vision regarding data-driven decision-making and provided teachers with supports such as professional development and time for collaborative inquiry encultured a positive environment for data use that teachers embraced. Therefore, it is vital administrators engage in and model effective data use in order to promote faculty data use.

Administrators should also develop a school-wide vision and goal regarding data-driven decision-making. Such actions have resulted in setting clear and concise expectations, ensuring teachers receive the time to participate in collective inquiry, and providing professional development that focuses on data use (Datnow et al., 2007; Hamilton et al., 2009; Lachat & Smith, 2005; Mandinach, 2012; Marsh et al., 2006; Means et al., 2009; Suppovitz & Klein, 2003; Wayman et al., 2010; Young, 2006). It is also important to note that administrators’ development of a school-wide vision and facilitation of data use has been found to provide equitable learning opportunities for all students as such actions include students' social environment, culture, and experiences (Datnow & Park, 2018; Garner et al., 2017). These considerations are important factors in relation to academic achievement. Additionally, since data use is a theme for supporting effective decision-making, research has suggested school-wide visions and goals must be reviewed over time to ensure they continue to create an environment that strategically frames effective data use for improved student learning (Datnow et al., 2007; Feldman & Tung, 2001; Young, 2006). As these tasks are seemingly an incredible feat to undertake, there is evidence that administrators require more training to develop a culture of data use.

For instance, despite the need for a district-wide vision regarding data-driven decision-making practices as well as administrators modeling such behavior to provide strong leadership and guidance among teachers (Choppin, 2002; Feldman & Tung, 2001; Ikemoto & Marsh, 2007; Kerr et al., 2006; Lachat & Smith, 2005; Long et al., 2008), research has shown principals are not properly trained to implement these qualities of leadership, which results in a disconnection between the goal of data-driven instruction and the reality of teacher data use (Hamilton et al., 2009; Wayman et al., 2010). In particular, one study found principals were often ill-equipped to aid teachers in effective data use and rarely took part in collaboration efforts to discuss student data and guide decisions (Wayman et al., 2010). On the other hand, Means et al. (2009) found administrator leadership may not be as strongly linked to teachers' participation in data-driven decision-making practices as more recent studies have shown the presence of other school leaders.

For instance, such studies have reported the use of data coaches to work with teachers on data use and effectively participating in the data-driven decision-making process (Huguet et al., 2015; Lachat & Smith, 2005; Marsh et al., 2015). Regardless of the level of support, such efforts from multiple leadership roles to increase teachers' data literacy skills have been found to be wholly insufficient as teachers receive little to no training in data use during their years learning to become an educator

(Mandinach & Gummer, 2013; Mandinach et al., 2011). Furthermore, while there are other supports that have been found to aid teachers in data use such as professional development, there is compelling evidence that administrators tend to attach negative connotations to teacher data use.

To explain, teachers have been found to either be supported through professional development and collaboration time to collect, analyze, and use data to inform instruction for improved student learning or are regulated in their data-use practices in terms of focusing on accountability measures and continuous school improvement demands (Datnow & Park, 2018). Additionally, while the data-driven decision-making conceptual framework provides the opportunity for interventions for each of the six required skills for effective data use – collecting, organizing, analyzing, summarizing, synthesizing, and prioritizing – teachers were found to be reluctant to participate in data-use interventions for fear their data use skills would be held against them for evaluative purposes (Marsh, 2012; Means et al., 2010). In support, Schildkamp and Poortman's (2015) study found principals were using data to put teachers at fault, which resulted in not only poor modeling of effective data use but also humiliation and wariness on the teachers' behalf. Thus, trust is a vital component on influencing teachers' beliefs regarding data use (Tschannen-Moran & Hoy, 2001). All things considered, regardless of the role of the administrator in developing a positive culture for data use, teachers must be willing to participate in and embrace the data-driven decision-making process to ensure success.

## Teachers' Perceptions of Data-Driven Instruction

### *Attitudes*

Existing literature has provided a wide array of teacher attitudes and beliefs regarding data-driven instruction. However, it is important to note these attitudes and beliefs are often in discordance with data-driven decision-making and are frequently intertwined with federal and state accountability policies (Datnow & Hubbard, 2016; Ingram et al., 2004). Since accountability measures require teachers to use data to improve student learning, some teachers have conveyed they feel data use directly correlates to accountability policies, and they partook as a way to persevere through the stringent requirements (Datnow & Park, 2014; Mandinach et al., 2006a). For instance, over a several year study of three school districts' participation in data-informed decision-making and the resulting processes and outcomes, Datnow and Park (2014) found teachers who projected negative attitudes about data use actively linked the activity to No Child Left Behind. Additionally, the teachers in this study who embraced data use and welcomed the positive aspects data provided in improving student learning felt the data did not provide a holistic picture to efficiently increase student academic achievement (Datnow & Park, 2014). Similarly, Mandinach et al.'s (2006b) study indicated a group of teachers viewed the accountability measures regarding data use as another cycle of requirements that will inevitably fade with time. Even though attitudes such as these are detrimental to the effective use of data to inform instruction, the inharmonious use of data in regards to the data-driven decision-making process does not end with federal and state accountability policies.

For instance, Schildkamp and Kuiper (2010) found the lack of data use was due to teachers' beliefs that improving student learning was not dependent on data. Instead, student achievement was dependent on whether a student was well-behaved or ill-behaved. Additionally, the amount of data used to inform instruction is questionable as teachers often chose to overlook student test data and based their decisions on personally created performance metrics and curriculum to determine student proficiency as accountability measures did not allow for flexibility to alter instruction or content (Ingram et al., 2004; Marsh et al., 2006). Not to mention, existing research has found teachers' perceived lack of quality data has negatively affected their use of data (Choppin, 2002; Feldman & Tung, 2001; Ingram et al., 2004; Kerr et al., 2006). Despite these outwardly negative attitudes, there are teachers who exhibit positive attitudes towards data use.

To enumerate, Datnow and Park's (2014) study reported that even though teachers found some of the data provided information they previously surmised from their professional judgement – a powerful tool in itself (Wayman, 2010) – other data was seemingly relevant and shed light on measures to take to improve student achievement. For example, teachers have been found to often focus on low-performing students and instructional practices to improve their learning. Instead, teachers in the previously mentioned study found through analyzing student data that their advanced students were increasingly declining in academic achievement – a result that would not have been acknowledged had teachers not embraced data use (Datnow & Park, 2014). Altogether, teachers found data use was beneficial in targeting student weaknesses and strengths as well as informing instructional modification (Datnow & Park, 2014). However, ensuring all teachers obtain a positive attitude toward data use is a feat not easily attained without focusing capacity building efforts on teachers' beliefs.

***Competency/Efficacy***

Bandura (1997) describes efficacy as a belief that an individual encompasses through self-reflection regarding skills or a capacity level needed to successfully complete any given task. In terms of education and data-driven decision-making, a teacher's sense of efficacy is comprised of their beliefs that they have the skill set and capacity to participate in the data-driven decision-making process to improve student academic achievement regardless of a student's skill level (Bandura, 1977; Dunn et al., 2013a; Dunn et al., 2013b; Tschannen-Moran & Hoy, 2001). Furthermore, since a teacher's sense of efficacy is directly correlated to their emotional state and thinking process, it has a significant impact on their effort, motivation, and behavior towards teaching as well as their ability to participate in the data-driven decision-making process (Bandura, 1993; Bandura, 1997; Datnow & Hubbard, 2016; Dunn et al., 2013a; Dunn et al., 2013b; Tschannen-Moran & Hoy, 2001; Woolfolk et al., 1990). To clarify, if a teacher believes he/she has the capability to successfully accomplish a task such as using data to inform instruction, then that task is more likely to be approached in a positive manner.

Existing research has indicated teachers with a strong sense of self-efficacy in terms of teaching are more likely to embrace data-driven decision-making practices (Dunn et al., 2013b). However, existing evidence has also suggested teachers' low levels of confidence and self-efficacy have become a prominent obstacle for schools when integrating data-driven decision-making practices as teachers experience strong bouts of anxiety related to the skills needed for successful data-driven decision-making – a factor that significantly influences the decline of teacher efficacy (Bandura, 1977; Bandura, 1997; Dunn et al., 2013b; U.S. Department of Education, 2008; Wayman, 2005). In a study conducted by Dunn et al. (2013b), teachers' anxiety levels and self-efficacy regarding data-driven decision-making were found to be inversely proportional – as anxiety levels decreased, teachers' sense of efficacy increased, and as anxiety levels increased, teachers' sense of efficacy decreased. Additionally, teachers who have reported a low sense of self-efficacy regarding improving student achievement lacked buy-in to the data-driven decision-making process, which is a vital component for meaningful and effective data-driven decision-making (Ingram et al., 2004). This lack of buy-in is also attributed to teachers' perceived competency in relation to the skills within the data-driven decision-making process.

As discussed, data-driven decision-making is a labor-intensive and time-consuming process, and not only is the immense amount of data available for teacher use overwhelming but also the skills needed to successfully make informed decisions are quite daunting (Datnow & Hubbard, 2016; Marsh et al., 2006). For instance, teachers often reported feeling incapable of actively participating in data-driven inquiry as well as simply using data to inform instruction (Means et al., 2009; Woolfolk et al., 1990), feeling hindered when trying to access student data (Kerr et al., 2006), and feeling challenged by the minimal time allotted to both participate in the data-driven instruction process and teach the required content (Ingram et al., 2004). Not to mention, teachers often take data personally due to their close involvement and impact on students' lives and future endeavors, which has an effect on teachers' perceived competence and efficacy in data use (Datnow & Park, 2014). With this in mind, competency in using data to drive instruction was reported when teachers had access to professional development, were trained with the skill set that enables data use, and had access to filtered data for easy interpretation (Marsh et al., 2006). Of course, as previously noted, the quality of professional development pertaining to data-driven decision-making leaves much to be desired.

***Professional Development***

Even when training sessions over the data-driven decision-making process are conducted in a holistic approach, these sessions often disregard teachers' beliefs about data use (Datnow & Hubbard, 2016; Hamilton et al., 2009). Furthermore, teachers who reported feeling incompetent in using data to drive instruction also reported lack of support from administrators regarding professional development that focused on data use (Kerr et al., 2006). This lack of support and quality training may be attributed to district-wide collaboration efforts. For instance, in a three-year study of how three school districts use data, it was summarized that teachers experienced a sense of success and accomplishment when working together in examining data (Wayman et al., 2010). Similarly, Lachat and Smith's (2005) study found collaborative inquiry provided the space and time for teachers' beliefs to be addressed in terms of data-driven decision-making and time to focus on the factors that might have an impact on improving student learning.

As previously mentioned, collaboration is a form of professional development, and both aspects have been found to significantly enhance teachers' capacity to participate in the data-driven decision-making process and effectively use data to inform instruction (Means et al., 2011; Means et al., 2010). While both collaboration and professional development are seemingly broad in application, there are specific suggestions regarding facilitation and content to build teachers' capacity for data use. For example, Suppovitz and Klein (2003) suggested that building teacher confidence in utilizing data management systems directly correlated with teacher buy-in of data use, which resulted in daily participation in data-driven instruction. In another study, Dunn et al. (2013b) found there was a clear distinction between teachers' perceived confidence in using data to inform instruction compared to analyzing, summarizing, and synthesizing data. To improve the quality of professional development, schools should take such factors into consideration.

Moreover, teachers have expressed that collecting and organizing data is not the issue at hand, and while they do not necessarily want to be absent from their classroom, they have conveyed the desire to be trained in analyzing, summarizing, synthesizing, and prioritizing data (Datnow & Park, 2014; U.S. Department of Education, 2008; Wayman et al., 2010). These findings are essential considering current literature tends to focus on teachers' overall lack of capacity to participate in the data-driven decision-making process rather than providing a distinction regarding specific skills teachers need help attaining for successful data use (Mandinach et al., 2006b; Means et al., 2011; Wayman et al., 2006). Thus, the quality and targeted relevance of the professional development and capacity building efforts is vital to ensure teachers' time away from their classroom is worthwhile.

Overall, in light of what is known regarding teachers' perceptions of data-driven instruction, it is important to note a significant amount of the knowledge was contributed by studies conducted in urban school settings (e.g., Datnow & Park, 2014; Feldman & Tung, 2001; Kerr et al., 2006; Marsh et al., 2006). Educational research has often failed to address the needs and culture of rural schools as results from urban-based research is not necessarily applicable in rural education (DeYoung, 1987; Sherwood, 2000). Furthermore, the amount of research focused in rural school settings is astoundingly limited (Arnold et al., 2005; DeYoung, 1987; Sherwood, 2000). This lack of research and information regarding rural schools is a prevailing hindrance that will ensure rural schools continue to face existing challenges.

**Rural Education**

Rural schools face similar obstacles as urban schools regarding increasing student achievement as not only are they required to follow the same guidelines set by federal and state educational law but also the student population is becoming more diverse as years progress, which can have a detrimental impact on rural schools regarding federal aid through adequate yearly progress (Arnold et al., 2005; Brenner, 2016). For instance, in a small rural school, a test score from any one student identifying within a minority subgroup has a drastic impact on whether said subgroup meets the targeted proficiency levels deemed necessary to receive federal education aid. Rural school systems also face a unique set of challenges such as retaining highly qualified teachers, having significantly limited resources for internal support, and having limited financial support (AASA, The School Superintendents Association, 2017; Arnold et al., 2005). These obstacles not only have an impact on meeting the demands of ESSA but also heighten Mandinach's (2012) suggestion that an already existing challenge in increasing teachers' capacity for data use is a lack of funding for resources such as professional development, time, and collaboration. Furthermore, little is known regarding data-driven decision-making within rural education, which may be an additional challenge in ensuring continuous school improvement and increased student learning.

Research in rural education has been deemed low-quality and highly sparse as there is a limited amount of funding available to conduct research in a rural educational setting, and such research is seemingly discouraged (Arnold et al., 2005; DeYoung, 1987; Sherwood, 2000). Additionally, the studies that have been conducted in a rural educational setting do not provide a sufficient amount of information regarding any particular topic for an educational leader to rely on when making an informed decision (Arnold et al., 2005). Thus, there is a need for a plethora of rural educational research, which includes data-driven decision-making in rural schools. Correspondingly, the National Rural Education Association (2020) has provided a research agenda for 2016-2021 with 10 priority research topics – one of which is teachers' participation in data-driven decision-making to improve student achievement. These topics were created to be broad in nature so that researchers have the opportunity to narrow their inquiries and begin building a healthy body of literature pertaining to each topic (National Rural Education Association [NREA], 2020).

**Summary**

Data-driven decision-making is a fundamental component for continuous school improvement and improving student academic achievement across the nation (Datnow & Park, 2014; Gamble-Risley, 2006; Marsh et al., 2006). However, teachers' beliefs about data use must be addressed and nurtured to ensure they not only willingly embrace the process but also become fluent in collecting, organizing, analyzing, summarizing, synthesizing, and prioritizing data to inform instruction for enhanced student learning. As suggested, a school district has the opportunity to build teachers' capacity for data use by providing professional development, time for collaborative inquiry, external supports such as a data coach, technology, and simply time to interact with and interpret data (Kerr et al., 2006, Marsh et al., 2006; Means et al., 2011; Wayman, 2010). With this in mind, little research has provided insight to teachers' attitudes, beliefs, and ability to use data; thus, limited evidence is available for schools to make guided decisions to build teachers' capacity efforts – specifically in rural education.

