Teacher Attitudes and Beliefs about Data-Driven Decision-making: The Impact on Engagement in a Data Team Setting

by

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DISSERTATION ABSTRACT

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Title: Teacher Attitudes and Beliefs about Data-Driven Decision-making: The Impact on Engagement in a Data Team Setting

This study examines teachers' attitudes and beliefs about data-driven decision-making (DDDM) and how these perceptions shape their engagement in collaborative data teams. Using a qualitative case study approach, semi-structured interviews and field observations revealed three interconnected themes. First, time was a significant barrier, as teachers struggled to balance data collection and analysis with instructional responsibilities. Second, teachers expressed a strong desire for control over data-related processes, including what data is collected, how it is analyzed, and who is involved in decision-making. This need for autonomy influenced their engagement with mandated assessments. Third, teachers valued data that was directly aligned with their instruction, often questioning the relevance and validity of standardized assessments. These findings highlight the complex interplay between time, control, and data use in shaping teachers' experiences with DDDM. The study underscores the need for school and district leaders to create data-use policies that respect teachers' professional expertise, allocate sufficient time, and ensure instructional relevance.

Keywords: data-driven decision-making, qualitative, engagement, teacher attitudes

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DEDICATION

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TABLE OF CONTENTS

Chapter Page

Chapter Page

Chapter Page

Chapter Page

LIST OF FIGURES

Figure Page

LIST OF TABLES

Table Page

CHAPTER I

INTRODUCTION

The era of school accountability traces its roots to the development of standardized measures of intelligence and achievement, passage of several key pieces of legislation, and an ever-mounting pressure for schools to produce results. As states have focused an increasingly narrowed lens on achievement based on data, school districts have responded by requiring data as the focal point for decision-making. This has not always been the case in public schools. The *No Child Left Behind Act* (NCLB), legislation passed in 2001 under President George W. Bush, ushered in a different relationship with data and data-driven decision-making (DDDM).

Federal and State Assessment Background

Starting in 1872, the first record of data collection in schools shows basic statistics centered around elementary and secondary school enrollment, attendance, teachers, and teacher salaries (Grant, 1993). By 1920, data collection had expanded to include a breakdown of school expenditures and income by source. Around this same time, several developments in standardized testing were also happening alongside the collection and reporting of school statistics. Alfred Binet, a French psychologist, developed an individually administered test to measure intelligence initially used to identify "slow children who would not profit from schooling" (Walsh & Betz, 1995, p. 2). This system for measuring intelligence was brought to the United States by H.H. Goddard in 1911 and was initially used by the U.S. military to test soldiers' mental abilities (Gallagher, 2003). In 1919, Lewis Terman reworked the military intelligence test into the National Intelligence Tests for schoolchildren, and the era of standardized testing was born.

Standardized testing became the norm with the Stanford Achievement Test (SAT) introduced in 1923, the Iowa Test of Basic Skills (ITBS) in 1929, and the American College Test (ACT) in 1959 (Gallagher, 2003). These standardized tests were used to determine which students should be promoted or retained, receive academic honors, and assigned to special education placements.

The 1960s ushered in a decade of legislation tied to data use. The *Elementary and Secondary Education Act* (ESEA) passed in 1965 required schools to administer standardized tests and submit those results to receive federal funding. In 1969, the federal government introduced the National Assessment of Educational Progress (NAEP), which measured student achievement in math, science, and reading (Gallagher, 2003). The following decades of the 1970s and 1980s witnessed increasing demand for educational accountability based on data. In 1974, Title 1 funding was tied to school programming, and standardized tests were used to qualify for federal dollars. By the early 1980s, 33 states required some form of standardized testing. The publication *A Nation at Risk* (National Commission on Excellence in Education, 1983) urged public schools and universities to adopt rigorous standards and ensure performance or suffer the consequences of falling behind:

> Our nation is at risk. Our once unchallenged preeminence in commerce, industry, science, and technological innovation is being overtaken by competitors from throughout the world… the educational foundations of our society are presently being eroded by a rising tide of mediocrity that threatens our very future as a Nation and a people. (p. 5)

As a result of *A Nation at Risk*, 47 states had adopted policies that expanded state-wide testing programs by the 1990s.

NCLB aimed to close the achievement gap in reading and math that persisted in public schools in the United States (Adler-Greene, 2019). To close this achievement gap, NCLB called for 100% of students to reach proficiency in reading and math by 2014. Individual states were required to assess every student in reading and math in grades 3 through 8 and 11. Pressure on schools to test students and demonstrate proficiency in math and reading created a high stakes environment, and teachers focused energy on tests to escape consequences for failure (Adler-Greene, 2019).

Although NCLB intended to close achievement gaps and increase achievement for all students through annual test score reporting, there were unintended consequences. Achievement gaps, as defined by the National Center for Education Statistics, "occur when one group of students (e.g., students grouped by race/ethnicity, gender) outperforms another group and the difference in average scores for the two groups is statistically significant." Schools shifted their instructional emphasis to reading, writing, and math and away from science, social studies, foreign languages, physical education, and art (Oregon Department of Education [ODE], 2017). In 2015, Congress passed the *Every Student Succeeds Act* (ESSA), which shifted accountability for achievement to individual states (see Table 1). Flexibility to set goals for improving student achievement and graduation rates and support for school districts were passed to state departments of education (ODE, 2017).

In Oregon, students in grades 3 through 8 and 11 participate in summative tests in reading and math as outlined in the ODE's approved ESSA plan (ODE, 2017). This plan also outlines goals for graduation rates as well as English language proficiency. All data are made available to educators, and schools must continue to show growth on these data-based measures. Data-based decision-making (DBDM) and data-driven decision-making (DDDM) are often used

interchangeably, but they have distinct nuances. DBDM refers to using multiple sources of data—both qualitative and quantitative—to inform decisions, allowing for professional judgment alongside data. In contrast, DDDM typically emphasizes a more structured, systematic reliance on quantitative data, often tied to accountability measures and standardized assessments.

Table 1

Comparison of NCLB and ESSA Requirements

Requirement	NCLB	ESSA
Accountability	All students tested annually in grades 3-8 and 11 in math and reading	All students tested annually in grades 3-8 and 11 in math and reading
School improvement	Defined progress primarily on test scores; provided by the same goal (all students "proficient" by 2014) for all schools and all states.	States determine their own definition of progress, using multiple measures. States also determine how much weight to put place on each measure.
School intervention funding	Provided no additional dollars for school improvement.	Does not specifically authorize new money but allows states and districts to direct a portion of Title 1 dollars for school interventions.
Teacher evaluation	Obama administration required states to establish teacher evaluation systems based in part on student test scores to waive some of the law's requirements.	Allows, but does not require, states to evaluate teachers based on student achievement and use federal funds for that purpose.

Note. Adapted from Murphy & Warren (2015).

The most recent data reported by the ODE shows 40% of third graders proficient in reading and only 26% of eighth graders proficient in math (ODE, 2023). These proficiency levels fall short of the overall state goal of 80% proficiency in reading and math for all Oregon students. To make progress toward this goal, both teachers and school leaders must navigate data analysis and employ data-driven decision-making to shift classroom instruction in ways that meet student learning needs. Key factors in school improvement are access to rich sources of data and teachers skilled in data use and data-driven decision-making (Darling-Hammond et al.,

2014). These data sources include embedded curriculum assessments; state assessments validating math, English Language Arts (ELA), and science learning; and locally developed assessments.

Given the scrutiny of the current climate of assessment and achievement, it is critical that teachers and school leaders both become data literate and develop skills in data-driven decision-making. A study by Hamilton et al. (2008) suggests several key relationships between NCLB, high stakes testing, and standards-based instruction. In addition to a focus on testing rather than standards and skills, data-driven decision-making for instruction was moved from the classroom level to the district and state level. This change resulted in a lack of clarity regarding data use for learning and often led to a focus on low-level skills reflected on the tests (Hamilton et al., 2008).

Research Problem

Datnow and Hubbard (2015) conducted a review of international research on teacher capacity for and beliefs about data-driven decision-making. The review included 65 reports and quantitative and qualitative research studies. Sources were included in the review based on the following criteria: (a) a publication date of 2001 or later, and (b) the publication had to include information on efforts to build K-12 teachers' capacity to use data or teachers' beliefs about data use, or both. In all, 65 manuscripts were examined. According to Datnow and Hubbard (2015), "only a handful of studies focused specifically on teacher capacity for and/or beliefs about data use. A greater number of studies focused on capacity building than teacher beliefs" (p. 9). Although teachers' capacity for DDDM is important, the influence of attitudes, beliefs, and perceptions about DDDM impact their ability to engage in data use and DDDM.

A second extensive literature review was conducted by Erten and Koseoglu (2022) with a focus on the general research trends in the field of education within the theory of planned

behavior. The 77 studies included in the literature review were based on the following criteria: (a) studies must include teachers, pre-service teachers, and students as the population sample; (b) studies conducted in primary and secondary schools and universities, and (c) studies published between 1990 and 2020. Studies fell into four broad categories: explaining student behaviors, explaining teacher behaviors, identifying cultural differences, and comparing the abilities of theories to explain behavior. Within the teacher-focused studies, most were centered on technology integration and special needs integration. Application of the theory of planned behavior to teacher attitudes and perceptions of DDDM is an area in need of further study.

Purpose and Research Questions

The purpose of this study is threefold: to (a) identify teacher attitudes and beliefs about data-driven decision-making, (b) identify patterns in DDDM behavior in a data-team context based on attitudes and beliefs, and (c) provide recommendations for educational leaders to support teachers within DDDM structures. Better understanding the attitudes and beliefs of teachers could enable educational leaders to intervene and support teachers as they engage with data-driven decision-making, particularly in the setting of a data-team meeting. Using the theory of planned behavior as a theoretic framework, this research aims to connect beliefs and attitudes with behaviors. The importance of data use for instructional improvement necessitates a deep understanding of the connection between an individual's beliefs and their behavior.

CHAPTER II

LITERATURE REVIEW

Research and literature using key terms across a variety of research data bases (see Table 2) informed the literature review. Sources included both qualitative and quantitative empirical studies, meta-analyses, and reports.

Table 2

Summary of Literature Review Parameters

Keywords	Databases	Types of Literature
Data-driven decision-making Attitudes and beliefs Theory of planned behavior Data Teams	Google Scholar ERIC Academic Search Premier	Qualitative studies Quantitative studies Meta-analyses Reports (university, government, foundation) Books Conference papers

Data-driven Decision-making in Education

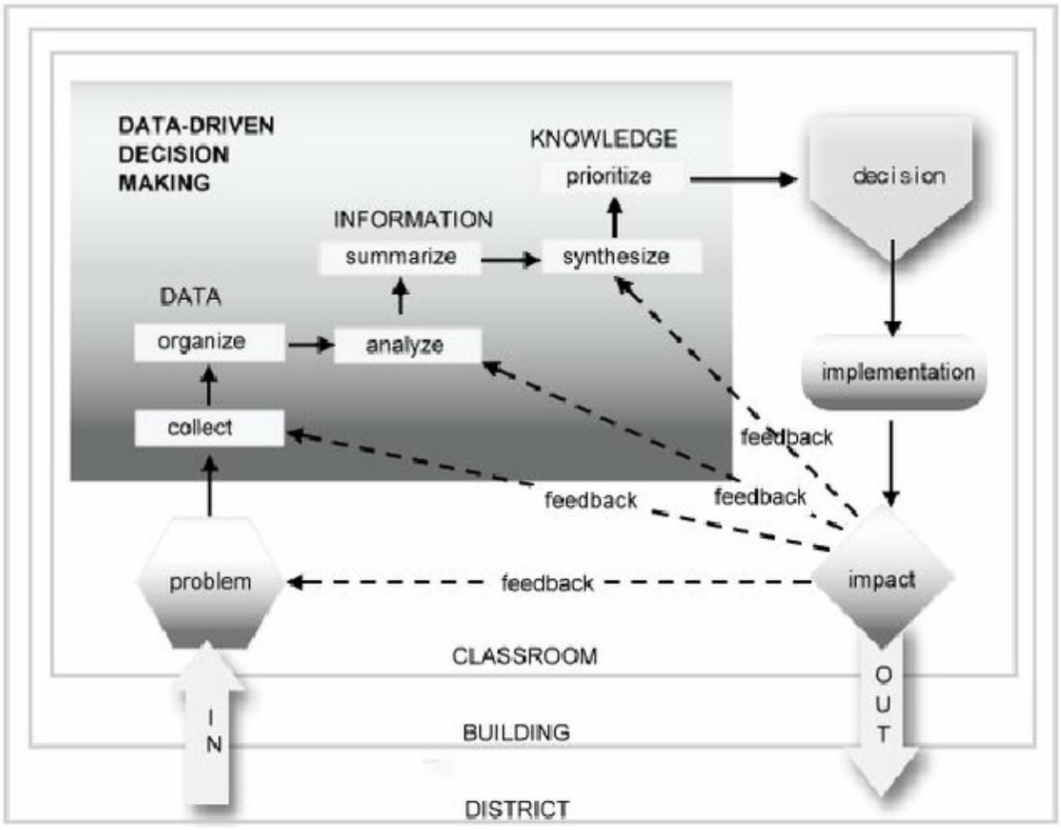
Data use for decision-making in the classroom prior to the historic *No Child Left Behind* legislation was primarily limited to individual teachers administering tests and homework, taking attendance, and creating and distributing report cards. The major shift towards DDDM in public schools stemmed from high-stakes accountability legislation that requires schools to use data to measure progress toward state and district adopted standards and hold them accountable for student achievement. To understand how teacher attitudes and beliefs impact decision-making with data, it is important to understand how DDDM works and how DDDM evolved in educational settings. There exist both benefits and challenges that impact the implementation of DDDM in schools.

Definition and Principles of DDDM

The most basic definition of DDDM refers to administrators, principals, and teachers "systematically collecting and analyzing data to guide a range of decisions to help improve the success of students and schools" (Ikemoto & Marsh, 2007, p. 108). The DDDM process, as outlined in Figure 1, which was adapted from Mandinach et al. (2006), starts with data collection and organization, which is then transformed into information. This information is then applied to knowledge, which is applied to make decisions.

Figure 1

Framework for Data-Driven Decision-making



A wide variety of data are available to classroom teachers (Ikemoto & Marsh, 2007; Mandinach, 2012; Mandinach et al., 2006). These include data related to demographics of the school population, information about student performance such as assignments and tests, and

summative data such as state assessments. Although there are a wide variety of data available, the climate of accountability driven by state and federal requirements can impact the types of data on which teachers focus.