When observing existing research holistically, it has explored and examined the ways in which teachers engage in data-driven instruction regarding the various types of data being used by educators, factors that influence educators' use of data, and the growing need for support systems in schools for data-literacy development (Abrams et al., 2016; Datnow & Hubbard, 2016; Dunlap & Piro, 2016;

Mandinach & Gummer, 2013; Marsh et al., 2006; Militello et al., 2013). For example, these studies have found educators do not have the necessary components of data-driven decision-making available to make informed decisions for data-driven instruction such as access to data; time to collect, analyze, and interpret data; or the data-literacy skills needed for effective use of data.

In contrast, little research has been conducted on factors that influence teachers' sense of efficacy and competence in using student data to inform instruction and how schools are addressing the prevalent issue of educators acquiring data-literacy skills (Choppin, 2002; Dunn et al., 2013b; Mandinach & Gummer, 2012; Mandinach & Gummer, 2013; Mandinach & Gummer, 2016; Wayman, 2005), what methods of interventions are successful in building teachers' capacity to use data (Datnow & Hubbard, 2016), the specific data types most useful to teachers of differing subjects, or the preparation procedures and support systems teachers need for successful data-driven instruction (Abrams et al., 2016; Datnow et al., 2013; Mandinach & Gummer, 2013; Marsh et al., 2006; Wayman & Stringfield, 2006). Additionally, while studies have been conducted on educator data use, such studies have not investigated a population involving a large sample of schools with similar demographics (Kerr et al., 2006; Militello et al., 2013). However, these future research needs are based off current research, which is predominately grounded in urban school settings.

Little is known regarding any facet of data-driven decision-making in rural education, which has been deemed a top 10 priority for future rural educational research (NREA, 2020). Additionally, despite the amount of time schools have invested in teachers' engagement in data-driven decision-making such as professional development, data management systems, and external sources, research has continued to suggest teachers are unable to effectively use data to inform instruction (Dunn et al., 2013b; U.S. Department of Education, 2008). Therefore, the researcher intends to address this major gap of knowledge in the field of education by examining rural public high school teachers' perceptions of data-driven instruction in Indiana.

# Chapter 3: Methodology

The current emphasis in K-12 education in the United States is on the use of student data to inform instruction for increased student achievement. Under federal educational legislation such as the Every Student Succeeds Act (ESSA) and state educational policies such as the Interstate Teaching Assessment and Support Consortium (InTASC) and the Professional Standards for Educational Leaders (PSEL), teachers are required to be able to use a variety of student data with fidelity to improve student learning and achievement (ESSA, 2015; InTASC, 2013; NPBEA, 2015). Thus, there is an ever apparent need to ensure educators have the capacity to use student data to inform their pedagogical practices.

Existing research has provided a wealth of knowledge regarding data-driven decision-making in urban schools and data-driven instruction practices in the classroom (Abrams et al., 2016, Datnow & Hubbard, 2016; Dunlap & Piro, 2016; Mandinach & Gummer, 2013; Marsh et al., 2006). However, there is a lack of research in terms of data-driven decision-making in rural schools such as rural teachers' perceptions of using student data to drive instruction (Arnold et al., 2005; NREA 2020). Therefore, this study contributed to existing literature regarding data-driven decision-making in terms of rural teachers' perceptions in using student data to drive instruction in Indiana.

## Purpose

The purpose of this quantitative study was to examine rural public high school teachers' perceptions of data-driven instruction in Indiana. Specifically, this study identified rural public high school teachers' perceptions in terms of the types of data they used to support instruction, their attitudes toward data use, their competence in using data to drive instruction, and the support systems that help or hinder their ability participate in data-driven instruction effectively. Additionally, this study examined possible relationships among demographic variables of rural public high school teachers and their corresponding perceptions of data-driven instruction.

**Research Questions**

The research questions that follow guided this study and aided in examining rural public high school teachers' perceptions in using student data to drive instruction.

1. What types of data do rural public high school teachers use to drive their instruction?
2. What are rural public high school teachers' perceptions of their attitude toward using data to drive instruction?
3. What are rural public high school teachers' perceptions of their competence in using data to drive instruction?
4. What are rural public high school teachers' perceptions regarding supports and barriers to using data to drive their instruction?
5. To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict state data is used to drive instruction?
6. To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict periodic data is used to drive instruction?
7. To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict local data is used to drive instruction?
8. To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict personal data is used to drive instruction?

9. To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict attitude toward using data to drive instruction?
10. To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict competence in using data to drive instruction?

**Instrumentation**

The purpose of the survey instrument that was used for this study was to measure teachers' perceptions of data-driven instruction. The survey provided quantitative data pertaining to teachers' use of specific student data to drive instruction, their attitude toward using data to influence their instructional practices, their perceptions of their data literacy skills, and their perceptions of support systems in place that help or hinder their ability to participate in data-driven instruction effectively. The survey, which is known as the Teacher Data Use Survey: Teacher Version, was developed at the Institute of Education Sciences by Wayman et al. (2016a). With approval from the authors, the survey was slightly modified to include demographic data to fit the needs of the researcher. See Appendix A for a copy of the survey instrument.

Despite the scales slightly differing among the various components addressed within the survey, content validity is assured through the triangulation of the use of content experts, interviews regarding creating scales, and the use of scales from a comparable, unpublished survey known as the Survey of Educator Data Use (Wayman et al., 2016a). Additionally, the results of the pilot study of the Teacher Data Use Survey: Teacher Version indicate that the survey can be considered reliable with a Cronbach's alpha value greater than .8 for all survey scale reliabilities (Wayman et al., 2016a). Due to the assured reliability and validity of the survey instrument, the survey was distributed to the targeted population.

At the onset of the survey, respondents answered questions pertaining to demographic information – gender, age, years of teaching experience, subject taught, and highest level of education attained. This information aided in answering research questions five, six, seven, eight, nine, and ten as well as provided descriptive statistics for a better understanding of the participating population. Additionally, it is important to note that the questions regarding years of teaching experience and subject taught specifically refer to the teachers' current institution. This eliminated responses that may include information about a population aside from the intended study.

The first component of the survey focused on the specific types of data teachers use to inform their instruction, which refers to research question one, five, six, seven, and eight. The first question of the survey was dichotomous in the form of yes or no that asked whether each type of data (state, periodic, local, personal, and other) was available to the teacher. The second survey question, which used a Likert scale in terms of frequency, referred to whether teachers used said data to help plan for instruction to meet student learning needs. These two questions determined which portions of the remainder of the survey the teachers completed. For example, if a teacher responded that state data was not available to him/her or that he/she did not use state data to inform instruction, then there was no need for the respective teacher to respond to questions pertaining solely to state data. The final question within this portion of the survey referred to the usefulness of each type of data to the teacher's practice. This question used a Likert scale in terms of intensity where participants chose from *Not at all*, *Slightly useful*, *Useful*, *Very useful*, or *No opinion*. All Likert scale items were coded with a numerical value and analyzed using descriptive statistics.

The second component of the survey focused on how teachers used each type of data and how they were supported in the use of data, which provided supplemental information for research question one. Each statement for periodic, local, and personal data used a Likert scale in terms of frequency where respondents chose from the following: *Less than once a month*, *Once or twice a month*, *Weekly*, *A few times a week*, or *Not at all*. In contrast, because of the limited amount of state data available, the frequency measures for these same statements in terms of state data were as follows: *One or two times a year*, *A few times a year*, *Monthly*, *Weekly*, or *Not at all*.

Examples of these statements include: In a typical school year, how often do you do the following: (a) use state data to identify instructional content to use in class; (b) use state data to tailor instruction to individual student learning needs; (c) use state data to develop recommendations for additional instructional support; (d) use state data to form small groups of students for targeted instruction; (e) meet with a specialist (i.e., instructional coach or data coach) about state data; and (f) meet with another teacher about state data. All Likert scale items were coded with a numerical value and analyzed using descriptive statistics.

The third component of the survey focused on teachers' perceptions of their attitude toward using data to drive instruction as well as the impact their attitude had on student learning, which refers to research question two and nine. Each statement used a Likert scale in terms of intensity where respondents chose from the following: *Strongly disagree*, *Disagree*, *Agree*, *Strongly agree*, or *No opinion*. Examples of these statements include the following: (a) data help teachers plan instruction; (b) data offer information about students that was not already known; (c) data help teachers know what concepts students are learning; (d) students benefit when teacher instruction is informed by data; and (e) I think it is important to use data to inform education practice. All Likert scale items were coded with a numerical value and analyzed using descriptive statistics.

The fourth component of the survey focused on teachers' perceptions of their data literacy skills and ability to effectively participate in data-driven instruction, which referred to research question three and ten. Each statement used a Likert scale in terms of intensity where respondents chose from the following: *Strongly disagree*, *Disagree*, *Agree*, *Strongly agree*, or *No opinion*. Examples of these statements include the following: (a) I am good at using data to diagnose student learning needs; (b) I am good at adjusting instruction based on data; (c) I am good at using data to plan lessons; and (d) I am good at using data to set student learning goals. All Likert scale items were coded with a numerical value and analyzed using descriptive statistics

The fifth and final component of the survey focused on teachers' perceptions of the support systems that either help or hinder their ability to use data to inform their instruction and improve student learning, which addressed the fourth research question. These questions align to existing research regarding the vital components needed in a school district for effective and successful data-driven decision-making. Such components include technology and data warehouses for teacher access to data (Coburn & Turner, 2011; Gamble-Risley, 2006; Marsh et al., 2006), collaborative inquiry among all stakeholders concerning improved student learning (Coburn & Turner, 2011; Datnow et al., 2013; Gamble-Risley, 2006; InTASC, 2013; Marsh et al., 2006; Mokhtari et al., 2007), administrator support, and professional development regarding data-driven instruction (Coburn & Turner, 2011; Datnow et al., 2013; Marsh et al., 2006).

Most of the fifth component of the survey used a Likert scale in terms of intensity where respondents chose from the following: *Strongly disagree*, *Disagree*, *Agree*, *Strongly agree*, or *No opinion*. However, because of the significant amount of existing research on the importance of collaborative inquiry in the data-driven decision-making process, an additional section of collaborative efforts in using data had been included in the survey. This section used a Likert scale in terms of frequency where respondents chose from the following: *Less than once a month*, *Once or twice a month*, *Weekly*, *A few times a week*, or *Not at all*.

Example statements of teachers' perceptions of support systems include the following: (a) My principal or assistant principal(s) has made sure teachers have plenty of training for data use; (b) My principal or assistant principal(s) creates protected time for using data; (c) The computer systems in my district provide me access to lots of data; (d) The computer systems in my district generate displays (i.e., reports, graphs, tables) that are useful to me; (e) My principal or assistant principal(s) fosters a trusting environment for discussing data in teams; and (f) We [collaborative teams] use data to make links between instruction and student outcomes. All Likert scale items were coded with a numerical value and analyzed using descriptive statistics.

**Participants**

The population of this study consisted of rural public high school teachers in Indiana; thus, a purposive and convenience sampling was used to recruit participants. To identify the appropriate schools, a list was accessed from the Indiana Department Education, which defined rural by using United States Census locale codes. Once the list was accessible, the researcher contacted each rural public school district in Indiana and its respective high school administration office to obtain permission to distribute the survey. After permission was granted, the researcher sent the survey to all teachers within the high school of each participating school district. The participants varied in gender, age, years of teaching experience, subject taught, and highest level of education attained. In total, the goal was to obtain at least 30 responses.

The intention of using the proposed population was to address the gap of knowledge pertaining to a large sample of schools with similar demographics and teachers' perceptions of data-driven instruction. Additionally, the proposed population provided the opportunity to gain an understanding of the data-driven decision-making process in schools of similar demographics in terms of community as well as federal and state educational funding. Not to mention, the intended research contributed to the already designated high priority need of knowledge regarding data-driven decision-making in a rural educational setting (NREA, 2020). Overall, while the participating schools differed drastically in terms of socioeconomic status and ethnicity, the overarching commonalities within a rural community provided the opportunity for analysis of a cohesive group, and, therefore, an analysis of how rural teachers meet the demands of using student data to drive instruction with fidelity for improved student achievement.

**Research Design**

The research approach of this study was quantitative as the survey provided the researcher with quantitative data to aid in answering the research questions. The study had concurrent timing as all of the data was collected at once. Additionally, the researcher investigated the relationship among multiple quantitative variables where the independent variable was not manipulated. Due to these characteristics, the design of the study was a correlational research design (Price et al., 2017). Using a correlational research design allowed the researcher to examine the statistical relationship among teacher characteristics (gender, age, years of teaching experience, subject taught, and level of education) and the types of data used to drive instruction, teachers' attitude toward using data to drive instruction, and teachers' competence in using data to drive instruction. Thus, descriptive statistics were used to answer research questions one, two, three, and four, and a stepwise multiple regression analysis was applied to answer research questions five, six, seven, eight, nine, and ten.

**Research Procedures**

This research began after successful completion of the dissertation proposal and upon approval by the Institutional Review Board (IRB) at the University of Southern Indiana. Furthermore, prior to the start of the study, all identified rural public high schools in Indiana had an email sent to their corresponding administration office requesting permission to send the survey instrument to their teachers. Upon approval of participation by the administration, a list of the teachers' email addresses were obtained through the respective school's website. At that point, an email containing the survey, which was created through Qualtrics, and a letter of informed consent were sent to the teachers. See Appendix B for the letter of informed consent. Through the informed consent, participants were notified of the purpose of the study, benefits in relation to participating in the study, the voluntary nature of the study, and that the only risks involved in participating were those encountered in everyday life. The maximum time it took to complete the survey was 15 minutes. The survey was administered over a duration of two weeks. After the initial email was sent, a reminder to complete the survey was emailed to the teachers of participating schools on days five, eight, and thirteen of the two-week window in order to increase the response rate.

**Data Analysis**

Once survey responses were no longer being collected, the information was downloaded from Qualtrics and entered into the Statistical Package for the Social Sciences (SPSS). Survey questions were categorized to aid in answering each research question by using the *Guide to using the Teacher Data Survey* (Wayman et al., 2016b). The guide was written by the authors of the Teacher Data Use Survey: Teacher Version, which was the survey used for this study.

Descriptive statistics were used to analyze the demographic data, which provided a detailed description of the participating population. Since this study relied on quantitative data and the survey consists of Likert scale questions, which is ordinal data, descriptive statistics and a stepwise multiple regression analysis were applied to the survey questions to aid in addressing the research questions pertaining to the study. For statistically significant results on research questions five, six, seven, eight, nine, and ten, a comparison of means was conducted to define the characteristics that could be used as predictors.

***Research Question 1***

Descriptive statistics were used to determine the types of data rural public high school teachers use to drive their instruction. SPSS was utilized for this analysis.

***Research Question 2***

Descriptive statistics were used to determine rural public high school teachers' perceptions of their attitude toward using data to drive instruction. SPSS was utilized for this analysis.

***Research Question 3***

Descriptive statistics were used to determine rural public high school teachers' perceptions of their competence in using data to drive instruction. SPSS was utilized for this analysis.

***Research Question 4***

Descriptive statistics were used to determine rural public high school teachers' perceptions regarding supports and barriers to using data to drive their instruction. SPSS was utilized for this analysis.

***Research Question 5***

A stepwise multiple regression analysis was used to determine to what extent the characteristics of rural public high school teachers predict state data is used to drive instruction. SPSS was utilized for this analysis.

***Research Question 6***

A stepwise multiple regression analysis was used to determine to what extent the characteristics of rural public high school teachers predict periodic data is used to drive instruction. SPSS was utilized for this analysis.

***Research Question 7***

A stepwise multiple regression analysis was used to determine to what extent the characteristics of rural public high school teachers predict local data is used to drive instruction. SPSS was utilized for this analysis.

***Research Question 8***

A stepwise multiple regression analysis was used to determine to what extent the characteristics of rural public high school teachers predict personal data is used to drive instruction. SPSS was utilized for this analysis.

***Research Question 9***

Attitude was addressed in three different ways within the survey: perceptions of how useful data are in informing teacher practice, perceptions of the value of data for informing teacher practice, and perceptions of attitude toward data. Five questions pertained to the perceptions of the usefulness of data, and all responses were averaged per participant in order to obtain an overall value for perceived usefulness of data. Five questions pertained to perceptions of the value of data for informing teacher practice, and all responses were averaged per participant in order to obtain an overall value for perceived valued of data. Finally, four questions pertained to perceptions of attitude toward data, and all responses were averaged per participant in order to obtain an overall value for perceived attitude toward data.

A stepwise multiple regression analysis was used on each of the three components to determine to what extent the characteristics of rural public high school teachers predict attitude toward using data to drive instruction. SPSS was utilized for this analysis.

***Research Question 10***

Participants were asked four questions regarding competence within the survey. Responses for the four questions were averaged per participant, which provided one overall value regarding participants' perceived competence in using data to drive instruction. A stepwise multiple regression analysis was then used to determine to what extent the characteristics of rural public high school teachers predict competence in using data to drive instruction. SPSS was utilized for this analysis.

**Limitations**

The unanticipated coronavirus disease (COVID-19), which was declared a pandemic by the World Health Organization on March 11, 2020 (Centers for Disease Control and Prevention, 2020), had drastic effects on education across the United States. School facilities were closed to prevent transmission of COVID-19, which resulted in virtual learning replacing traditional learning and the cancellation or considerable revisions of personal, local, periodic, and state testing. In Indiana, specifically, personal, local, and periodic assessments were adapted for distance learning, the Indiana Department of Education canceled the spring 2020 assessment window for ISTEP at the high school level, and nation-wide spring assessments were either canceled, such as the SAT test, or significantly modified to be administered virtually, such as the Advanced Placement tests. Thus, the effect of COVID-19 across education in Indiana provides limitations to this study.

For instance, student assessment data from the spring of 2020 will be highly limited for teacher data use across personal, local, periodic, and state assessments. While some districts may have continued personal, local, and periodic assessments where others discontinued them, the student data may be skewed due to the alternate formatting of both instruction and assessment. The mandated quarantine by Indiana Governor Holcomb began on March 24, 2020 – following the shutdown of some schools throughout Indiana – and ultimately led to the closure of schools for the remainder of the spring semester. This closure may have limited not only access to student data and corresponding support systems but also collaboration efforts with other school personnel in the data-driven decision-making process.

Additionally, even though the researcher gained a considerable amount of information, the potential lack of participation of all rural public high schools in Indiana and lack of teacher participation within each school impacted the generalizability of the results. Lack of teacher participation may have been due to factors such as being overburdened with pre-existing work, which results in lack of time to volunteer for a non-mandatory survey or reluctance to complete another survey among the many they receive on a daily basis regardless of the short time commitment. Also, teachers who chose to volunteer to complete the survey may have done so due to their confidence in their data literacy skills and comfortableness in sharing their experiences. This further supports the fact the results were not generalizable for all rural public high school teachers in Indiana.

On a final note, because the survey was based online with little to no interaction with the researcher, there was potential for questions to be interpreted incorrectly. This would lead to inaccuracy of the analysis of the data. Also, there may have been inconsistency with answers. For example, in addition to the questions based on collaboration and labeled as such, there were several singular questions embedded throughout the survey that pertained to collaboration and were not labeled. In stating questions in this manner, the researcher was able to determine where the inconsistencies occurred and possible explanations for such occurrences. Overall, the results of the study were limited by the accuracy and dependability of participants' responses.

**Delimitations**

In addition to limitations, there were also delimitations of the study. For instance, due to the population of interest, participant exclusion limited the applicability of the results. Since the research was conducted in a rural educational setting, the results are not applicable to an urban educational setting nor any non-public educational setting. Additionally, the results of the study do not apply to all teachers of rural public schools as the participants were restricted to high school teachers. When considering the focus of the study, the research was also limited to the research questions pertaining to teachers' perceptions of data-driven decision-making. For instance, the research did not address what data-driven instruction looks like in the classroom nor how teachers build their capacity to participate in the data-driven decision-making process.

## Chapter 4: Findings

The purpose of this quantitative study was to examine rural public high school teachers' perceptions of data-driven instruction in Indiana. Specifically, the intent of the study was to identify rural public high school teachers' perceptions in terms of what types of data they use to support instruction, their attitudes toward data use, their competence in using data to drive instruction, and support systems that help or hinder their ability to effectively participate in data-driven instruction. Additionally, this study sought to examine possible relationships among demographic variables of rural public high school teachers and their corresponding perceptions of data-driven instruction. The results of this study begin with participant demographic data and follow with results for each of the research questions, which are provided below:

1. What types of data do rural public high school teachers use to drive their instruction?
2. What are rural public high school teachers' perceptions of their attitude toward using data to drive instruction?
3. What are rural public high school teachers' perceptions of their competence in using data to drive instruction?
4. What are rural public high school teachers' perceptions regarding supports and barriers to using data to drive their instruction?
5. To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict state data is used to drive instruction?
6. To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict periodic data is used to drive instruction?

7. To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict local data is used to drive instruction?
8. To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict personal data is used to drive instruction?
9. To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict attitude toward using data to drive instruction?
10. To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict competence in using data to drive instruction?

**Participant Demographic Data**

The sample population for this study consisted of rural public high school teachers in Indiana where rural was defined by the Indiana Department of Education using United States Census locale codes. Of the 44 school districts identified, only 34% ($N$ = 15) opted to participate in the study. Across the 15 school districts, approximately 405 teachers were emailed the Teacher Data Use Survey through Qualtrics. The response rate of the teachers was approximately 11% ($N$ = 43). The majority of the participants identified as female ($n$ = 31, 72%), and the remainder identified as male ($n$ = 12, 28%). The ages of the participants varied from 20 – 29 years to over 60 years of age as is noted in Table 1.

**Table 1**

*Frequency and Percent of Age*

| Age range | *n* | % |
|---|---|---|
| 20 – 29 years | 7 | 16 |
| 30 – 39 years | 12 | 28 |
| 40 – 49 years | 15 | 35 |
| 50 – 59 years | 6 | 14 |
| 60+ years | 3 | 7 |

*Note. N = 43.*

The participants were also asked to provide the number of years of teaching experience in their current institution. The purpose of this was to ensure they were answering the survey questions in relation to their experience in a rural public educational setting. Thus, their actual years of teaching experience may be different from their survey answers. The various years of teaching experience are displayed in Table 2 and range from being a first-year teacher to having more than 20 years of teaching experience.

**Table 2**

*Frequency and Percent of Years of Teaching Experience*

| Years of experience | *n* | % |
|---|---|---|
| This is my first year | 4 | 9 |
| 1 – 5 years | 15 | 35 |
| 6 – 10 years | 6 | 14 |
| 11 – 15 years | 5 | 12 |
| 16 – 20 years | 3 | 7 |
| More than 20 years | 10 | 23 |

*Note. N = 43.*

In a high school setting, multiple subjects are taught. However, it is important to note that in a rural public educational setting, not all subjects are available. For instance, not all schools within the study offered family and consumer science courses. Nevertheless, of the twelve subjects listed in the survey, ten are represented in the study as is noted in Table 3.

**Table 3**

*Frequency and Percent of Subject Taught*

| Subject taught | *n* | % |
|---|---|---|
| English/language arts | 4 | 9 |
| Art, music, or fine arts | 5 | 12 |
| Mathematics | 6 | 14 |
| Physical education or health | 4 | 9 |
| Science | 4 | 9 |
| Social studies | 4 | 9 |
| Foreign language | 2 | 5 |
| Career and technical education | 7 | 16 |
| Special education | 5 | 12 |
| Family and consumer science | 2 | 5 |

*Note. N = 43. The two subjects in the survey that are not represented within the study are bilingual/English as a second language and computer science.*

An additional demographic collected pertains to highest degree or level of education completed by the participants. Participants had various levels of education with the smallest number having earned an associate's degree (*n* = 1, 2%), quite a few having earned a bachelor's degree (*n* = 18, 42%), and the majority having earned a master's degree (*n* = 24, 56%). While a doctorate degree or higher and trade school were options within the survey, no participants noted they had earned either level of education.

On a final note, of the 15 school districts that opted to participate in the study, it is important to clarify that only one school district employed a data specialist at the high school level. Also, none of the school districts employed an instructional coach. These two positions were addressed in the survey regarding teachers having access to a data coach [specialist] or instructional coach as a resource for support in the data-driven decision-making process.

**Statistical Results**

Descriptive statistics such as frequency, percent, mean, and standard deviation were used to answer research questions one, two, three, and four. To determine the extent characteristics of rural public high school teachers predict types of data used to drive instruction, predict perceived attitude toward using data to drive instruction, and predict perceived competence in using data to drive instruction, a stepwise multiple regression analysis was used, which refers to questions five, six, seven, eight, nine, and ten.

***Research Question 1***

What types of data do rural public high school teachers use to drive their instruction? In order to examine the types of data teachers use to drive their instruction, the participants were asked to respond to questions regarding the frequency of their use of state, periodic, local, personal, and other data as well as the actions they take with state, periodic, local, and personal data. The responses for the frequency of teachers' use of various data were based on a Likert scale and assigned a numerical value: 1 = *Do not use*, 2 = *Less than once a month*, 3 = *Once or twice a month*, 4 = *Weekly*, and 5 = *A few times a week*. As can be seen in Table 4, periodic data ($n$ = 23) was used by the least number of teachers and personal data ($n$ = 41) was used by the majority of the teachers to inform instruction. Additionally, the largest mean value suggests personal data was used the most often ($M$ = 4.07, $SD$ = .99) where state data ($M$ = 1.86, $SD$ = .86) and periodic data ($M$ = 1.87, $SD$ = .97) were used the least often.

**Table 4**

*Frequency of Use of State, Periodic, Local, and Personal Data*

| Type of data | *n* | Minimum | Maximum | *M* | *SD* |
|---|---|---|---|---|---|
| State | 37 | 1 | 5 | 1.86 | .86 |
| Periodic | 23 | 1 | 5 | 1.87 | .97 |
| Local | 24 | 1 | 5 | 3.08 | 1.18 |
| Personal | 41 | 1 | 5 | 4.07 | .99 |
| Other | 3 | 2 | 4 | 3.33 | 1.16 |

*Note. N = 43.*

Of the teachers that use state data to inform instruction, the actions taken were minimal as is noted in Table 5. Due to the limited amount of state data available, the frequency measures for these items on the Likert scale were 1 = *Not at all*, 2 = *One or two times a year*, 3 = *A few times a year*, 4 = *Monthly*, and 5 = *Weekly*. All of the actions were conducted on average one or two times a year to a few times a year.

**Table 5**

*Actions Teachers Take with State Data*

| Actions with data | *n* | Minimum | Maximum | *M* | *SD* |
|---|---|---|---|---|---|
| Use state data to identify instructional content to use in a class | 37 | 1 | 4 | 2.00 | .91 |
| Use state data to tailor instruction to individual students' needs | 37 | 1 | 4 | 2.11 | 1.17 |
| Use state data to develop recommendations for additional instructional support | 37 | 1 | 4 | 2.16 | 1.07 |
| Use state data to form small groups of students for targeted instruction | 37 | 1 | 5 | 1.89 | 1.20 |
| Discuss state data with a parent or guardian | 37 | 1 | 4 | 1.51 | .80 |
| Discuss state data with a student | 37 | 1 | 4 | 1.57 | .87 |
| Meet with a specialist (i.e., instructional coach or data coach) about state data | 37 | 1 | 4 | 1.57 | .87 |
| Meet with another teacher about state data | 37 | 1 | 4 | 1.81 | .88 |

*Note. N = 43.*

The responses for the remaining data – periodic, local, and personal – and corresponding actions taken by teachers were also based on a Likert scale and assigned a numerical value: 1 = *Do not use*, 2 = *Less than once a month*, 3 = *Once or twice a month*, 4 = *Weekly*, and 5 = *A few times a week*. As can be seen in Table 6, actions taken with periodic data follows a similar trend as state data. On average, any given action was conducted either less than once a month or twice a month.

**Table 6**

*Actions Teachers Take with Periodic Data*

| Actions with data | *n* | Minimum | Maximum | *M* | *SD* |
|---|---|---|---|---|---|
| Use periodic data to identify instructional content to use in a class | 23 | 1 | 4 | 1.96 | .98 |
| Use periodic data to tailor instruction to individual students' needs | 23 | 1 | 5 | 2.00 | 1.13 |
| Use periodic data to develop recommendations for additional instructional support | 23 | 1 | 5 | 2.09 | 1.16 |
| Use periodic data to form small groups of students for targeted instruction | 23 | 1 | 5 | 1.96 | 1.15 |
| Discuss periodic data with a parent or guardian. | 23 | 1 | 3 | 1.35 | .65 |
| Discuss periodic data with a student | 23 | 1 | 3 | 1.65 | .83 |
| Meet with a specialist (i.e., instructional coach or data coach) about periodic data | 23 | 1 | 3 | 1.43 | .73 |
| Meet with another teacher about periodic data | 23 | 1 | 3 | 1.78 | .85 |

*Note. N = 43.*

As can be observed in Table 7, the frequency of actions taken increases with local data. On average, any given task was conducted anywhere from once or twice a month to weekly.

**Table 7**

*Actions Teachers Take with Local Data*

| Actions with data | *n* | Minimum | Maximum | *M* | *SD* |
|---|---|---|---|---|---|
| Use local data to identify instructional content to use in a class | 24 | 1 | 5 | 3.17 | 1.24 |
| Use local data to tailor instruction to individual students' needs | 24 | 1 | 5 | 3.13 | 1.26 |
| Use local data to develop recommendations for additional instructional support | 24 | 1 | 5 | 2.83 | 1.20 |
| Use local data to form small groups of students for targeted instruction | 24 | 1 | 5 | 2.75 | 1.33 |
| Discuss local data with a parent or guardian. | 24 | 1 | 5 | 2.00 | 1.14 |
| Discuss local data with a student | 24 | 1 | 5 | 2.42 | 1.25 |
| Meet with a specialist (i.e., instructional coach or data coach) about local data | 24 | 1 | 5 | 2.00 | 1.14 |
| Meet with another teacher about local data | 24 | 1 | 5 | 2.46 | 1.14 |

*Note. N = 43.*

Actions taken with personal data, which was data most used by teachers to inform instruction, occurred the most often. However, these actions also had the widest range of use as any given task was conducted either once or twice a month, weekly, or a few times a week as is noted in Table 8. A common trend among all four data types was that the teachers did not often meet with a specialist (i.e., instructional coach or data coach) about data, and collaborative efforts regarding discussion about data were conducted the least amount in comparison to individual actions.