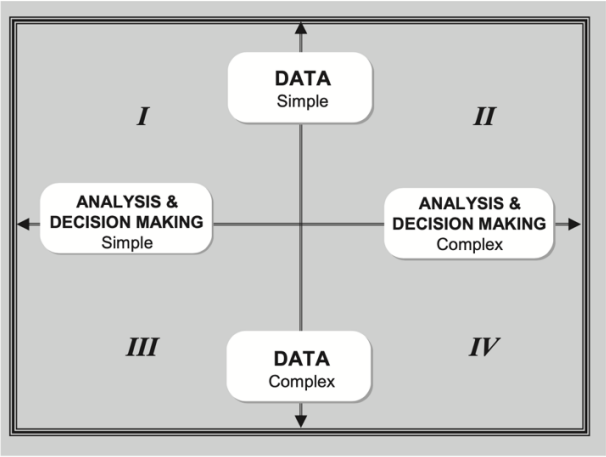
Decades of accountability have given data a narrow definition. Data use, according to Mandinach and Gummer (2016), has historically been limited to assessments in reading and math used specifically for accountability. This narrow focus does not fit the expanded definition proposed by Mandinach and Gummer. Data literacy, which includes assessment literacy, is much broader and comprehensive in scope. Data literacy must include a deep understanding of specific content domains, the data embedded within those domains, as well as an understanding of the connection to learning outcomes for students (Mandinach & Gummer, 2016). This deep understanding requires five components: (a) identifying problems and framing questions, (b) using data, (c) transforming data into information, (d) transforming information into a decision, and (e) evaluating outcomes (Mandinach & Gummer, 2016). Green et al. (2016) emphasize that educators need to know how to summarize data from multiple sources and use those data to make instructional decisions that improve student learning. Establishing a data-driven culture within schools is necessary, and deepening educators' understanding of the benefits of data literacy and how to use data for increasing student improvement are part of a data literate school climate (Green et al., 2016).

Once data have been collected, they are analyzed and interpreted to form meaning (Coburn & Turner, 2011; Mandinach, 2012; Mandinach et al., 2006). The analysis of the data requires educators to construct new meaning based on previous understanding and preexisting beliefs, and each person will interpret data through their own unique beliefs and perspectives (Hora et al., 2017). This step of the DDDM process can lead to very different outcomes and is

dependent on the attitudes and beliefs the educator has about the data itself. Ikemoto and Marsh (2007) argue that the type of data collected and the way in which the data are analyzed can lead to different outcomes (see Figure 2, adapted from Ikemoto & Marsh, 2007). Simple forms of data tend to be less comprehensive and less complicated, come from one point in time, and from one perspective (Ikemoto & Marsh, 2007). Complicated forms of data, in contrast, are multidimensional, and are collected over time, contain more than one component, and can be composed of multiple types of data. The combination of the type of data (simple v. complex) and the analysis of the data leads to different types of decisions. Basic DDDM combines simple data with simple analysis, and more complicated DDDM combines complex data with complex decision-making.

Figure 2

Simple v. Complex DDDM Outcomes Based on Data



The decision-making component of DDDM is a result of the interpretation and analysis of data. Based on the complexity of the data and the analysis, decision-making then falls into four quadrants or categories (Ikemoto & Marsh, 2007). Quadrant I (basic) is based on simple data and decision-making typically done by a single individual. Quadrant II (analysis-focused) still relies on simple data, but the analysis is done in a group setting. Quadrant III (data-focused)

entails use of complex and multiple forms of data, but generally decisions are made by an individual, and does not draw on collective knowledge or expertise. Quadrant IV (inquiry-focused) involves multiple forms of data and analysis, and decision-making occurs in a group setting, generally over multiple meetings.

In a qualitative study of seven school districts, Ikemoto and Marsh (2007) identified 36 instances of DDDM across two previous studies. Of those 36 instances, 15 fell into the basic quadrant while only five instances of DDDM qualified as inquiry focused. DDDM at its most sophisticated is inquiry focused, relies on multiple data sources collected over time, and takes place in an ongoing collaborative setting. DDDM occurs when teachers collect and organize data, summarize and analyze those data, and apply knowledge to synthesize the data to make instructional decisions. DDDM in educational settings is a relatively recent practice primarily driven by accountability-focused legislative requirements.

Evolution and Adoption of DDDM in Education

Educators have been making decisions using data for decades, but until recently that decision-making was not formalized or systemic. Teachers observed students in their classrooms, scanned for signs of understanding or misconceptions, and graded student work. Depending on the skill of the teacher, sometimes this process of data collection and analysis led to changes in instruction, but the current model of DDDM was not practiced.

Early versions of standardized tests appeared between 1910 and 1920, but the purpose of these assessments was to evaluate the overall effectiveness of particular schools (Haertel & Herman, 2005). Individual teachers were not involved in the analysis of these data, and the process did not involve the assessment of individual students. The advent of IQ testing in the 1920s led to sorting and comparing students for placement purposes but IQ scores were not used

for instructional improvement or for increasing student achievement. The beginning of student assessments for accountability and student learning improvement can be seen in the 1930s with the development of comprehensive evaluations intended to educate the public about learning objectives and to clarify educational goals for teachers (Haertel & Herman, 2005). Mastery learning was the educational focus of school throughout the 1960s and 1970s and in this environment, assessments were intended to inform teachers about which students had mastered learning and which had not. The hope was that these data about mastery would lead to differentiated instruction for students, and that each student would receive what was needed based on data.

However, it was not until the passage of the *Elementary and Secondary Education Act* (ESEA) in 1965, tying federal school funding to educational outcomes, that wide-spread use of standardized testing for accountability became prevalent. Even with widespread distribution of these assessments, data showed students in the United States were falling behind, and policymakers shifted the focus to outcomes. This focus continued for decades with little improvement. Collecting standardized test scores was not leading to improved achievement for students. *No Child Left Behind,* passed in 2001, turned the focus to research-based instructional practice, and increased attention on many kinds of student learning data. Although the amount and types of data collected were increased, the majority DDDM remained centered around accountability rather than instructional improvement (Mandinach, 2012).

The shift from DDDM for compliance and accountability to informing instruction can be seen in an extensive report prepared by Means et al. (2010) for the Department of Education. Using purposeful sampling of school districts over a three-year period, they reported several key findings about DDDM in schools:

1. Data at the school level are used primarily for curriculum decision and grouping of students for support services such as special education and remedial instruction.
2. The use of DDDM to improve classroom instruction emerges much later than data use to group students and to design curriculum to match accountability tests.
3. There are several barriers to DDDM for teachers, including a lack of time, a perception that data are not useful, and district policies around pacing that prevent instructional shifts.

Challenges of DDDM

Application of data within a decision-making structure presents several challenges. Successful data-driven decision-making occurs when certain conditions, attitudes, and system components are present. Current literature on data-driven decision-making yields common themes necessary for application of data to improve student outcomes.

Time Presents a Large Challenge

Schools that provide sufficient time for data analysis and decision-making show higher levels of data-driven decision-making for instructional purposes (Ikemoto & Marsh, 2007; Schildkamp et al., 2017). Time is perhaps the major limiting factor to successful implementation of data for decision-making. The entire process of DDDM—which includes identification and selection of data, analysis and synthesis of that data, and ultimately application of knowledge to make decisions—takes time. Ikemoto and Marsh (2007) found that for schools that engaged in high-level inquiry-focused DDDM, setting aside time for this process was a priority. When data teams lack time to identify multiple data points or use existing data for student improvement, data-driven decision-making tends to suffer (Schildkamp & Datnow, 2022; Schildkamp et al., 2017). Research by Abrams et al. (2021) found multiple layers of time available for DDDM

increase teacher data use. Time throughout the school day, in addition to time at critical points in the school year, led to more successful implementation of data-driven decision-making.

A Focus on Accountability Impedes True DDDM

Research shows most teacher data use centers on accountability instead of continuous improvement and student achievement. Data use for accountability leads to shallow data analysis, infrequent data use, and a lack of trust in the validity of the data sources. Mandinach and Schildkamp (2021) found that many teachers correlated data literacy with assessment, and the primary use of data was for accountability instead of improvement to student learning. A focus on accountability instead of instructional improvement can also lead to deficit thinking when educators look at student data (Lasater et al., 2021). Schildkamp and Datnow (2022) found that successful data teams focus on continual improvement, and data are framed and used to increase student learning throughout the school year.