**Table 8**

*Actions Teachers Take with Personal Data*

| Actions with data | *n* | Minimum | Maximum | *M* | *SD* |
|---|---|---|---|---|---|
| Use personal data to identify instructional content to use in a class | 41 | 1 | 5 | 3.98 | 1.06 |
| Use personal data to tailor instruction to individual students' needs | 41 | 1 | 5 | 3.93 | 1.23 |
| Use personal data to develop recommendations for additional instructional support | 41 | 1 | 5 | 3.83 | 1.18 |
| Use personal data to form small groups of students for targeted instruction | 41 | 1 | 5 | 3.20 | 1.50 |
| Discuss personal data with a parent or guardian | 41 | 1 | 5 | 2.93 | 1.21 |
| Discuss personal data with a student | 41 | 1 | 5 | 3.49 | 1.34 |
| Meet with a specialist (i.e., instructional coach or data coach) about personal data | 41 | 1 | 5 | 2.02 | 1.35 |
| Meet with another teacher about personal data | 41 | 1 | 5 | 2.68 | 1.35 |

*Note. N = 43.*

***Research Question 2***

What are rural public high school teachers' perceptions of their attitude toward using data to drive instruction? In order to examine teachers' perceptions of their attitude toward using data to drive instruction, participants were asked to respond to questions in terms of intensity. Questions regarding perceptions of the usefulness of state, periodic, local, personal and other data were based on a Likert scale and assigned a numerical value as follows: 0 = *No opinion*, 1 = *Not at all*, 2 = *Slightly useful*, 3 = *Useful*, and 4 = *Very useful*. The results suggest other data was the most useful (*M* = 3.67, *SD* = .58) followed by personal data (*M* = 3.46, *SD* = .84), local data (*M* = 2.87, *SD* = .90), periodic data (*M* = 1.96, *SD* = 1.02) and finally state data (*M* = 1.84, *SD* = .99).

The remaining questions pertaining to teachers' perceptions of their attitude toward using data to drive instruction were based on a Likert scale in terms of level of agreement and were assigned a numerical value as follows: 0 = *No opinion*, 1 = *Strongly disagree*, 2 = *Disagree*, 3 = *Agree*, and 4 = *Strongly agree*. As noted in Table 9, teachers' perceptions of the effectiveness of data towards instructional practices were, on average, consistently between disagreement and agreement.

**Table 9**

*Perceptions of the Effectiveness of Data towards Pedagogical Practices*

| Variable | *n* | Minimum | Maximum | *M* | *SD* |
|---|---|---|---|---|---|
| Data help teachers plan instruction. | 43 | 0 | 4 | 2.93 | .80 |
| Data offer information about students that was not already known. | 43 | 0 | 4 | 2.49 | .96 |
| Data help teachers know what concepts students are learning. | 43 | 0 | 4 | 2.81 | .90 |
| Data help teachers identify learning goals for students. | 43 | 0 | 4 | 2.81 | .96 |
| Students benefit when teacher instruction is informed by data. | 43 | 0 | 4 | 2.77 | .95 |

*Note. N = 43.*

Using the same Likert scale mentioned above, teachers' perceptions of their attitude toward data were fairly unwavering. On average, teachers' attitudes were more positive towards feeling it was important to use data to inform instruction (*M* = 2.70, *SD* = 1.06) and using data helped them be a better teacher (*M* = 2.70, *SD* = 1.06) compared to liking to use data (*M* = 2.42, *SD* = 1.05) and finding data useful (*M* = 2.67, *SD* = 1.02).

### *Research Question 3*

What are rural public high school teachers' perceptions of their competence in using data to drive instruction? To examine teachers' perceptions of their competence in using data to drive instruction, participants responded to four questions based on a Likert scale in terms of intensity. Each response was assigned a numerical value as follows: 0 = *No opinion*, 1 = *Strongly disagree*, 2 = *Disagree*, 3 = *Agree*, and 4 = *Strongly agree*. As noted in Table 10, teachers felt most competent in adjusting instruction based on data (*M* = 2.81, *SD* = .66) and least competent in using data to set student learning goals (*M* = 2.63, *SD* = .87).

**Table 10**

*Perceptions of Competence in Using Data to Inform Pedagogical Practices*

| Variable | *n* | Minimum | Maximum | *M* | *SD* |
|---|---|---|---|---|---|
| I am good at using data to diagnose student learning needs. | 43 | 0 | 4 | 2.72 | .85 |
| I am good at adjusting instruction based on data. | 43 | 0 | 4 | 2.81 | .66 |
| I am good at using data to plan lessons. | 43 | 0 | 4 | 2.67 | .81 |
| I am good at using data to set student learning goals. | 43 | 0 | 4 | 2.63 | .87 |

*Note. N = 43.*

***Research Question 4***

What are rural public high school teachers' perceptions regarding supports and barriers to using data to drive their instruction? Several supports and barriers exist in terms of using data to drive instruction: availability of data, school supports (i.e., professional development, data coach), principal leadership, technology, and collaborative inquiry. Participants were asked to respond to questions related to each of these supports and barriers. Beginning with the first question regarding availability of data, responses were dichotomous in the form of yes or no. State data was available to 37 teachers (86%), periodic data was available to 23 teachers (54%), local data was available to 24 teachers (56%), personal data was available to 41 teachers (95%), and other data was available to 3 teachers (7%).

For the remaining questions regarding supports and barriers, each response was based on a Likert scale in terms of agreement and was coded with a numerical value as follows: 0 = *No opinion*, 1 = *Strongly disagree*, 2 = *Disagree*, 3 = *Agree*, and 4 = *Strongly agree*. As depicted in Table 11, teachers' perceptions of school supports for data use were, on average, in more disagreement than agreement. It is important to note teachers disagreed ($M$ = 2.00, $SD$ = 1.05) with the statement that their district's professional development was useful for learning about data use.

**Table 11**

*Perceptions of School Supports for Data Use*

| Variable | *n* | Minimum | Maximum | *M* | *SD* |
|---|---|---|---|---|---|
| I am adequately supported in the effective use of data. | 43 | 0 | 4 | 2.47 | .86 |
| I am adequately prepared to use data. | 43 | 0 | 4 | 2.63 | .98 |
| There is someone who answers my questions about data use. | 43 | 0 | 4 | 2.44 | 1.10 |
| There is someone who helps me change my practice (teaching) based on data. | 43 | 0 | 4 | 2.07 | 1.08 |
| My district provides enough professional development about data use. | 43 | 0 | 4 | 2.09 | 1.04 |
| My district's professional development is useful for learning about data use. | 43 | 0 | 4 | 2.00 | 1.05 |

*Note. N = 43.*

Perceptions of principal leadership in supporting teacher data were, on average, between strongly disagree and agree. As noted in table 12, teachers leaned towards agreeing that their principal or assistant principal(s) encouraged data use as a tool to support effective teaching ($M$ = 2.60, $SD$ = 1.03). However, teachers disagreed that they received protected time for using data ($M$ = 1.94, $SD$ = .95) as well as felt they did not have plenty of training for data use ($M$ = 1.98, $SD$ = 1.08).

**Table 12**

*Perceptions of Administrator Leadership in Supporting Teacher Data Use*

| Variable | *n* | Minimum | Maximum | *M* | *SD* |
|---|---|---|---|---|---|
| My principal or assistant principal(s) encourages data use as a tool to support effective teaching. | 43 | 0 | 4 | 2.60 | 1.03 |
| My principal or assistant principal(s) creates many opportunities for teachers to use data. | 43 | 0 | 4 | 2.12 | 1.07 |
| My principal or assistant principal(s) has made sure teachers have plenty of training for data use. | 43 | 0 | 4 | 1.98 | 1.08 |
| My principal or assistant principal(s) is a good example of an effective data user. | 43 | 0 | 4 | 2.16 | 1.19 |
| My principal or assistant principal(s) discusses data with me. | 43 | 0 | 4 | 2.23 | 1.04 |
| My principal or assistant principal(s) creates protected time for using data. | 43 | 0 | 4 | 1.84 | .95 |

*Note. N = 43.*

In terms of technology, teachers' perceptions were, on average, between disagreement and agreement. For instance, as is noted in Table 13, with a mean of 2.81, teachers were in most agreement that they had the proper technology to efficiently examine data (*SD* = 1.01). On the other hand, with a mean of 2.33, teachers were in most disagreement that the computer systems available in their district provided displays that were useful (*SD* = 1.19).

**Table 13**

*Perceptions of Technology Support for Data Use*

| Variable | *n* | Minimum | Maximum | *M* | *SD* |
|---|---|---|---|---|---|
| I have the proper technology to efficiently examine data. | 43 | 0 | 4 | 2.81 | 1.01 |
| The computer systems in my district provide me access to lots of data. | 43 | 0 | 4 | 2.58 | 1.16 |
| The computer systems (for data use) in my district are easy to use. | 43 | 0 | 4 | 2.74 | 1.12 |
| The computer systems in my district allow me to examine various types of data at once (i.e., attendance, achievement, demographics) that are useful to me. | 43 | 0 | 4 | 2.42 | 1.22 |
| The computer systems in my district generate displays (i.e., reports, graphs, tables) that are useful to me. | 43 | 0 | 4 | 2.33 | 1.19 |

*Note. N = 43.*

The final support and barrier addressed was collaboration. To begin, participants were asked to provide the frequency in which they have scheduled meetings to work in collaborative teams. Each response was coded with a numerical value as follows: 1 = *I do not have scheduled meetings*, 2 = *Less than once a month*, 3 = *Once or twice a month*, 4 = *Weekly or almost weekly*, and 5 = *A few times a week*. Of the 43 participants, 19 did not have scheduled meetings (44%). Therefore, only 24 participants answered the remaining questions regarding collaboration, and it is important to note they met in collaborative teams, on average, once or twice a month ($M$ = 2.92, $SD$ = .97).

The final collaboration questions were separated into two facets: perceptions of collaborative team trust and perceptions of collaborative inquiry actions. All items were based on a Likert scale in terms of agreement and were coded with a numerical value as follows: 0 = *No opinion*, 1 = *Strongly disagree*, 2 = *Disagree*, 3 = *Agree*, and 4 = *Strongly agree*. When observing teachers' perceptions of collaborative team trust as shown in Table 14, results indicated teachers did not wholly agree that their principal or assistant principal(s) fostered a trusting environment for discussing data in teams (*M* = 2.62, *SD* = 1.31).

**Table 14**

*Perceptions of Collaborative Team Trust*

| Variable | *n* | Minimum | Maximum | *M* | *SD* |
|---|---|---|---|---|---|
| Members of my team trust each other. | 24 | 1 | 4 | 3.21 | .78 |
| It’s ok to discuss feelings and worries with other members of my team. | 24 | 0 | 4 | 3.00 | .98 |
| Members of my team respect colleagues who lead school improvement efforts. | 24 | 0 | 4 | 2.88 | .95 |
| Members of my team respect those colleagues who are experts in their craft. | 24 | 0 | 4 | 3.00 | .98 |
| My principal or assistant principal(s) fosters a trusting environment for discussing data in teams. | 24 | 0 | 4 | 2.62 | 1.31 |

*Note. N = 43.*

More notably, teachers’ perceptions of collaborative inquiry actions resulted in more disagreement than agreement as noted in Table 15. For instance, teachers felt when participating in collaborative inquiry they did not approach an issue by looking at data (*M* = 2.08, *SD* = 1.02) and they did not identify questions to answer through using data (*M* = 2.13, *SD* = .99). Even more profound was the result that teachers felt, on average, that they did not draw conclusions based on data when working collaboratively (*M* = 2.38, *SD* = 1.06).

**Table 15**

*Perceptions of Collaborative Inquiry Actions*

| Variable | *n* | Minimum | Maximum | *M* | *SD* |
|---|---|---|---|---|---|
| We approach an issue by looking at data. | 24 | 0 | 4 | 2.08 | 1.02 |
| We discuss our preconceived beliefs about an issue. | 24 | 0 | 4 | 2.08 | 1.06 |
| We identify questions that we will seek to answer using data. | 24 | 0 | 4 | 2.13 | .99 |
| We explore data by looking for patterns and trends. | 24 | 0 | 4 | 2.04 | .96 |
| We draw conclusions based on data. | 24 | 0 | 4 | 2.38 | 1.06 |
| We identify additional data to offer a clearer picture of the issue. | 24 | 0 | 4 | 2.29 | .96 |
| We use data to make links between instruction and student outcomes. | 24 | 0 | 4 | 2.38 | 1.01 |
| When we consider changes in practice, we predict possible student outcomes. | 24 | 0 | 4 | 2.54 | 1.14 |
| We revisit predictions made in previous meetings. | 24 | 0 | 4 | 2.04 | 1.04 |
| We identify actionable solutions based on our conclusions. | 24 | 0 | 4 | 2.42 | 1.06 |

*Note. N = 43.*

***Research Question 5***

To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict state data is used to drive instruction? A stepwise multiple regression analysis was conducted to predict rural public high school teachers' use of state data to inform instruction based on teachers' characteristics: gender, age, years of teaching experience, subject taught, and highest degree earned. The prediction model did not provide any of the independent variables as a predictor. Thus, a standard multiple regression was conducted. A statistically significant regression was not found ($F$(5,31) = .51, $p$ > .05) with an $R^2$ of .08 and an adjusted $R^2$ of -.08. Therefore, the independent variables gender, age, years of teaching experience, subject taught, and highest degree earned were not significant predictors of teachers using periodic data to drive instruction. Pearson correlations for characteristics of rural public high school teachers' use of state data to inform instruction are noted in Table 16.

**Table 16**

*Correlations of Teachers' Use of State Data to Inform Instruction*

| | Teacher use of state data | Gender | Age | Years experience | Subject taught | Highest degree |
|---|---|---|---|---|---|---|
| Teacher use of state data | _____ | | | | | |
| Gender | .11 | _____ | | | | |
| Age | -.13 | .17 | _____ | | | |
| Years experience | .04 | .17 | .56** | _____ | | |
| Subject taught | .10 | -.08 | .05 | -.13 | _____ | |
| Highest degree | .05 | .24 | .26 | .32* | -.27 | _____ |

*Note.* $N$ = 37.

*$p < 0.05$. **$p < 0.01$.

***Research Question 6***

To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict periodic data is used to drive instruction? A stepwise multiple regression analysis was conducted to predict rural public high school teachers' use of periodic data to inform instruction based on teachers' characteristics: gender, age, years of teaching experience, subject taught, and highest degree earned. The prediction model did not provide any of the independent variables as a predictor. Thus, a standard multiple regression was conducted. A statistically significant regression was not found ($F(5,17) = .35$, $p > .05$) with an $R^2$ of .09 and an adjusted $R^2$ of -.17. Therefore, the independent variables gender, age, years of teaching experience, subject taught, and highest degree earned were not significant predictors of teachers using periodic data to drive instruction. Pearson correlations for characteristics of rural public high school teachers' use of periodic data to inform instruction are noted in Table 17.

**Table 17**

*Correlations of Teachers' Use of Periodic Data to Inform Instruction*

| | Teacher use of periodic data | Gender | Age | Years experience | Subject taught | Highest degree |
|---|---|---|---|---|---|---|
| Teacher use of periodic data | _____ | | | | | |
| Gender | .09 | _____ | | | | |
| Age | -.10 | .14 | _____ | | | |
| Years experience | .15 | .18 | .66** | _____ | | |
| Subject taught | -.08 | -.19 | .14 | .04 | _____ | |
| Highest degree | -.03 | .10 | .35 | .18 | -.26 | _____ |

*Note. N* = 23.

**p* < 0.05. ***p* < 0.01.

***Research Question 7***

To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict local data is used to drive instruction? A stepwise multiple regression analysis was conducted to predict rural public high school teachers' use of local data to inform instruction based on teachers' characteristics: gender, age, years of teaching experience, subject taught, and highest degree earned. The prediction model did not provide any of the independent variables as a predictor. Thus, a standard multiple regression was conducted. A statistically significant regression was not found ($F$(5,18) = .13, $p$ > .05) with an $R^2$ of .03 and an adjusted $R^2$ of -.23. Therefore, the independent variables gender, age, years of teaching experience, subject taught, and highest degree earned were not significant predictors of teachers using local data to drive instruction. Pearson correlations for characteristics of rural public high school teachers' use of local data to inform instruction are noted in Table 18.

**Table 18**

*Correlations of Teachers' Use of Local Data to Inform Instruction*

| | Teacher use of local data | Gender | Age | Years experience | Subject taught | Highest degree |
|---|---|---|---|---|---|---|
| Teacher use of local data | _____ | | | | | |
| Gender | -.09 | _____ | | | | |
| Age | -.15 | .11 | _____ | | | |
| Years experience | -.10 | .31 | .36* | _____ | | |
| Subject taught | -.09 | -.02 | .12 | -.08 | _____ | |
| Highest degree | -.06 | .37* | .25 | .52** | -.24 | _____ |

*Note.* $N$ = 24.

*$p$ < 0.05. **$p$ < 0.01.

***Research Question 8***

To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict personal data is used to drive instruction? A stepwise multiple regression analysis was conducted to predict rural public high school teachers' use of personal data to inform instruction based on teachers' characteristics: gender, age, years of teaching experience, subject taught, and highest degree earned. The prediction model was comprised of one of the five predictors. Teachers' use of personal data to inform instruction was predicted by age. A statistically significant regression was found ($F(1,39) = 4.07$, $p < .05$) and accounted for approximately 11% of the variance of teachers' use of personal data to inform instruction ($R^2$ = .11, adjusted $R^2$ = .08). Therefore, the independent variable age provided the largest unique prediction regarding rural public high school teachers' use of personal data to inform instruction (standardized coefficient $\beta$ = -.32, $r$ = -.32). To determine which age group was the likely predictor of the use of personal data to inform instruction, a comparison of means was completed.

As can be seen in Table 19, as age increased, the less often personal data was used in instructional practices. As a reminder, the numerical values were coded as follows: 1 = *Do not use*, 2 = *Less than once a month*, 3 = *Once or twice a month*, 4 = *Weekly*, and 5 = *A few times a week*. Thus, 20-29 year old participants used personal data to inform instruction most often ($M$ = 4.43, $SD$ = .54), and the frequency declined as age groups increased ending with participants of 60+ years of age having used personal data to inform instruction the least often ($M$ = 2.50, $SD$ = 2.12).

**Table 19**

*Comparison of Means of Participant Age in Relation to Use of Personal Data*

| Age | *n* | *M* | *SD* |
|---|---|---|---|
| 20-29 years | 7 | 4.43 | .54 |
| 30-39 years | 11 | 4.27 | .47 |
| 40-49 years | 15 | 4.00 | 1.20 |
| 50-59 years | 6 | 4.00 | .89 |
| 60+ years | 2 | 2.50 | 2.12 |
| Total | 41 | 4.07 | .99 |

Pearson correlations for characteristics of rural public high school teachers' use of personal data to inform instruction are noted in Table 20.

**Table 20**

*Correlations of Teachers' Use of Personal Data to Inform Instruction*

| | Teacher use of personal data | Gender | Age | Years experience | Subject taught | Highest degree |
|---|---|---|---|---|---|---|
| Teacher use of personal data | _____ | | | | | |
| Gender | .10 | _____ | | | | |
| Age | -.32* | .03 | _____ | | | |
| Years experience | -.13 | .12 | .47** | _____ | | |
| Subject taught | -.03 | -.13 | .22 | -.02 | _____ | |
| Highest degree | .02 | .24 | .21 | .30* | -.13 | _____ |

*Note.* $N = 41$.

*$p < 0.05$. **$p < 0.01$.

***Research Question 9***

To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict attitude toward using data to drive instruction? Within the survey, teachers' perceptions of their attitude toward using data to drive instruction were addressed in three different components: perceptions of how useful data were in informing teacher practice, perceptions of attitude toward data, and perceptions of the value of data in informing teacher practice. Due to these distinct evaluations, three stepwise multiple regression analysis were conducted in order to examine the differences in attitude. Additionally, each component was comprised of multiple questions where the responses were averaged in order to reduce the number of variables into one factor. Five questions were asked on the survey regarding perceptions of how useful data were in informing teacher practice, five questions were asked regarding perceptions of the value of data in informing teacher practice, and four questions were asked regarding perceptions of attitude toward data.

To begin, a stepwise multiple regression analysis was conducted to predict rural public high school teachers' perceptions of their attitude toward how useful data are to teacher practice based on teachers' characteristics: gender, age, years of teaching experience, subject taught, and highest degree earned. The prediction model was comprised of one of the five predictors. Teachers' perceptions of their attitude toward the usefulness of data in informing instruction was predicted by age. A statistically significant regression was found ($F(1,41) = 8.18$, $p < .05$) and accounted for approximately 17% of the variance of teachers' perceptions of their attitude toward the usefulness of data in informing instruction ($R^2$ = .17, adjusted $R^2$ = .15). Therefore, the independent variable age provided the largest unique prediction regarding rural public high school teachers' perceptions of their attitude toward the usefulness of data in informing instruction (standardized coefficient $\beta$ = -.48, $r$ = -.41). To determine which age group was the likely predictor of participants' perceptions of their attitude toward the usefulness of data, a comparison of means was completed.

As can be seen in Table 21, as age increased, the less useful data was perceived regarding instructional practices. As a reminder, the numerical values were coded as follows: 0 = *No opinion*, 1 = *Not at all*, 2 = *Slightly useful*, 3 = *Useful*, and 4 = *Very useful*. Thus, 20-29 year old participants perceived data as useful towards informing instructional practices ($M$ = 3.02, $SD$ = .71), and the perceived usefulness declined as age groups increased ending with participants of 60+ years of age perceiving data on average between not at all useful and slightly useful ($M$ = 1.67, $SD$ = .58).

**Table 21**

*Comparison of Means of Participant Age in Relation to Attitude toward Usefulness of Data*

| Age | *n* | *M* | *SD* |
|---|---|---|---|
| 20-29 years | 7 | 3.02 | .71 |
| 30-39 years | 12 | 2.86 | .76 |
| 40-49 years | 15 | 2.55 | .78 |
| 50-59 years | 6 | 2.46 | .64 |
| 60+ years | 3 | 1.67 | .58 |
| Total | 43 | 2.64 | .78 |

Pearson correlations for characteristics of rural public high school teachers' perceptions of their attitude toward how useful data were to teacher practice are noted in Table 22.

**Table 22**

*Correlations of Teachers' Perceptions of their Attitude toward Usefulness of Data*

| | Usefulness of data | Gender | Age | Years experience | Subject taught | Highest degree |
|---|---|---|---|---|---|---|
| Usefulness of data | _____ | | | | | |
| Gender | .15 | _____ | | | | |
| Age | -.41** | .05 | _____ | | | |
| Years experience | -.23 | .12 | .51** | _____ | | |
| Subject taught | -.12 | -.11 | .16 | -.06 | _____ | |
| Highest degree | -.19 | .23 | .25 | .33* | -.16 | _____ |

*Note.* $N = 43$.

$^{*}p < 0.05$. $^{**}p < 0.01$.

A stepwise multiple regression analysis was conducted to predict rural public high school teachers' attitude toward data based on teachers' characteristics: gender, age, years of teaching experience, subject taught, and highest degree earned. The prediction model was comprised of one of the five predictors. Teachers' attitude toward data was predicted by age. A statistically significant regression was found ($F(1,41) = 4.04$, $p < .05$) and accounted for approximately 12% of the variance of teachers' attitude toward data ($R^2 = .12$, adjusted $R^2 = .10$). Therefore, the independent variable age provided the largest unique prediction regarding rural public high school teachers' attitude toward data (standardized coefficient $\beta = -.35$, $r = -.35$). To determine which age group was the likely predictor of participants' perceptions of their attitude toward the usefulness of data, a comparison of means was completed.

The general pattern suggested as age increased, participants' perceived attitude toward data became increasingly negative as is noted in Table 23. As a reminder, the numerical values were coded as follows: 0 = *No opinion*, 1 = *Strongly disagree*, 2 = *Disagree*, 3 = *Agree*, and 4 = *Strongly Agree*. Thus, 20-29 year-old participants had a positive attitude toward data ($M = 3.14$, $SD = .35$) whereas 50-59 year-old participants had the least positive attitude toward data ($M = 1.96$, $SD = .80$).

**Table 23**

*Comparison of Means of Participant Age in Relation to Attitude toward Data*

| Age | *n* | *M* | *SD* |
|---|---|---|---|
| 20-29 years | 7 | 3.14 | .35 |
| 30-39 years | 12 | 2.73 | .70 |
| 40-49 years | 15 | 2.63 | 1.04 |
| 50-59 years | 6 | 1.96 | .80 |
| 60+ years | 3 | 2.25 | 1.30 |
| Total | 43 | 2.62 | .89 |

Pearson correlations for characteristics of rural public high school teachers' attitude toward data are noted in Table 24.

**Table 24**

*Correlations of Teachers' Attitude toward Data*

| | Attitude toward data | Gender | Age | Years experience | Subject taught | Highest degree |
|---|---|---|---|---|---|---|
| Attitude toward data | _____ | | | | | |
| Gender | -.02 | _____ | | | | |
| Age | -.35* | .05 | _____ | | | |
| Years experience | -.23 | .12 | .51** | _____ | | |
| Subject taught | -.28* | -.11 | .16 | -.06 | _____ | |
| Highest degree | -.05 | .23 | .25 | .33* | -.16 | _____ |

*Note.* $N$ = 43.

*$p$ < 0.05. **$p$ < 0.01.

A stepwise multiple regression analysis was conducted to predict rural public high school teachers' perceptions of the value of data for everyday pedagogical practices based on teachers' characteristics: gender, age, years of teaching experience, subject taught, and highest degree earned. The prediction model was comprised of one of the five predictors. Teachers' perceptions of the value of data for teacher practices was predicted by subject taught. A statistically significant regression was found ($F$(1,41) = 2.31, $p$ < .05) and accounted for approximately 10% of the variance of teachers' perceptions of the value of data on instructional practices ($R^2$ = .10, adjusted $R^2$ = .08). Therefore, the independent variable subject taught provided the largest unique prediction regarding rural public high school teachers' perceptions of the value of data for everyday practice (standardized coefficient $\beta$ = -.32, $r$ = -.32). To determine which subject taught by participants was the likely predictor of participants' perceptions of the value of data towards instruction, a comparison of means was completed.

The results suggested the subject taught predicted participants' perceived attitude toward the effectiveness of data in instructional practices as is noted in Table 25. As a reminder, the numerical values were coded as follows: 0 = *No opinion*, 1 = *Strongly disagree*, 2 = *Disagree*, 3 = *Agree*, and 4 = *Strongly Agree*. Participants who taught mathematics (*M* = 3.20, *SD* = .25) or foreign language (*M* = 3.50, *SD* = .14) perceived data to be valuable towards everyday pedagogy. On the other hand, participants who taught family and consumer science did not perceive data to be valuable in informing instruction (*M* = .60, *SD* = .85).

**Table 25**

*Comparison of Means of Subject Taught in Relation to Attitude toward the Value of Data*

| Subject taught | *n* | *M* | *SD* |
|---|---|---|---|
| English/language arts | 4 | 2.75 | 1.05 |
| Art, music, or fine arts | 5 | 2.96 | .33 |
| Mathematics | 6 | 3.20 | .25 |
| Physical education or health | 4 | 2.95 | .10 |
| Science | 4 | 2.45 | .68 |
| Social studies | 4 | 2.75 | .34 |
| Foreign language | 2 | 3.50 | .14 |
| Career and technical education | 7 | 2.63 | .47 |
| Special education | 5 | 2.92 | .67 |
| Family and consumer science | 2 | .60 | .85 |
| Total | 43 | 2.76 | .73 |

Pearson correlations for characteristics of rural public high school teachers' perceptions of the value of data for everyday pedagogical practices are noted in Table 26.

**Table 26**

*Correlations of Teachers' Perceptions of the Value of Data toward Pedagogical Practices*

| | Value of data | Gender | Age | Years experience | Subject taught | Highest degree |
|---|---|---|---|---|---|---|
| Value of data | _____ | | | | | |
| Gender | -.02 | _____ | | | | |
| Age | -.30* | .05 | _____ | | | |
| Years experience | -.16 | .12 | .51** | _____ | | |
| Subject taught | -.32* | -.11 | .16 | -.06 | _____ | |
| Highest degree | .05 | .23 | .25 | .33* | -.16 | _____ |

*Note.* $N = 43$.

*$p < 0.05$. **$p < 0.01$.

***Research Question 10***

To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict competence in using data to drive instruction? The purpose of this research question was to examine the extent teacher characteristics predicted teacher perceptions regarding their skills or expertise at using data to inform their instructional practices. Since four questions within the survey addressed teacher competence in using data for everyday pedagogical practices, the responses for each question were averaged in order to reduce the number of variables into one factor – overall competence.

Once this was completed, a stepwise multiple regression analysis was conducted to predict rural public high school teachers' competence in using data to inform instruction based on teachers' characteristics: gender, age, years of teaching experience, subject taught, and highest degree earned. The prediction model did not provide any of the independent variables as a predictor. Thus, a standard multiple regression was conducted. A statistically significant regression was not found ($F(5,37) = .71$,

$p$ > .05) with an $R^2$ of .09 and an adjusted $R^2$ of -.04. Therefore, the independent variables gender, age, years of teaching experience, subject taught, and highest degree earned were not significant predictors of teachers' competence in using data to drive instruction. Pearson correlations for characteristics of rural public high school teachers' competence in using data to inform instruction are noted in Table 27.

**Table 27**

*Correlations of Teachers' Perceptions of Their Competence in Using Data to Inform Instruction*

| | Teacher competence | Gender | Age | Years experience | Subject taught | Highest degree |
|---|---|---|---|---|---|---|
| Teacher competence | _____ | | | | | |
| Gender | .08 | _____ | | | | |
| Age | -.23 | .05 | _____ | | | |
| Years experience | -.09 | .12 | .51** | _____ | | |
| Subject taught | -.13 | -.11 | .16 | -.06 | _____ | |
| Highest degree | .10 | .23 | .25 | .33* | -.16 | _____ |

*Note.* $N$ = 43.

*$p$ < 0.05. **$p$ < 0.01.

In Chapter 5, the summary of the findings will be discussed in further detail for each of the research questions as well as implications for educational leaders, specifically in rural public high schools. Additionally, limitations of the study and opportunities for future research will be addressed.