Access to Data is Essential for DDDM

The process of DDDM begins with identification and collection of data. Lack of access to data for DDDM has been identified as another barrier to success implementation (Ikemoto & Marsh, 2007; Schildkamp et al., 2017). Lack of access to multiple forms of data in a timely manner has been found to limit the effectiveness and implementation of DDDM in schools. School districts that regularly collect and publish data beyond test scores, attendance, and demographic data such as parent and student survey data and other qualitative sources demonstrate both higher levels of DDDM and more complex DDDM (Ikemoto & Marsh, 2007).

Educators Need Knowledge and Skills for Effective DDDM

Data-driven decision-making is a complicated process, and effective DDDM requires data literacy and skill in collaboration and problem solving. Although data literacy has been

more sharply defined over time, the specific terms used to describe data literacy are still evolving (Henderson & Corry, 2020). A large hurdle to efficient and successful data use is a lack of understanding of data literacy. Lack of clearly defined terms of data literacy hinders educators' use of data for instructional decision-making. Henderson and Corry (2020) determined that insufficient training in data literacy for both pre- and in-service teachers contributes to low levels of data use for decision-making.

Insufficient training highlights the gap between educators' use of data and the state and federal expectation of continuous data use for accountability. Militello et al. (2013) conducted a series of case studies to determine how data are used and misused by educators. Findings suggest that although teachers are aware that data use for instructional decision-making is important, the primary use of data is for accountability and assessment purposes.

Benefits of DDDM

A deep understanding of data literacy, combined with conditions shown to increase data use for decision-making, leads to increased opportunities for raising student achievement. Educators often need help connecting data with student outcomes, and research suggests a focus on professional learning paired with focused, school-wide goals can bridge the gap between knowing and doing.

A Focus on Student Achievement Can Drive DDDM

A collective effort across the system to raise student achievement increases data-driven decision-making. In a mixed methods study, Datnow et al. (2007) analyzed student achievement results from four urban schools in both California and Texas identified as high achieving schools that also engaged in a high level of data informed decision-making. Findings identified all schools to have goals aligned with student achievement, and educators connected those goals to

diverse data points. Poortman and Schildkamp (2016) reported similar results with a study to determine the extent to which teacher teams raise student achievement with data-driven decisions. When data are used in a systematic way and are linked to a specific goal to raise student achievement, scores in reading and math are higher. Successful implementation of data-driven decision-making requires a culture of collective responsibility for student achievement and a school-wide goal related to student learning (Hoogland et al., 2016).

In contrast, when data are omitted from the decision-making process, research has shown not only a lack of student achievement overall, but a decrease in achievement for special education students and students experiencing poverty. (Vanlommel & Pepermans, 2021). Data must be included in decision-making to balance out the intuitive approach most common in classrooms. Beliefs about learning influence teaching and when educators omit data from the decision-making process outcomes are less likely to lead to increased student achievement (Brookheart, 2011). Goals based on student data result in better outcomes than goals developed without data.

Professional Learning. Lai and McNaughton (2016) studied the impact of data use professional learning on student achievement. In a quasi-experimental design, a data-use professional learning model was used in 53 schools over an eight-year period. The professional learning intervention involved collaboratively analyzing data to determine achievement problems and then co-creating solutions. For schools receiving professional learning, improvements were seen in reading comprehension and writing. In a similar study across 59 school districts, when educators focused on data literacy and data-driven decision-making through professional learning, benchmarked data in reading and mathematics showed increased achievement (Carlson et al., 2011). Professional learning specific to principals around data-driven decision-making is

also an important factor connected to student achievement. Data analysis and assessment design skills are critical for principals as well as teachers, and in schools where principals lack skill around data analysis and application, student achievement remains low (Byrd & Eddy, 2010). In contrast, principals with high data literacy skills and working knowledge of data analysis make a positive impact.

Goal Setting. Grissom et al. (2021) determined that setting challenging student achievement goals school-wide was a precondition to successful data-driven decision-making. Principals are responsible for school-wide goals that rely on student data and ensuring these goals are communicated to teachers. A shared school-wide curriculum is an important component to goal setting, and effective principals develop and monitor implementation (Grissom et al., 2021). Levin and Datnow (2012), in a case study of effective school leadership actions, determined goal formation and communication to be important. Principals also need to develop a rationale for types of data to measure and support school-wide goals (Young, 2006).

Complex DDDM that leads to increased student achievement requires structures that support teachers within the DDDM process. Adequate time, access to relevant and timely data, goals built around student data, and access to professional learning to improve data literacy can increase both the amount and sophistication of DDDM. As teachers engage with the various components of DDDM, their attitudes and beliefs impact decision-making outcomes. The theory of planned behavior can be used as a framework to investigate how attitudes and beliefs impact the decision-making process.

Theoretical Framework: The Theory of Planned Behavior

The theory of planned behavior (TPB) explains how individuals act in certain contexts (Ajzen, 1991). TPB is an extension of the theory of reasoned action (Fishbein & Ajzen, 1975),

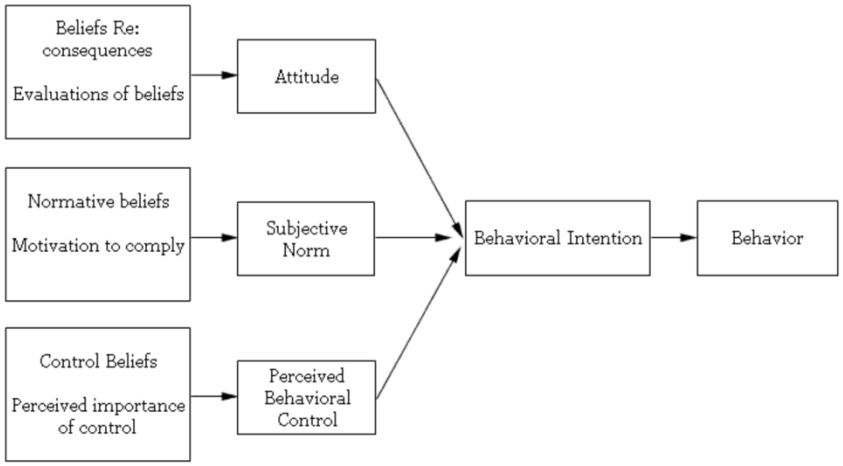
which states that an individual's behavior is the result of the intention to perform a behavior. The theory of planned behavior expands on the theory of reasoned action by identifying beliefs and attitudes that drive intentions. Intentions, defined as the determination or plan to do a specific action, are in turn determined by three independent and interacting beliefs and attitudes: behavioral beliefs/attitudes, normative beliefs, and perceived behavioral control (see Figure 3).

Human behavior is an aggregate of unique factors specific to situation and a combination of attitude, subjective norms, and perceived behavioral control around each specific behavior can help predict outcomes (Ajzen, 1991). The aggregate is a better predictor of behavior than any one single factor, which is known as the principal of aggregation. Ajzen (1991) states:

> The principal of aggregation, however, does not explain behavioral variability across situations. Nor does it permit prediction of a specific behavior in a given situation. It was meant to demonstrate that general attitudes and personality traits *are* implicated in human behavior, but that their influence can be discerned only by looking at broad, aggregated valid samples of behavior (p. 181).

Figure 3

Framework for the Theory of Planned Behavior



Note: Adapted from Ajzen (1991).

Looking at patterns of attitudes, normative beliefs, and control beliefs can help identify behavioral intentions that lead to behavior. Knowing and understanding teachers' attitudes and beliefs around intentions to use data for decision-making can help educational leaders provide supports to encourage desired behavioral outcomes around data use.