# Chapter 5: Conclusions

The purpose of this quantitative study was to examine rural public high school teachers' perceptions of data-driven instruction in Indiana. Specifically, the intent of the study was to identify rural public high school teachers' perceptions in terms of what types of data they use to support instruction, their attitudes toward data use, their competence in using data to drive instruction, and support systems that help or hinder their ability to effectively participate in data-driven instruction. Additionally, this study sought to examine possible relationships among demographic variables of rural public high school teachers and their corresponding perceptions of data-driven instruction.

This chapter discusses the findings of each research question and the implications of the findings on educational leaders' research and practice regarding the use of student data. Additionally, limitations of this study and recommendations for future research will be discussed. On a final note, all conclusions are based on the findings of the study and either support or contribute to existing research.

## Discussion

### *Research Question 1*

What types of data do rural public high school teachers use to drive their instruction? Existing research has expressed there are multiple types of data teachers use to drive instruction such as state, periodic, local, and personal data (Datnow & Park, 2018; Hamilton et al., 2009; InTASC, 2013; Mandinach et al., 2006a; Marsh et al., 2006; Mokhtari et al., 2007; Wayman, 2010). The findings from this study indicate, in order from most used to least used, participants use personal data most often when informing instruction followed by other data, local data, periodic data, and finally state data. These results conflict with findings from studies conducted by Breiter and Light (2006) and Marsh et al. (2006) where teachers often reported using state tests scores to inform instruction. However, the results do support other existing research, which suggests many teachers have been found to overlook test data and base their decisions on personal data (Ingram et al., 2004; Marsh et al., 2006). Additionally, the increased use of periodic and local data compared to state data contributes to existing findings that school districts across the nation have amplified the implementation of periodic and local assessments in schools to gain more reliable data as well as regular feedback for informed instruction to improve student academic achievement (Datnow & Hubbard, 2015; Datnow & Park, 2014; Marsh et al., 2006; Pella, 2012). Consequently, the actions taken with state, periodic, local, and personal data resulted in similar findings.

This study shows actions taken with personal data were conducted most often where actions with state data were conducted the least often. Such actions include but are not limited to using data to tailor instruction for individual student needs or small group needs, using data to identify content for classroom instruction, and using data to develop recommendations for instructional support. These findings support the study conducted by Marsh et al. (2006) where personal and local data were most commonly used to differentiate curriculum for whole class needs, small group needs, and individual needs as well as to provide guidance on student growth in terms of academic achievement.

***Research Question 2***

What are rural public high school teachers' perceptions of their attitude toward using data to drive instruction? A wide range of teacher attitudes regarding data-driven instruction has been established throughout existing research. Datnow and Park (2014) found teachers who held a negative attitude towards data use actively linked it to federal accountability measures. Additionally, teachers who were found to exude positive attitudes toward data use still held the belief that student test data were not entirely useful in that they did not provide a holistic view of student performance or effectively aid in improving student learning (Datnow & Park, 2014). Furthermore, Schildkamp and Kuiper (2010) found teachers believed student academic achievement was not dependent on data, and Mandinach et al.'s (2006b) study resulted in a group of teachers viewing the use of data as another cycle of requirements that will certainly fade with time and be replaced with new accountability measures. The findings of this study negate existing research in that participants did find some data useful for instructional purposes.

Participants indicated other data is most useful in informing instruction (*M* = 3.67) followed by a close second with personal data being useful (*M* = 3.46). In contrast, local data, periodic data, and state data were found to be less useful with averages of 2.87, 1.96, and 1.84, respectively, which were determined from the following options: 1 = *Not at all*, 2 = *Slightly useful*, 3 = *Useful*, and 4 = *Very useful*. It is important to note that participants also indicated they agreed it is important to use data to inform instruction, contrary to what current literature suggests as previously stated.

On the other hand, the findings of this study regarding teachers' perceptions of the effectiveness of data towards pedagogical practices does support existing research. Datnow and Park (2014) reported teachers found data use beneficial in targeting student strengths and weaknesses as well as for informing instruction. Similarly, participants in this study indicated data helps plan their instruction (*M* = 2.93), informs them of the concepts students are learning or are not learning (*M* = 2.81), and helps them identify learning goals for students (*M* = 2.81). The averages were determined from the following options: 0 = *No opinion*, 1 = *Strongly disagree*, 2 = *Disagree*, 3 = *Agree*, and 4 = *Strongly agree*.

### ***Research Question 3***

What are rural public high school teachers' perceptions of their competence in using data to drive instruction? The findings of this study indicate participants feel they are most competent in modifying instruction based on student data (*M* = 2.81) followed by using data to diagnose student learning needs (*M* = 2.72). These results are based on a Likert scale where 2 = *Disagree* and 3 = *Agree* for numerical analysis. Thus, while the participants may feel most competent in the mentioned areas, their level of agreement is seemingly lacking. Additionally, participants felt least competent in being good at using data to plan lessons (*M* = 2.67) and at setting student learning goals (*M* = 2.63).

These results correlate with the findings of the research conducted by Means et al. (2009) where teachers often reported feeling incapable of using data to inform instruction. Additionally, the low averages of this study regarding teacher competence can be attributed to the lack of supports in place by the school district, which has been found to have a negative effect on teacher perceived competence (Marsh et al., 2006). Such supports are discussed in the following results for the fourth research question.

***Research Question 4***

What are rural public high school teachers' perceptions regarding supports and barriers to using data to drive their instruction? To begin, the results were based off of a Likert scale, which was coded with numerical values as follows: 0 = *No opinion*, 1 = *Strongly disagree*, 2 = *Disagree*, 3 = *Agree*, and 4 = *Strongly agree*. The supports and barriers addressed within the survey are school supports (i.e., professional development, data coach), administrator leadership, technology, and collaborative inquiry. While many factors contribute to whether teachers effectively participate in data-driven instruction, these components have been found to influence pedagogical practices (Datnow & Hubbard, 2016; Datnow & Park, 2014; Datnow et al., 2007; Halverson et al. 2007; Kerr et al., 2006; Mandinach & Honey, 2008; Marsh et al., 2006; Means et al., 2011; Schildkamp & Poortman, 2015; Wayman, 2010). Thus, it was important to include each component in the survey to determine whether each is perceived as a support or barrier in the data-driven decision-making process.

**School Supports.** To begin, participants indicated they did not feel they are provided enough professional development about data use (*M* = 2.09) and the professional development they do receive is not useful for learning about data use (*M* = 2.00). These findings correlate to existing research, which has shown there is little evidence teachers are receiving the professional development they need to be data literate (Datnow & Hubbard, 2016; Kerr et al., 2006; Jimerson & Wayman, 2015; Means et al., 2011). Furthermore, Means et al. (2010) found that even though professional development was provided to educators, it was not sufficient in ensuring participants received the training they needed to effectively participate in data-driven instruction, which is similar to the findings of this study.

In terms of a data coach, Gleason et al. (2019) found schools that employed a data coach were able to develop a culture of data use that teachers embraced and became active participants, which, in turn, enabled teachers to use data to inform instruction. In support of existing research, participants in this study reported they did not feel adequately supported in the effective use of data (*M* = 2.47) nor did they have someone who could help them use data to inform their everyday pedagogy (*M* = 2.07). Consequently, with the lack of support, participants in this study did not regularly make links between instruction and student outcomes (*M* = 2.38). While school supports are a vital component in ensuring teachers have the capacity to effectively use data to inform instruction, they appear to be an overall barrier to using data to drive instruction for participants of this study.

**Administrator Leadership.** Many factors comprise principal leadership in supporting teacher data use: modeling successful data use, encouraging data use to inform instruction, providing training for effective data use, creating opportunities for teachers to use data, and creating time for data use (Datnow et al., 2007; Hamilton et al., 2009; Lachat & Smith, 2005; Mandinach, 2012; Marsh et al., 2006; Means et al., 2009; Suppovitz & Klein, 2003; Wayman et al., 2010; Young, 2006). For instance, Ikemoto and Marsh (2007) found administrators who created a culture for data use by providing teachers with supports such as training, time to use data, and time for collaborative inquiry developed an environment where teachers embraced data use. In contrast, Wayman et al. (2010) found principals rarely participated in collaborative efforts with teachers to discuss student data and guide decisions for informed instruction, which is similar to the results of this study.

Participants reported that their principal or assistant principal(s) did not make sure teachers have plenty of training for data use ($M$ = 1.98) nor did they create time for teachers to use data ($M$ = 1.84). Additionally, participants felt their principal or assistant principal(s) did not model effective data use ($M$ = 2.16), which is a quality administrators must possess in order to provide strong leadership and guidance among teachers (Choppin, 2002; Feldman & Tung, 2001; Ikemoto & Marsh, 2007; Kerr et al., 2006). Overall, participants' perceptions of administrator leadership were negative with a total average of 2.16, which suggests administrator leadership is a barrier for teachers regarding using data for informed instruction.

**Technology.** In this study, participants responded to questions regarding having access to technology, access to data in computer systems, ease of use of computer systems, and computer system functionality and reports. Participants reported they feel they have the technology needed to efficiently examine data ($M$ = 2.81), and the available computer systems are easy to use ($M$ = 2.74). However, the expressed lack of access to numerous data ($M$ = 2.58), lack of capability in examining multiple data sets simultaneously (M = 2.42), and lack of reports generated by the provided computer systems (M = 2.33) is concerning as the data-driven decision-making process cannot be effectively utilized if a sufficient amount of data is not available nor collected and organized for analyzation. Even though teachers voiced they have access to technology that is easy to use, the overall use of computer systems for data-driven decision-making and, in turn, data-driven instruction is seemingly a barrier.

These results support existing research regarding teachers' perceptions of computer systems [data management systems]. Teachers have reported having difficulty accessing and manipulating useful data (Kerr et al., 2006; Marsh et al., 2006; Means et al., 2009; Wayman, 2010) and not having access to multiple data sets simultaneously (Dunn et al., 2013b; Marsh et al., 2006; Wayman et al., 2010). Additionally, many teachers have reported they lack the proper training to efficiently navigate data management systems (Mandinach et al., 2006b; Means et al., 2009), which is a skill that is needed to ensure teachers comprehend the full capabilities of the computer system such as accessing a system's generated reports.

**Collaborative Inquiry.** Collaboration among educators is a vital component for effective data-driven decision-making (Coburn & Turner, 2011; Datnow et al., 2013; InTASC, 2013; Lachat & Smith, 2005; Park & Datnow, 2009; Wayman, 2010; Wayman & Stringfield, 2006). Thus, it is important to note the lack of participants in this study who take part in the collaborative inquiry process. Of the 43 participants, only 24 (56%) reported they have scheduled meetings to work in collaborative teams, and the frequency of such meetings is approximately once or twice a month ($M$ = 2.92). This average was calculated based on a Likert scale coded with numerical values as follows: 1 = *I do not have scheduled meetings*, 2 = *Less than once a month*, 3 = *Once or twice a month*, 4 = *Weekly or almost weekly*, and 5 = *A few times a week*. The remaining results of the survey regarding collaboration were answered by the 24 participants who participate in collaborative inquiry, and the results were categorized under two components: perceptions of collaborative team trust and perceptions of collaborative inquiry actions. All questions within each component were based on a Likert scale and were coded with a numerical value as follows: 0 = *No opinion*, 1 = *Strongly disagree*, 2 = *Disagree*, 3 = *Agree*, and 4 = *Strongly agree*.

To begin, participants reported an overall perception of existing trust and respect within their collaborative team(s). A mean value of 3.02 was calculated when analyzing, in unison, perceived trust with members of their team, ability to discuss feelings and worries with members of their team, and respect amongst their team regarding school leaders and experts in their craft. Comparatively, existing research has found when educators participate in effective collaborative inquiry, they exhibit mutual trust and respect, which is a vital quality to ensure collaborative efforts have a direct, positive effect on student improvement (Wallace & Louden, 1994). However, participants in this study did not wholly agree that their principal or assistant principal(s) fosters a trusting environment for discussing data in teams (M = 2.62). In contrast, Datnow et al. (2013) found teacher's participation in collaboration over data use was due to administrators' guidance on setting norms and expectations for data discussion and providing structured collaboration time.

In terms of collaborative inquiry actions, the results of this study show participants felt their team lacked the capacity to participate in the data-driven decision-making process. For instance, participants reported they did not approach an issue by looking at data ($M = 2.08$), they did not identify questions to answer by using data ($M = 2.13$), they did not look for patterns or trends in data ($M = 2.04$), and they did not use data to make links between instruction and student outcomes ($M = 2.38$), to name a few. When looking at collaborative actions as a whole, the calculated mean is 2.28, which supports the notion that participants perceive collaborative inquiry actions as a barrier to data-driven instruction. These results support existing research.

For example, due to the plethora of data available to educators for analysis, meaningful questions must be asked to narrow the type of data needed to contribute to improved student learning. However, existing research has found teachers are unable to effectively ask meaningful questions and, thus, are unable to identify patterns and make connections between data and instruction (Choppin, 2002; Feldman & Tung, 2001; Ikemoto & Marsh, 2007; Kerr et al., 2006; Means et al., 2009; Suppovitz & Klein, 2003). Futhermore, there is a suggested gap in knowledge among educators pertaining to how to correctly interpret and use data to inform decisions and pedagogical practices (Feldman & Tung, 2001; Kerr et al., 2006; Mandinach et al., 2011; Marsh et al., 2006).

***Research Question 5***

To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict state data is used to drive instruction? Research questions five, six, seven, eight, nine, and ten were driven by curiosity and lack of research regarding whether teacher characteristics predict any facet of teacher participation within the data-driven decision-making process and, in turn, data-driven instruction. For research question five, a stepwise multiple regression analysis was conducted where results were found to not be statistically significant. Thus, the results of this study suggest neither gender, age, years of teaching experience, subject taught, or level education contribute to whether teachers use state data to inform instruction. As stated, there is no existing research that has examined a relationship between a specific teacher characteristic and use of state data regarding data-driven instruction.

***Research Question 6***

To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict periodic data is used to drive instruction? Similarly, after conducting a stepwise multiple regression analysis for research question six, results were found to not be statistically significant. Thus, neither gender, age, years of teaching experience, subject taught, or level of education contribute to whether teachers use periodic data to inform instruction. Little to no existing research has investigated such a relationship. Therefore, these results contribute to existing research by providing insight regarding the lack of a relationship between teacher characteristics and use of periodic data to inform instruction.

***Research Question 7***

To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict local data is used to drive instruction? For research question seven, a stepwise multiple regression analysis was conducted in order to determine the relationship between teacher characteristics and use of local data to inform instruction. The results were not found to be statistically significant. Therefore, neither gender, age, years of teaching experience, subject taught, or level education contribute to whether teachers use local data to inform instruction. As little to no research exists to support the findings of this study, these results contribute to existing research by providing insight regarding the lack of a relationship between teacher characteristics and use of local data to inform instruction.

***Research Question 8***

To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict personal data is used to drive instruction? The results for research question eight indicate there is a statistically significant relationship between a teacher's age and the use of personal data to inform instructional practices. Even though a stepwise multiple regression prediction model found age predicts teachers' use of personal data, further analysis was required to determine the relationship among the differing age groups and personal data use. Therefore, a comparison of means was calculated using the numerical values from the associated Likert scale: 1 = *Do not use*, 2 = *Less than once a month*, 3 = *Once or twice a month*, 4 = *Weekly*, and 5 = *A few times a week*.

Findings suggest the younger the teacher, the more likely they will use personal data to inform instruction. For instance, 20-29 year-old participants use personal data between weekly and a few times a week ($M$ = 4.43) along with 30-39 year-old participants ($M$ = 4.27). The next two age groups, 40-49 year-old and 50-59 year-old, use personal data weekly ($M$ = 4.00; $M$ = 4.00, respectively). Finally, 60+ year-old participants use personal data to inform instruction the least often, which is approximately less than once a month to once or twice a month ($M$ = 2.50).

***Research Question 9***

To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict attitude toward using data to drive instruction? For research question nine, teachers were asked to respond to questions regarding their attitude toward using data to drive instruction. Specifically, the survey addressed attitude in three ways: perceptions of how useful data are in informing teacher practice, perceptions of attitude toward data, and perceptions of the value of data for informing teacher practice. Due to these distinct evaluations, three stepwise multiple regression analysis were conducted in order to examine the differences in perceived attitude.

**Perceptions of the Usefulness of Data.** Results of the study indicate there is a statistically significant relationship between teachers' perceptions of their attitude toward the usefulness of data in informing instruction and teacher age. Therefore, according to the prediction model, among the teacher characteristics comprising of gender, age, years of teaching experience, subject taught, and highest degree earned, teacher age was the only predictor of teachers' perceptions of the usefulness of data. In order to determine the relationship among the differing age groups and teachers' perceptions, a comparison of means was calculated using a Likert scale coded with numerical values as follows: 0 = *No opinion*, 1 = *Not at all*, 2 = *Slightly useful*, 3 = *Useful*, and 4 = *Very useful*.

Findings suggest as age increases, the less useful data is perceived regarding instructional practices. For instance, 20-29 year-old participants perceive data as useful ($M$ = 3.02) followed by 30-39 year-old participants who mostly perceive data to be useful ($M$ = 2.86). The next two age groups, 40-49 year-old and 50-59 year-old, perceive data to be anywhere from slightly useful to useful ($M$ = 2.54; $M$ = 2.46, respectively). Finally, 60+ year-old participants find data to be not at all useful to slightly useful ($M$ = 1.67). While little to no existing research exists to support such results, these findings do correlate with the results of teacher's use of personal data to inform instruction.

**Perceptions of Attitude toward Data.** Results of the study indicate there is a statistically significant relationship between teachers' perceptions of their attitude toward data and age. Therefore, according to the stepwise regression prediction model, among the teacher characteristics comprising of gender, age, years of teaching experience, subject taught, and highest degree earned, teacher age was the only predictor of teachers' perceptions of their attitude toward data. In order to determine the relationship among the differing age groups and teachers' perceptions, a comparison of means was calculated using a Likert scale coded with numerical values as follows: 0 = *No opinion*, 1 = *Strongly disagree*, 2 = *Disagree*, 3 = *Agree*, and 4 = *Strongly agree*.

The general pattern suggests as age increases, participants' perceived attitude toward data becomes increasingly negative. For example, 20-29 year-old participants' attitude toward data use is positive ($M$ = 3.14) followed by 30-39 year-old participants who reported they are, on average, between a negative and positive attitude ($M$ = 2.73), which is the same perceived feeling of the 40-49 year-old group ($M$ = 2.63). The trend shifts in a different direction to show 60+ year-old participants have a more positive attitude than the 50-59 year-old group ($M$ = 2.25; $M$=1.96, respectively). However, regardless of the fractional difference in the findings, both age groups reported a negative perceived attitude toward data. While little to no research exists to support such results, a common trend within this study continues where the findings correlate with the results of teacher's use of personal data to inform instruction as well as teacher's perceived attitude toward the usefulness of data.

**Perceptions of the Value of Data.** Results of the study indicate there is a statistically significant relationship between teachers' perceptions of their attitude toward the value of data regarding informing instructional practices and the subject taught. Therefore, according to the stepwise regression prediction model, among the teacher characteristics comprising of gender, age, years of teaching experience, subject taught, and highest degree earned, the specific subject taught was the only predictor of teachers' perceptions of their attitude of the effectiveness of data toward pedagogical practices. In order to determine the relationship between subject taught and teachers' perceptions, a comparison of means was calculated using a Likert scale coded with numerical values as follows: 0 = *No opinion*, 1 = *Strongly disagree*, 2 = *Disagree*, 3 = *Agree*, and 4 = *Strongly agree*.

The results suggest a limited number of subjects predict participants' perceived attitude of the effectiveness of data towards instructional practices as positive: mathematics ($M$ = 3.20); foreign language ($M$ = 3.50); art, music, and fine arts ($M$ = 2.96); physical education or health ($M$ = 2.95); and special education ($M$ = 2.92). The subject areas that were anywhere from agree to disagree on the value of data towards instruction were English/language arts ($M$ = 2.75), science ($M$ = 2.45), social studies ($M$ = 2.75), and career and technical education ($M$ = 2.63). The single subject that had a distinct negative attitude towards the value of data regarding instructional practices was family and consumer science ($M$ = .60). Since little to no existing research exists to support such results, these findings contribute to what is known about teacher attitudes toward data-driven instruction.

***Research Question 10***

To what extent can characteristics (gender, age, years of teaching experience, subject taught, and level of education) of rural public high school teachers predict competence in using data to drive instruction? The purpose of research question ten was to examine the extent teacher characteristics predict teacher perceptions regarding their capacity at using data to inform their everyday pedagogical practices. After conducting a stepwise regression analysis, results indicate there was not a statistically significant relationship between the teacher characteristics (gender, age, years of teaching experience, subject taught, highest degree earned) and teacher perceived competence in using data. Since little to no existing research exists to support such results, these findings contribute to what is known about teacher competence in using data to inform instruction.

**Limitations**

Even though this study does contribute to the existing body of research regarding teachers' use of data to inform instruction, there are several limitations. To begin, this survey is grounded in quantitative data, which was collected from a survey where teachers self-reported perceptions about using data to guide instructional practices. The survey did not include information regarding teacher preparation programs for data use or the impact of data-driven instruction on student academic achievement. Both of these concepts provide opportunities for further research.

Second, since this study was conducted in rural public high schools in Indiana, the results are not generalizable for rural public high schools outside of Indiana nor all rural public high schools in Indiana. A small portion of the population participated in the study, and within those participating high schools, an even smaller portion of teachers participated. Furthermore, while the survey was sent to all participating high school teachers across all subject areas, not all subject areas are represented, and those that are present in the study are disproportionately represented. Thus, their perceptions and beliefs regarding using data to make informed decisions cannot be generalized towards all non-participating rural public high schools.

Third, producing sound conclusions regarding the results of the survey is difficult as there are a multitude of factors that may have swayed a participant to provide a certain response. For instance, teachers who are quite confident in their abilities to respond to questions about data may have been the sole participants. Teachers within school districts that promote data use and create an environment conducive to a culture of data may represent a disproportionate number of participants. On the other hand, teachers who have had a negative experience with data use may have been eager to participate in order to stimulate a change in the current culture of data use. Regardless of the single variable that prompted a teacher to participate in the study and provide specific responses, the results of the study –

while an important contribution to existing research – are not generalizable. However, these results do provide implications for future educator practice.

**Implications for Practice**

The findings of this study suggest that while teachers use various types of data to some extent to inform instruction (i.e., state, periodic, local, personal, and other), there are many improvement efforts school districts must make in order to ensure teachers are data literate and effectively using data to guide everyday pedagogical practices for improved student learning. As surmised from the results of this study, such improvements efforts include, but are not limited to, providing professional development regarding data use, employing a data expert (i.e., data coach, school data expert), modeling successful data use as an administrator, providing teacher training regarding data management systems, and encouraging collaborative inquiry.

Participants of this study indicated that data aids in planning instruction as it provides information regarding student strengths and weaknesses. However, teacher self-reported competence indicated teachers lack the skills needed to effectively use the data to actively make informed decisions regarding instructional modification, diagnosing student learning needs, and setting student learning goals. Overall, participants of this study felt incapable of using data to inform instruction, which can be attributed to the lack of supports in place by the school district such as professional development. The results of this study suggest teachers are not provided enough professional development regarding data use, and when such professional development is offered, it is not useful.

Professional development is a vital support for teachers to effectively participate in the data-driven decision-making process and, in turn, data-driven instruction (Choppin, 2002; Feldman & Tung, 2001; Ikemoto & Marsh, 2007; Mandinach, 2012; Mandinach & Honey, 2008; Mason, 2002; Means et al., 2009; Suppovitz & Klein, 2003). Thus, school districts should be implementing professional development multiple times throughout the school year that not only is structured around accessing and utilizing a data management warehouse to collect and organize the data but also how to synthesize and prioritize data to actively make informed decisions for improved student learning. In addition to this suggested support, school districts should consider implementing external sources for teacher support such as a data coach or data expert.

School districts that have employed a data coach have been found to successfully develop a culture of data use that teachers embraced and became active participants (Gleason et al., 2019). According to this study, teachers are not currently working in a data conducive environment as they do not feel adequately supported in the effective use of data nor do they have an individual within their school district who is available to answer inquiries. To aid teachers in their endeavors to effectively use data, school districts should consider hiring a data coach to not only train teachers how to use data to inform instruction for improved student learning but also be available to answer teacher inquiries as well as be an expert in the federal and state requirements regarding data literacy in schools. Considering additional employment may not be feasible depending on financial stability, school districts should, at the very least, consider training a handful of employees to become school data leaders to ensure data support for teachers exists.

Additionally, administrators must begin actively fostering a culture of data use within their schools and across the school district. Administrators are key players in enculturing the practice of data-driven decision-making among teachers, which is a strategy that has been reported as effective in increasing staff buy-in (Datnow & Hubbard, 2016; Datnow & Park, 2014; Datnow et al., 2007; Halverson et al., 2007; Mandinach & Honey, 2008; Mandinach et al., 2006b; Marsh et al., 2006; Wayman et al., 2010). Participants in this study felt their administrators did not encourage data use as they did not provide opportunities to learn about data use, they did not create time for teachers to use data, and they did not model effective data use. This lack of support and model behavior is detrimental to teacher competence and attitudes regarding using data to inform instruction. Thus, administrators must start reflecting on their actions, the school environment, and their improvement efforts in order to ensure all are conducive to a school culture of data use.

Another support that has been found to be a key component in developing a data-driven decision-making culture within a school is technology (Hamilton et al., 2009; Wayman & Stringfield, 2006). While participants did report that they have access to technology to examine data, they did not have the skill set needed to appropriately examine the data and generate reports. Thus, school districts must begin creating structured time to train teachers to effectively utilize data management systems – using data to inform instruction cannot be done unless teachers are able to first access and examine data. Once this task has been completed, school districts can begin building structured time for collaborative inquiry – the final improvement effort.

Collaboration is a form of professional development as it allows data-driven decision-making to become a part of how a school system functions for continuous improvement rather than regarded as extra work (Coburn & Turner, 2011; Datnow et al., 2013; Means et al., 2011). According to this study, the issue in current educational practice is that a limited number of teachers participate in collaborative efforts, and among those respective teachers, there is a severe lack of action taken regarding data-driven decision-making. Teachers do not participate in data-driven inquiry, they do not examine data by looking for patterns or trends, they do not draw conclusions based on data, and they do not make links between instruction and student outcomes. All of these tasks are vital to ensure improved student learning is achieved. Therefore, after school districts have established professional development, training with technology, and a data expert, they should create structured collaboration time among teachers to provide the opportunity to effectively participate in the data-driven inquiry process for improved student learning.

This study has provided numerous implications for practice and how school districts and administrators can approach the issue surrounding teachers' lack of data literacy skills. While not all suggested improvement efforts can be launched at once, school districts can begin the process of creating a school improvement plan that identifies stages of established improvement efforts. The overarching goal should consist of providing teachers the support they need to be data literate and effectively use the data to inform instruction for improved student learning.

**Recommendations for Future Research**

This study contributes to the existing body of research regarding data-driven instruction in rural public high schools; however, there are opportunities for additional research. To begin, this study focuses on teachers' perceptions of data use according to their experiences in a rural public high school setting. To truly understand teachers' capacity building efforts to be data literate, more research should be conducted regarding teacher preparation programs and to what extent those programs train teachers to be data literate and participate in the data-driven decision-making process. The existence of these programs could account for some of the variation of the responses among participants of this study regarding their use of data, attitude toward data, and competence toward data use.

Additionally, this study did not account for the impact of teachers' participation in data-driven instruction on actual student academic achievement. Federal and state educational legislation requires teachers to effectively use data to inform instruction for improved student learning, but until educators delve deeper into the issue of the effect data-driven instruction has on student achievement, it will remain to be seen whether educators are satisfying the mandated requirements.

In this study, the researcher found that not only is subject taught a predictor for teacher attitude toward the value of data toward pedagogical practices but also age is a predictor for the extent personal data is used to inform instruction, teacher attitudes toward data, and teacher attitudes toward the usefulness of data. However, because the sample population was diverse regarding demographic data, future research could be conducted on a group of rural public high school teachers with a specific demographic to determine if the trend in responses are unwavering.

Another opportunity for future research pertains to the effect different school improvement efforts have on building teachers' capacity to be data literate. For instance, qualitative research could be conducted in a school that has successfully established collaboration time among teachers to participate in the data-driven decision-making process regarding data-driven instruction. Other successful support efforts may include data management systems, administrator leadership, data coaches, or professional development. Regardless, the results of such research on a successful support system could aid school districts and administrators in establishing similar programs to not only support their teachers but also build teachers' data literacy skills for improved student academic achievement.

Finally, since only rural public high school teachers in the state of Indiana participated in the study, the results are not generalizable to similar locations. Therefore, future research should include teachers from rural public high schools in other areas across the United States. In doing so, researchers can begin building a robust foundation of knowledge to begin replacing the current lack of rural educational research.

**Summary**

Teachers are required to be able to effectively use data to tailor instruction to students' needs for improved student academic achievement. However, teachers are not being provided the proper support to develop the skill level needed to participate in data-driven instruction, which is a disservice to both teachers and students. Teachers deserve to have the proper training, equipment, and support needed to effectively collect, organize, analyze, summarize, synthesize, and prioritize data to inform everyday pedagogical practices, and students deserve to have the opportunity to achieve academic growth. These tasks can begin to be accomplished by school districts through establishing a culture of data use, encouraging teachers to use data, and providing the supports needed for effective data use.

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Appendices

## Appendix A: Survey Instrument

### Teacher Data Use Survey: Teacher Version

The purpose of this survey is to measure teachers' perceptions of data-driven instruction for improved student achievement; thus, the survey will collect information pertaining to teachers' use of specific student data to drive instruction, their attitude toward using data to influence their instructional practices, their perceptions of their data literacy skills, and their perceptions of support systems in place that help or hinder their ability to effectively participate in data-driven instruction.

### Demographic Data

What gender do you identify as? (Check only one.)

- ☐ Male
- ☐ Female
- ☐ Other
- ☐ Prefer not to answer

What is your age? (Check only one.)

- ☐ 20-29 years
- ☐ 30-39 years
- ☐ 40-49 years
- ☐ 50-59 years
- ☐ 60+ years
- ☐ Prefer not to answer

How many years have you been teaching in your current institution? (Check only one.)