Attitude/Beliefs

An individual's personal attitudes and beliefs around a particular behavior has two components: instrumental and affective. Instrumental beliefs refer to the possible consequences, either harmful or beneficial, of performing a particular behavior. In the context of DDDM, a teacher may have negative instrumental beliefs if they feel vulnerable and unsafe when looking at student achievement data, which they may feel exposes weaknesses in their teaching practice. They may also feel a lack of safety with data use if they believe the data will be used for evaluative purposes. Positive instrumental beliefs, in contrast, occur when an individual sees a benefit to the behavior. Belief that decisions based on data will lead to improved student outcomes represents an example of positive instrumental belief. Affective beliefs refer to an individual's perceived enjoyment of the behavior. An individual who believes the behavior is enjoyable is more likely to engage in that behavior. A qualitative study by French et al. (2006) investigating participants' intention to increase physical activity found that affective beliefs accounted for 48% of the variance in intention around physical belief when compared to instrumental belief. A person's positive or negative feelings toward a behavior are an important variable and have been shown to impact intention.

Subjective Norms

The second component that determines intention are subjective norms. Subjective norms are the perceived social pressures to perform or not perform a particular behavior. DDDM occurs

in a collaborative setting involving other people, and the impact of an individual's beliefs of the expectations and attitudes of others can determine the intention to behave in a certain way. Subjective norms can be divided into two parts: injunctive norms and descriptive norms (Ajzen, 1991). Injunctive norms refer to an individual's belief about how other people involved in the behavior feel. Descriptive norms refer to whether others perform the behavior. Coburn and Taylor (2011) state that the process of data use is shaped significantly by the organizational and political context of schools, and "data use routines structure who teachers and others interact with, around what data, and in what ways" (p. 175). The norms of collaborative data use in schools are an example of subjective norms, and they impact how individuals engage in DDDM.

Perceived Behavioral Control

The third factor to impact behavioral intentions is perceived behavioral control which refers to the amount of control a person believes they have over a particular behavior. Ajzen (2002) defines perceived behavioral control as "the subjective degree of control over the performance of the behavior itself" (p. 668). It is a combination of an individual's perception of how easy or difficult the behavior is to perform and their internal beliefs about their capability to perform. Perceived behavioral control includes the concept of self-efficacy, which refers to an individual's beliefs in their ability to successfully perform a behavior. Ruble et al. (2018) applied the theory of planned behavior to understand early childhood teachers' data collection practices. The researchers collected data in all three areas that influence intention and found perceived behavioral control accounted for the most variance in the actual collection of data.

Application and Relevance of the TPB in Educational Research

The theory of planned behavior has been applied to a wide variety of research topics in the field of education. Empirical research documents the ability to predict teacher behaviors

towards technology (Ates et al., 2022; Salleh, 2016; Teo et al., 2016), special education (MacFarlane & Woolfson, 2013; Ruble et al., 2018; Wang et al., 2015), assessment (Opoku at al., 2021; Pierce et al., 2013) and curriculum implementation (Kumar et al., 2015; Ramatlapana & Makonye, 2012; Underwood, 2012). A review of the literature yielded only a handful of studies using the theory of applied behavior to study teacher behaviors with data or data driven decision-making (Dunn, 2016; Dunn et at., 2019; Schelling & Rubenstein, 2021) and many of those studies focused on the attitudes, beliefs, and behaviors of pre-service teachers.

Data-driven decision-making, as previously discussed, involves several behaviors that lead to outcomes. These include collection and organization of data, which lead to analysis and a summary of the data. Once the data have been summarized, teachers must synthesize and then prioritize that data into a decision. Each behavior in the DDDM process can be impacted by personal attitudes, normative beliefs, and perceived behavioral control. The theory of planned behavior is a theoretical framework through which DDDM can be studied.

Limitations of the TPB

Although the theory of planned behavior can be used to predict individuals' behavior, there are limitations that should be considered. The theory of planned behavior was primarily developed in Western cultures, which may limit its applicability to non-Western contexts. Cultural differences in norms, values, and social influences can impact the predictive validity of the theory across different populations (Ajzen, 2002; Ajzen, 2011; Godin & Kok, 1996). The TPB also may have an overemphasis on rationality. The TPB assumes that individuals are rational decision-makers who carefully weigh the pros and cons before deciding on a behavior. This assumption overlooks the role of emotions, habits, and unconscious processes in influencing behavior (Fishbein & Ajzen, 2010). In addition, there can be a significant time gap between the

intention to perform a behavior and the actual behavior (Ajzen, 2011). This is not taken into consideration within the TPB, and the impact of this time gap might cause a disconnect between intention and behavior. TPB also assumes that attitudes, subjective norms, and perceived behavioral control remain stable over time. However, these factors can change due to life experiences, new information, or changes in the social environment, leading to fluctuations in behavioral intentions and actions (Manstead & van Eekelen, 1998). A final limitation of the TPB is operationalizing constructs such as attitudes, subjective norms, and perceived behavioral control into measurable variables, which can be challenging. Different measurement techniques and instruments may yield varying results, affecting the reliability and validity of TPB (Armitage & Conner, 2001). Despite the limitations of the theory of planned behavior, it may prove valuable in studying how teacher attitudes and beliefs can influence engagement in data-driven decision-making.

Teacher Attitudes and Beliefs

When teachers engage with data-driven decision-making, there are several factors that influence both their attitudes and belief towards data and DDDM as well as engagement in data team activities. Perceived usefulness and effectiveness of data-driven practices, teacher autonomy and professional judgement, and the support and resources available for the analysis and interpretation of data influence how teachers feel about data-driven decision-making. The ways teachers feel about data and how those data are used for instructional decision-making have an impact on how teachers engage in decision-making within a data team.

Importance of Attitudes and Beliefs in DDDM

The attitudes and beliefs teachers hold toward data and using data for decision-making are critically important. These attitudes and beliefs, whether positive or negative, can directly

impact the outcome of data-driven decision-making (DDDM). Teacher beliefs, knowledge, and motivation play an integral role in processes associated with data use.

Data-driven decision-making requires teachers to notice, interpret, and construct implications for next steps (Coburn & Turner, 2011). There is a large body of existing research to suggest that an individual's beliefs play a large role in noticing data and that people have a tendency to seek out data that aligns with and reinforces their assumptions and expectations and may even completely ignore data that contradicts these beliefs and assumptions (Hannaway, 1989; Ingram et al., 2004; Young & Kim, 2010).

Interpretation of data is also heavily influenced by teachers' attitudes and beliefs. When individuals examine and interpret data, they tend to either confirm those pre-existing beliefs and attitudes or discount the data entirely (Coburn, 2001; Coburn et al., 2009; Young & Kim, 2010). Ultimately, the decision about what to do with the data is influenced by beliefs and attitudes. When teachers make instructional choices about what to do with the data they have, beliefs and attitudes inform what to do in response to data.

An understanding of the relationship of beliefs and attitudes and DDDM can be framed in the theory of planned behavior, which states that all behaviors are a result of the connection between an individual's beliefs about the attributes of the behavior (behavioral beliefs), the expectations of other people (normative beliefs), and beliefs about factors that further or hinder performance of the behavior (control beliefs; Ajzen, 2002). Specifically, a person's behaviors are predicted by intentions, which are predicted by attitudes about the behavior (Ajzen, 1991). Attitudes and beliefs about data use and DDDM can predict teachers' intentions around making decisions using data. These intentions then drive the behaviors around DDDM. Understanding

the underlying attitudes toward DDDM is important for both educational leaders and teachers themselves as they interact with data for instructional decision-making.

Factors Influencing Attitudes and Beliefs in DDDM

The attitudes and beliefs teachers have about DDDM are influenced by multiple factors and range from personal attitudes toward using data, to the level of professional judgement a teacher believes they have, to the level of support and resources available for data analysis (Hoogland et al., 2016; Mandinach & Schildkamp, 2021; Schelling & Rubenstein, 2020, Schildkamp & Datnow, 2022).

Perceived Usefulness and Effectiveness of Data Practices

Educators' beliefs and attitudes about DDDM are influenced by their perception of the usefulness and effectiveness of practices associated with decision-making (Hoogland et al., 2016; Mandinach & Schildkamp, 2021; Schildkamp & Datnow, 2022). One of the important components of DDDM is the goal. When teams come together to examine data, the process is framed around a goal or outcome. The origin of the goal, and in particular *who* chose the goal, influences the DDM process. Negative attitudes and beliefs develop when teachers are excluded from the selection of the goal or when there does not seem to be a shared problem to solve with data (Hoogland et al., 2016).

In a multi-year qualitative study of teacher data teams in the Netherlands and the United States, Schildkamp and Datnow (2022) identified lack of a shared problem and goal as one of the primary barriers to data use. Teachers stated they disagreed with the selected goal and were unwilling to engage in the DDDM process. Conflicting goals also tend to be barriers to engagement with data. Mandinach and Schildkamp (2021) found that data use is linked to two distinct goals: accountability and school improvement. These goals are often in conflict, and as a

result teachers' analysis and interpretation of the data becomes challenging. Hoogland et al. (2016) found that when goals are set by external parties, either the district or by the state departments of education, teachers tap out of the process and view the entire DDDM as "fruitless and ineffective" (p. 382). When goals and outcomes conflict, teachers lose faith in the process and perceive it as ineffective and not useful. Goals within DDDM should be clearly defined, be focused on instructional improvement, and should involve teacher input on the goal construction.

The amount of data a teacher looks at also impacts their attitudes and beliefs about DDDM processes (Mandinach & Schildkamp, 2021; Schildkamp & Datnow, 2022). The amount of data available to teachers is vast, and more is not always better. When teachers feel overwhelmed and lost in the amount of data to look at, they become unwilling to look at any data. Data literacy can help teachers make sense of the wide variety of available data and create positive attitudes toward the first step of DDDM (collecting and organizing data). Research by Gummer and Mandinach (2015) determined that teachers comfortable with data understand (a) the purposes of different data, (b) what data are not applicable in each context, (c) problematic data and data quality, (d) assessment, and (e) how to find and retrieve data. Given the complexities of data selection, teacher attitudes toward data are influenced either positively or negatively at the outset depending on the teachers' skill with data.

Teacher Autonomy and Professional Judgement

The beliefs a teacher has around their level of autonomy and professional judgement impact their attitudes toward DDDM. The data used in the decision-making process are oftentimes generated by large-scale summative assessments rather than being teacher-generated. Teacher generated assessment do not always produce data that can be analyzed in a systematic way, and as a result the materials created by the teachers themselves are often ignored. However,

when the primary data used in the DDDM are not teacher generated, attitudes tend to be more negative (Hoogland et al., 2016; Schelling & Rubenstein, 2021; Schildkamp & Datnow, 2022). Research on elementary teacher data teams engaged in the DDDM process found that teachers prefer their own assessments and believe them to be higher quality and better measures of success than commercially produced standardized assessments (Schelling & Rubenstein, 2021).

Autonomy over the entire process of DDDM also comes into play and influences teachers' attitudes. When teachers feel that they are *required* to participate in DDDM by principals or other district leaders, attitudes tend to be more negative. For many school districts, the continued focus on data use for accountability creates a requirement for DDDM in schools. Shelling and Rubenstein found teachers participating in district-mandated DDDM used words and phrases such as "lack of usefulness, pain, something imposed, industrial, mechanical, and pointless" (p. 339). When autonomy is perceived as compromised, attitudes and beliefs in the entire process are more negative.

Available Support and Resources for Data Analysis

Access to data and the time to analyze, synthesize, and apply knowledge for decision-making impact how teachers feel about the DDDM process. Data-driven decision-making, especially in a team setting, requires large amounts of regularly dedicated time. In a research study on data teams, Schildkamp and Datnow (2022) found lack of time to be a primary barrier to effective DDDM. Teachers reported feeling frustrated and ineffective due to insufficient time to meet as well as thoroughly engage in the process. When teachers are not allowed enough time to look at data, make sense of data, and discuss solutions, attitudes toward the process are found to be significantly more negative than in settings where time for DDDM is a priority. Schildkamp et al. (2017) found high levels of data-driven decision-making in schools where the

principal established time during the school day for teacher collaboration. Time is one of the most impactful factors to collaboration, and principals who prioritize dedicated time for collaboration around data have high levels of data-driven decision-making in their schools (Grissom et al., 2012; Levin & Datnow, 2012; Schildkamp et al., 2017).

Behavior in Data-Team Settings

Data teams are used for DDDM and take place in a collaborative setting. The structures and functions of the data team are the mechanism for data-driven decision-making. Data teams are collaborative, and collaboration is a critical focus the effective decision-making. As teachers work in data teams, their attitudes and beliefs influence how engaged they are in data collection and organization, data analysis and synthesis, and decision-making.

Professional learning communities (PLCs) consist of educators working in small groups to focus on problems of practice and instructional improvement. The collaborative nature of PLCs allows educators to look at data as a team and use an inquiry process to make instructional decisions based on that data. DuFour (2015) identified using data to improve instruction as a defining characteristic of professional learning communities. Attention to student strengths, discussion of effective instructional strategies related to student data, and data use to plan for intervention and scaffolding are focus areas for PLCs shown to lead to increases in student performance. Schools that provide collaboration structures that are both horizontal (within grade level or content) and vertical (across grade levels or content) allow for multiple sources of data to inform decision-making (Marsh, 2012). Abrams et al. (2021) found that consistent and structured collaboration led to more efficient data use for decision-making. When teachers plan, share, and discuss instructional strategies with a focus on student data, data-driven decision-making skills

increase. Schools that employed a system-wide collaboration structure supported with time, an instructional vision, and common instructional goals showed higher levels of data use.

Research is limited on whether teacher collaboration automatically leads to improved student achievement. Most research has centered around teacher collaboration as a single construct, and whether collaboration leads to higher levels of teacher data use and teacher DDDM efficacy, yet some research suggests a positive correlation between teacher collaboration and student achievement (Dumay et al., 2013; Goddard et al., 2007; Lee & Smith, 1996; Louis et al., 2010;). Studies that have shown positive outcomes linked to teacher collaboration and data teams include several common structures.

Data Team Structures

The most prevalent structure of data teams is time, both in the general schedule of the school year and in the amount of time set aside for the process of DDDM during the meetings (Datnow & Park, 2016; DuFour, 2015; Supovitz & Klein; 2003). Regularly scheduled meeting times for teams to collaborate around data is essential for the success of data-driven decision-making within the data team. In a multi-year longitudinal study of data teams in 25 middle schools throughout the Pacific Northwest, Crone et al. (2016) found that although data team meetings occurred regularly, teams did not devote a large amount of time during those meetings to discussing student data. The average meeting lasted 49.5 minutes, but teams spent an average of eight minutes discussing data. Use of time set aside for data team collaboration can have an impact on data team outcomes, but the focus of that time must be on data and decision-making.

Effective data teams also have consistent team membership (Crone et al., 2016; Datnow & Park, 2016; Schildkamp et al., 2016). Collaborative data teams typically consist of teachers, administrators, data coaches, and other relevant school staff who work together to analyze

student data and make informed decisions. Including school leaders as members of the data team can offer both a different perspective and provide support with implementation of the action plan at the end of the decision-making process.