- ☐ This is my first year
- ☐ 1-5 years
- ☐ 6-10 years
- ☐ 11-15 years
- ☐ 16-20 years
- ☐ More than 20 years
- ☐ Prefer not to answer

What subject do you primarily teach? (Check only one.)

- ☐ English/Language Arts
- ☐ Art, Music, or Fine Arts
- ☐ Mathematics
- ☐ Physical Education or Health
- ☐ Science
- ☐ Social Studies
- ☐ Foreign Language
- ☐ Bilingual/ESL
- ☐ Computer Science
- ☐ Career and Technical Education
- ☐ Special Education
- ☐ Family and Consumer Science
- ☐ Other
- ☐ Prefer not to answer

What is the highest degree or level of education you have completed? (Check only one.)

- ☐ Associate's Degree
- ☐ Bachelor's Degree
- ☐ Master's Degree
- ☐ Doctorate or higher
- ☐ Trade School
- ☐ Prefer not to answer

**Instructions**

Please read each question carefully, and check the box under the one answer that most clearly fits your opinion regarding your experience in your current institution. The definitions for each type of data being addressed in this survey are provided below for your reference when answering the questions.

| **State data:** | **Periodic data:** | **Local data:** | **Personal data:** |
|---|---|---|---|
| standardized state assessments (i.e., ISTEP, ILearn, etc.) | commercially available periodically administered assessments (i.e., NWEA, Acuity, i-Ready, etc.) | district-developed assessments (i.e., common assessments, end-of-course exams, etc.) | classroom-based assessments (i.e., homework, quizzes, writing assignments, end-of-unit tests, portfolio, etc.) |

The following questions ask about various forms of data that you may use in your work.

1. Are the following forms of data available to you?

| Form of data | Yes | No |
|---|---|---|
| State data | ☐ | ☐ |
| Periodic data | ☐ | ☐ |
| Local data | ☐ | ☐ |
| Personal data | ☐ | ☐ |
| Other data | ☐ | ☐ |

If you indicated "no" to all options in question 1, skip to question 8. If you responded "yes" to any option, please proceed to question 2.

2. Teachers use all kinds of information (i.e., data) to help plan for instruction that meets student learning needs. How frequently do you use the following forms of data?

| Form of data | Less than once a month | Once or twice a month | Weekly | A few times a week | Do not use |
|---|---|---|---|---|---|
| State data | ☐ | ☐ | ☐ | ☐ | ☐ |
| Periodic data | ☐ | ☐ | ☐ | ☐ | ☐ |
| Local data | ☐ | ☐ | ☐ | ☐ | ☐ |
| Personal data | ☐ | ☐ | ☐ | ☐ | ☐ |
| Other data | ☐ | ☐ | ☐ | ☐ | ☐ |

3. How useful are the following forms of data to your practice?

| Form of data | Not at all | Slightly useful | Useful | Very useful | No opinion |
|---|---|---|---|---|---|
| State data | ☐ | ☐ | ☐ | ☐ | ☐ |
| Periodic data | ☐ | ☐ | ☐ | ☐ | ☐ |
| Local data | ☐ | ☐ | ☐ | ☐ | ☐ |
| Personal data | ☐ | ☐ | ☐ | ☐ | ☐ |
| Other data | ☐ | ☐ | ☐ | ☐ | ☐ |

If you indicated that state data is not available to you in question 1, OR if you indicated that you do not use state data in question 2, please go to question 5.

4. These questions ask about state data. In a typical school year, how often do you do the following?

| Action | One or two times a year | A few times a year | Monthly | Weekly | Not at all |
|---|---|---|---|---|---|
| Use state data to identify instructional content to use in a class. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Use state data to tailor instruction to individual students' needs. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Use state data to develop recommendations for additional instructional support. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Use state data to form small groups of students for targeted instruction. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Discuss state data with a parent or guardian. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Discuss state data with a student. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Meet with a specialist (i.e., instructional coach or data coach) about state data. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Meet with another teacher about state data. | ☐ | ☐ | ☐ | ☐ | ☐ |

If you indicated that periodic data is "not available" to you in question 1, OR if you indicated that you "do not use" periodic data in question 2, please go to question 6.

5. These questions ask about periodic data used in your school district. In a typical month, how often do you do the following?

| Action | Less than once a month | Once or twice a month | Weekly | A few times a week | Not at all |
|---|---|---|---|---|---|
| Use periodic data to identify instructional content to use in a class. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Use periodic data to tailor instruction to individual students' needs. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Use periodic data to develop recommendations for additional instructional support. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Use periodic data to form small groups of students for targeted instruction. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Discuss periodic data with a parent or guardian. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Discuss periodic data with a student. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Meet with a specialist (i.e., instructional coach or data coach) about periodic data. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Meet with another teacher about periodic data. | ☐ | ☐ | ☐ | ☐ | ☐ |

If you indicated that local data is "not available" to you in question 1, OR if you indicated that you "do not use" local data in question 2, please go to question 7.

6. These questions ask about local data developed and used in your school district. In a typical month, how often do you do the following?

| Action | Less than once a month | Once or twice a month | Weekly | A few times a week | Not at all |
|---|---|---|---|---|---|
| Use local data to identify instructional content to use in a class. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Use local data to tailor instruction to individual students' needs. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Use local data to develop recommendations for additional instructional support. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Use local data to form small groups of students for targeted instruction. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Discuss local data with a parent or guardian. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Discuss local data with a student. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Meet with a specialist (i.e., instructional coach or data coach) about local data. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Meet with another teacher about local data. | ☐ | ☐ | ☐ | ☐ | ☐ |

If you indicated that personal data is "not available" to you in question 1, OR if you indicated that you "do not use" personal data in question 2, please go to question 8.

7. These questions ask about personal data. In a typical month, how often do you do the following?

| Action | Less than once a month | Once or twice a month | Weekly | A few times a week | Not at all |
|---|---|---|---|---|---|
| Use personal data to identify instructional content to use in a class. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Use personal data to tailor instruction to individual students' needs. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Use personal data to develop recommendations for additional instructional support. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Use personal data to form small groups of students for targeted instruction. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Discuss personal data with a parent or guardian. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Discuss personal data with a student. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Meet with a specialist (i.e., instructional coach or data coach) about personal data. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Meet with another teacher about personal data. | ☐ | ☐ | ☐ | ☐ | ☐ |

The remainder of this survey asks general questions about the use of data to inform your education practice. For the rest of this survey, please consider only the following when you are asked about "data".

- State achievement tests.
- Periodic assessments.
- Locally developed assessments.

8. These questions ask about supports for using data. Please indicate how much you agree or disagree with the following statements:

| Statement | Strongly disagree | Disagree | Agree | Strongly agree | No opinion |
|---|---|---|---|---|---|
| I am adequately supported in the effective use of data. | ☐ | ☐ | ☐ | ☐ | ☐ |
| I am adequately prepared to use data. | ☐ | ☐ | ☐ | ☐ | ☐ |
| There is someone who answers my questions about using data. | ☐ | ☐ | ☐ | ☐ | ☐ |
| There is someone who helps me change my practice (teaching) based on data. | ☐ | ☐ | ☐ | ☐ | ☐ |
| My district provides enough professional development about data use. | ☐ | ☐ | ☐ | ☐ | ☐ |
| My district's professional development is useful for learning about data use. | ☐ | ☐ | ☐ | ☐ | ☐ |

9. These questions ask about your attitudes and opinions regarding data. Please indicate how much you agree or disagree with the following statements:

| Statement | Strongly disagree | Disagree | Agree | Strongly agree | No opinion |
|---|---|---|---|---|---|
| Data help teachers plan instruction. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Data offer information about students that was not already known. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Data help teachers know what concepts students are learning. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Data help teachers identify learning goals for students. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Students benefit when teacher instruction is informed by data. | ☐ | ☐ | ☐ | ☐ | ☐ |
| I think it is important to use data to inform education practice. | ☐ | ☐ | ☐ | ☐ | ☐ |
| I like to use data. | ☐ | ☐ | ☐ | ☐ | ☐ |
| I find data useful. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Using data helps me be a better teacher. | ☐ | ☐ | ☐ | ☐ | ☐ |

10. These questions ask how your principal and assistant principal(s) support you in using data. Principals and assistant principals will not be able to see your answers. Please indicate how much you agree or disagree with the following statements:

| Statement | Strongly disagree | Disagree | Agree | Strongly agree | No opinion |
|---|---|---|---|---|---|
| My principal or assistant principal(s) encourages data use as a tool to support effective teaching. | ☐ | ☐ | ☐ | ☐ | ☐ |
| My principal or assistant principal(s) creates many opportunities for teachers to use data. | ☐ | ☐ | ☐ | ☐ | ☐ |
| My principal or assistant principal(s) has made sure teachers have plenty of training for data use. | ☐ | ☐ | ☐ | ☐ | ☐ |
| My principal or assistant principal(s) is a good example of an effective data user. | ☐ | ☐ | ☐ | ☐ | ☐ |
| My principal or assistant principal(s) discusses data with me. | ☐ | ☐ | ☐ | ☐ | ☐ |
| My principal or assistant principal(s) creates protected time for using data. | ☐ | ☐ | ☐ | ☐ | ☐ |

11. Your school or district gives you programs, systems, and other technology to help you access and use student data. The following questions ask about these computer systems. Please indicate how much you agree or disagree with the following statements.

| Statement | Strongly disagree | Disagree | Agree | Strongly agree | No opinion |
|---|---|---|---|---|---|
| I have the proper technology to efficiently examine data. | ☐ | ☐ | ☐ | ☐ | ☐ |
| The computer systems in my district provide me access to lots of data. | ☐ | ☐ | ☐ | ☐ | ☐ |
| The computer systems (for data use) in my district are easy to use. | ☐ | ☐ | ☐ | ☐ | ☐ |
| The computer systems in my district allow me to examine various types of data at once (i.e., attendance, achievement, demographics). | ☐ | ☐ | ☐ | ☐ | ☐ |
| The computer systems in my district generate displays (i.e., reports, graphs, tables) that are useful to me. | ☐ | ☐ | ☐ | ☐ | ☐ |

12. These questions ask about your attitudes toward your own use of data. Please indicate how much you agree or disagree with the following statements:

| Statement | Strongly disagree | Disagree | Agree | Strongly agree | No opinion |
|---|---|---|---|---|---|
| I am good at using data to diagnose student learning needs. | ☐ | ☐ | ☐ | ☐ | ☐ |
| I am good at adjusting instruction based on data. | ☐ | ☐ | ☐ | ☐ | ☐ |
| I am good at using data to plan lessons. | ☐ | ☐ | ☐ | ☐ | ☐ |
| I am good at using data to set student learning goals. | ☐ | ☐ | ☐ | ☐ | ☐ |

The following questions ask about your work in collaborative teams.

13. How often do you have scheduled meetings to work in collaborative team(s)? (Check only one.)
    - ☐ Less than once a month.
    - ☐ Once or twice a month.
    - ☐ Weekly or almost weekly.
    - ☐ A few times a week.
    - ☐ I do not have scheduled meetings to work in collaborative teams.

If you answered “I do not have scheduled meetings to work in collaborative teams” in question 13, please end the survey

14. As you think about your collaborative team(s), please indicate how much you agree or disagree with the following statement(s):

| Statement | Strongly disagree | Disagree | Agree | Strongly agree | No opinion |
|---|---|---|---|---|---|
| Members of my team trust each other. | ☐ | ☐ | ☐ | ☐ | ☐ |
| It's ok to discuss feelings and worries with other members of my team. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Members of my team respect colleagues who lead school improvement efforts. | ☐ | ☐ | ☐ | ☐ | ☐ |
| Members of my team respect those colleagues who are experts in their craft. | ☐ | ☐ | ☐ | ☐ | ☐ |
| My principal or assistant principal(s) fosters a trusting environment for discussing data in teams. | ☐ | ☐ | ☐ | ☐ | ☐ |

15. How often do you and your collaborative team(s) do the following?

| Statement | Less than once a month | Once or twice a month | Weekly | A few times a week | Not at all |
|---|---|---|---|---|---|
| We approach an issue by looking at data. | ☐ | ☐ | ☐ | ☐ | ☐ |
| We discuss our preconceived beliefs about an issue. | ☐ | ☐ | ☐ | ☐ | ☐ |
| We identify questions that we will seek to answer using data. | ☐ | ☐ | ☐ | ☐ | ☐ |
| We explore data by looking for patterns and trends. | ☐ | ☐ | ☐ | ☐ | ☐ |
| We draw conclusions based on data. | ☐ | ☐ | ☐ | ☐ | ☐ |
| We identify additional data to offer a clearer picture of the issue. | ☐ | ☐ | ☐ | ☐ | ☐ |
| We use data to make links between instruction and student outcomes. | ☐ | ☐ | ☐ | ☐ | ☐ |
| When we consider changes in practice, we predict possible student outcomes. | ☐ | ☐ | ☐ | ☐ | ☐ |
| We revisit predictions made in previous meetings. | ☐ | ☐ | ☐ | ☐ | ☐ |
| We identify actionable solutions based on our conclusions. | ☐ | ☐ | ☐ | ☐ | ☐ |

## Appendix B: Consent Form

***UNIVERSITY OF SOUTHERN INDIANA***
***Data-Driven Decision-Making: Rural Public High School Teachers' Perceptions of Data-Driven Instruction***
***(1711260-1)***

### Informed Consent Document

You are invited to participate in a research study seeking to understand teachers' sense of efficacy in relation to data-driven instruction and support systems that help or hinder their ability to effectively use student data to inform instruction. This study is being conducted by Amber R. Hasenour-Bolling – an Educational Leadership Doctoral Student at the University of Southern Indiana – under the supervision of faculty sponsor Dr. Tori Colson. If you have any questions pertaining to the research study, please contact Amber R. Hasenour-Bolling at: 1110 S. Main St., Huntingburg, IN 47542, arhasenour@eagles.usi.edu, or (812) 683-2272.

This study will take approximately 10-15 minutes of your time. You will be asked to complete an online survey about your use of data, your attitude toward data, and your perception of supports for data use.

Your decision to participate or decline participation in this study is completely voluntary and you have the right to terminate your participation at any time without penalty. If you do not wish to complete this survey, simply close your browser.

Your participation in this research will be completely confidential as no identifying information will be collected. All surveys will be stored in Qualtrics and will be accessible only by the researcher and members of the researcher's dissertation committee until such an event the surveys are no longer needed. Surveys will be coded for confidentiality and anonymity. During data analysis, only coded survey data will be used. Also, all research results will be reported with aggregate data, which further ensures confidentiality. All data will be electronic and stored on a password protected computer accessible only by the researcher. After five years, all data will be deleted. You may choose to submit your email address at the end of the survey to be included in a drawing for one of four $25 gift cards to Amazon. As soon as winners have been notified, all email address will be permanently removed from the computer system.

You may benefit from participation by gaining a better understanding of your own use of student data to drive instruction as well as a possible increased understanding of the differing types of student data that could be used for data-driven instruction and support systems that could be implemented to aid in data-driven instruction. There are no foreseeable risks or discomforts to your participation beyond those that exist in daily life. If you have questions about your rights as a subject /participant in this research, or if you feel you have been placed at risk, you can contact the USI Office of Sponsored Projects & Research Administration at (812) 465-7000 or rcr@usi.edu.

Please print a copy of this consent form for your records, if you so desire.