Collaborative data teams develop and utilize data protocols and tools to guide their data analysis process, ensure consistency in data interpretation, and facilitate effective communication and collaboration (Boudett et al., 2005; Crone et al., 2016). Protocols include agendas, team norms, and notes. Data systems, including electronic forms of data that all members of the team can access, increase the effectiveness of data-driven decision-making practices.

Data Team Functions

Collaborative data teams share several common functions to support data-driven decision-making that align with the steps in the DDDM process identified by Mandinach et al. (2006). The team collects and analyzes various types of data, including student achievement data, attendance records, behavior reports, and demographic information, to identify trends, patterns, and areas for improvement (Boudett et al., 2013; Supovitz & Klein, 2003). Crone et al. (2016) found data teams primarily focus on scores from standardized state assessments, attendance data, grades, and anecdotal evidence from class performance.

Goal setting is another important function of data teams. Schildkamp et al. (2016) state that "data use in data teams starts with a purpose in the form of a problem definition and a related goal" (p. 231). Teams collaboratively set goals based on data analysis to drive instructional planning and school improvement efforts. This involves developing action plans and strategies to address identified needs and improve student outcomes. In a collaborative data team, goal setting serves as the compass guiding every member towards a shared vision of success. Setting clear and achievable goals not only aligns the team's efforts but also fosters

cohesion and synergy among individuals with diverse expertise. Each member understands their role within the broader context of the team's objectives, leading to enhanced communication, accountability, and productivity. Moreover, goal setting encourages innovation and continuous improvement, as team members strive to surpass benchmarks and deliver impactful insights. Ultimately, in the dynamic landscape of data analysis, effective goal setting not only drives performance but also cultivates a culture of excellence and achievement within the team.

Data teams participate in professional development opportunities based on data-driven insights to support their capacity to effectively implement instructional strategies and interventions. This may involve workshops, coaching, collaborative planning sessions, and peer learning opportunities. Earl and Katz (2002) report professional learning should focus on the purpose of varied data sources, recognizing sound data, and how data apply to student outcomes. Levin and Datnow (2012) identify building human capital as an effective leadership action. In the context of DDDM, this means building teacher knowledge and skill around data and data use. Professional learning should be ongoing, job embedded, and receive dedicated time and resources (Grissom et al., 2021; Marsh & Farrell, 2014; Schildkamp et al., 2017).

Influence of Teacher Attitudes and Beliefs on Participation in Data Teams

Data-driven decision-making is not done in isolation but in collaborative settings with others. Bocala and Boudett (2015) define data inquiry as "educators working in teams to analyze student progress using data, make recommendations about curricular and instructional next steps, and follow up on the results of those actions" (p. 2). Researchers have found that educators were more comfortable interpreting data when working with groups of colleagues (Means et al., 2010). The influence of attitudes and beliefs on the level of participation and engagement ultimately can determine the effectiveness of the data-driven decision-making process. Attitudes

and beliefs can be divided into themes of safety, trust, time, control, and relationships. Each of these themes can be found within the framework of the theory of planned behavior.

Behavioral Beliefs

The attitudes and beliefs that center around an individual's frame of the behavior as either enjoyable or not, as well as beneficial or not, are part of behavioral beliefs (Ajzen, 1991). In general, the more favorable an individual's attitude toward a behavior, the stronger the intention to perform the behavior. Teacher attitudes and beliefs about data-driven decision-making in data teams are around safety and trust.

Safety. The level of a teacher's perceived safety impacts participation and engagement in data teams (Means et al, 2010; Nelson, 2008). Teachers must feel a level of safety with team members when sharing and analyzing student learning data. Means et al. (2010) used a case study design to investigate schools with high levels of data use. One of the primary findings was a pervasive culture of safety around sharing data with others. This was accomplished by adding layers of anonymity to the data and attempting to remove the personal aspect of data use. A similar study by Nelson (2008) identified the importance of teacher safety while examining data with colleagues and found that anonymity was necessary to establish safety. The attempt to create a climate of safety, however, is sometimes not enough. A study by Supovitz and Weathers (2004) found that many teachers fear data will be used for evaluative purposes even with assurances that collected data would be used exclusively for instructional planning and problem solving. This fear led to an unwillingness to engage in data analysis and decision-making.

Trust. When teachers have a sense of trust in the collaborative process and with members of the team, it leads to better engagement with the data team. Trust and mistrust are behavioral attitudes and beliefs and have been found to determine the level of engagement a

teacher may have with collaborative DDDM. Bocala and Boudett (2015), in a study of pre-service teachers engaging in collaboration, found trust in team members to be a critical component of data team participation. Many teachers also do not trust that any data examined by others will not be used for evaluation or accountability. Datnow and Hubbard (2015) emphasized the importance of trust within team-based DDDM. Teachers reported a lack of trust both in the promised anonymity of the data and the possible misuse of the data to support a decision made by the principal. Both trust and safety contribute to an individual's intention to perform a behavior. High levels of trust and safety lead to increased intentions, while low levels of trust and safety contribute to low levels of intention.

Normative Beliefs

The second factor that leads to an individual's intention to perform a behavior are normative beliefs. Normative beliefs are centered around an individual's perception of whether others engage in the behavior or not, or if others encourage or discourage the behavior (Azjen, 1991).

Relationships. Because data teams are collaborative and involve a team of teachers or other individuals, the relationships between members of the team impact engagement. In a case study of grade-level data teams, Young (2006) found a relationship between individual teacher engagement in the data process and the established norms of the data team. Cohesive teams encouraged data use, and the positive influence of agreed-upon norms led to higher levels of data inquiry. When a data team is made of individuals with contrasting beliefs, knowledge, and skills, and motivations, participation in the data team decreases (Coburn & Turner, 2011). Team dynamics influence an individual's normative beliefs which then impact that individual's intention to engage in collaborative data-driven decision-making.

Control Beliefs

The third factor that influences an individual's behavior is perceived behavioral control. Participation in data teams is influenced by a teacher's perception of control over resources such as time and the degree of choice over that participation.

Time. How teachers perceive the value of time during the school day influences their intent to participate in data teams (Bolhuis, 2019; Militelo et al., 2013). In a case study of teachers participating in data teams, Bolhuis (2019) found that participants who perceived collaboration to be a useful use of time were more likely to engage in looking at data with team members and participate in discussions about data. Participants who did not actively engage in the data team process stated the data team was a "waste of time" and that "results take too long" to materialize, and that they "had better things to do during the day" (p. 105). Militelo (2013) reported similar findings in an earlier study of 50 teachers and principals and their perceptions of how data are used in a school setting. Using a Q-sort methodology, which allows participants to decide which pre-determined factors are important and hold value, the teacher participant data indicated that while teachers positively viewed data use in their individual classrooms, they had strong negative perceptions of data use with other teachers, particularly when asked about the value of time spent in collaboration. These studies suggest that how teachers perceive control over their time can positively or negatively influence data team participation.

Control. The degree to which teachers feel they can choose to participate in data teams influences their intentions. When teachers feel forced to participate in data teams, they are unmotivated and display negativity toward data and collaborative decision-making. Given a large degree of perceived choice to collaborate, teachers approach data use and collaborative decision-making with enthusiasm and display a higher level of engagement (Keuning et al., 2017).

Bolhuis (2019) found that when teachers do not feel they have control over the outcomes of collaborative data use and decision-making, they are less likely to actively participate in the data team. Additional findings from Bolhuis (2019) showed that teachers with a high level of perceived control over the outcomes of collaborative decision-making were more likely to engage with the data team. As with behavioral and normative beliefs, perceived behavioral control influences an individual's intent to engage in behaviors.

Summary

A review of the literature found that teachers have both positive and negative attitudes and beliefs toward data and DDDM. Several key pieces of legislation, including the *Elementary and Secondary Education Act* in 1965, *No Child Left Behi*nd in 2001, and the *Every Student Succeeds Act* in 2015, have created a climate of accountability, and schools have responded with a focus on data for decision-making. Studies investigating the basics of teacher data use began a few years after the passage of NCLB and focused on the mechanics of data use: the how, why, and who. Fewer research studies have been published investigating teacher attitudes and beliefs toward DDDM, and the connection between teacher attitudes and beliefs around DDDM and how that may influence participation in data teams is not well-researched. The theory of planned behavior states that an individual's attitudes and beliefs influence intention and behavior. Understanding teacher attitudes and beliefs about data and DDDM and how those attitudes and beliefs influence participation in data teams offers the possibility of helping educational leaders structure approaches to collaborative DDDM.

The research questions were identified to address the relationship between teacher attitudes and beliefs and their participation in data teams:

RQ1: What teacher attitudes and beliefs serve as barriers to data-driven decision-making?

RQ2: What teacher attitudes and beliefs serve as facilitators of data-driven decision-making?

RQ3: How do the professed attitudes and beliefs of classroom teachers manifest in situations involving data-driven decision-making?

CHAPTER III

METHOD

This research utilized a case study design. Case studies explore the complexities that occur within a system of people (Clark & Creswell, 2015). Case study design is used to "investigate a contemporary phenomenon within its real-life context" (Yin, 2003, p. 13). The research questions involve teachers and administrators in a public school setting, and a case study best captures the attitudes and experiences of these educator groups. The contemporary phenomenon includes data for instructional decision-making in classroom settings, and the analysis of case studies can provide implications for practicing educational leaders. More specifically, this research employs a holistic multiple case design. Multiple case study research is chosen to illustrate the experiences and phenomenon of subunits within a single case (Yin, 2003). The single, bounded case study involves teachers within one school district. The subunits are the individual teachers within the district. Studying the experiences of multiple individuals within the system increases the external validity of the research. Yin (2003) states that conclusions from multiple cases are more powerful than those from a single case.

Researcher Positionality

I am a principal in a public school district in Oregon. I have been an educator in various roles, including classroom teacher, instructional coach, and school-based administrator. In these various roles, I have had the opportunity to participate in collaborative teacher teams to analyze data for decision-making. As a building principal, I strongly believe in using data for decision-making. I am also used to looking at data and believe that all educators should be basing classroom instructional decisions on data. My assumptions and beliefs around data-driven decision-making, as well as my past experiences using data and helping others use data, reveal a

bias that needs to be explicitly identified. The interactions with participants, the design of the data collection tools, and the subsequent selection and interpretation of themes from the data can be influenced by my previous experiences and beliefs around data use.

Human Subjects Research Permission

An application for permission to conduct my research was submitted to the University of Oregon Institutional Review Board (IRB) in June 2024. IRB approved on July 2, 2024. Permission to conduct research in the selected school district was granted on August 13, 2024.

Participants

This study was conducted in a public suburban school district located in Oregon. The district serves several thousand students within the district boundaries. The participants work in a city with a population of approximately 60,000 people that has experienced a population growth rate of 0.7% over the last decade (US Census, 2023). Most of the population is white (80%), with the remainder comprised of people identifying as Latinx , Black, Asian, and Native American . Median income is between $50,000 and $80,000, and less than 20% of the population lives with poverty. While most of the city population has a high school diploma, only 18% are reported as having at bachelor's degree or higher. The school district serves students in special education (17%) and English Language Learners (13%). The demographics of the teacher participants are based on the demographics of all teachers in the state of Oregon (see Table 3).

Table 3

Oregon Teacher Demographics (%)

Asian	Black/African American	Hispanic	American Indian/Alaska Native	Multiracial	Native Hawaiian/Pacific Islander	White
2.0	0.7	5.9	0.6	1.9	0.2	88.6

Note. N = 31,951. Adapted from Educator Advancement Council (2022).

Participant Recruitment

Participants were screened and recruited using the *Data-driven Decision-making Self-Efficacy and Anxiety Inventory* (3D-MEA). This questionnaire is designed to assess teachers' beliefs in their abilities to effectively analyze and interpret student data and successfully connect their analysis of data findings to classroom instruction to improve student learning. All licensed secondary teaching staff in the research school district (n = 278) were invited via email to complete the 3D-MEA on August 27, 2024, and the survey remained available until September 8, 2024. Because this survey was used solely for screening purposes, no informed consent was required for teachers to complete the survey. Participants were sent the survey through email, and surveys were completed using Qualtrics software. In all, 33 teachers completed the survey, and five teachers started but did not complete all sections, a response rate of 13.6% (n = 38). This survey was used as a means of identifying potential participants for the case study.

Participant Selection

Case study participants were chosen using purposeful sampling. Purposeful sampling is the best choice for qualitative research because it allows for selection of individuals best suited to study the central phenomenon (Clark & Creswell, 2015). I used maximum variation sampling to select diverse cases to best describe multiple perspectives, attitudes, and beliefs (Creswell, 2007) based on responses to the survey instrument (3D-MEA) designed to measure educators' attitude toward use of data. Using maximum variation sampling, participants were chosen based on the scores on the 3D-MEA. Respondents who completed the survey were assigned an overall score and placed into quadrants and respondents who scored either in the bottom or top quartile of the questionnaire were invited to participate in both interviews and observations. This allowed for identification of participants who differ from one another in self-reported efficacy and

anxiety about DDDM, and this purposeful selection gave the opportunity to learn about their differing thoughts and attitudes on the topic. Based on their survey results, eight respondents were invited to participate in interview and observation data collection, and six respondents were ultimately selected for participation in the study: four from middle school (grades 6-8) and two from high school (grades 9-12) settings. The demographics of the participants are shown in Table 4.

Table 4

Case Study Participant Demographics

Name	Grade Band	Focus	Years Experience
Carl	9-10	general education	>20
Shelly	11-12	general education	>20
Robert	6-8	specialist	>20
Dylan	6-8	specialist	>20
Lucy	6-8	general education	>20
Maria	6-8	general education	>20

Note. All names given are pseudonyms. General education subjects include science, math, social studies, and language arts.

Data Collection and Identification

The study began with an initial screener survey followed by two phases of data collection using multiple sources of data to increase the trustworthiness and credibility of the results. No data from the survey was included in the study past the purpose of initial screening. Triangulation occurred using survey data, interviews, and observations. Noble and Heale (2019) identify the importance of data triangulation to overcome the biases that arise from a single data collection method. Denzin (2018) states that "triangulation should produce knowledge on

different levels, which means they go beyond the knowledge made possible by one approach and thus contribute to promoting quality in research" (p. 789). Although data was collected through the survey, it was used strictly to identify and select participants. Interview and observation data were informed results, with interviews informing research questions about attitudes and beliefs, and observation data informing the research questions about behavior in data team settings.

Survey

The 3D-MEA questionnaire was strictly used as a screener to select participants. The 3D-ME Inventory consists of 20 items, that use a 5-point Likert scale ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). It includes four subscales: (a) efficacy for data identification and access (three items); (b) efficacy for data technology use (three items); (c) efficacy for data interpretation, evaluation, and application (nine items); and (d) DDDM anxiety (five items, reverse coded). Items are listed in Appendix A.

An overall score was calculated for each respondent. Possible scores ranged from a floor of 15 to a ceiling of 75 on the efficacy sections of the survey instrument. Scores on the anxiety section of the questionnaire could have ranged from 5 to 25, with a low score indicating a low level of anxiety around DDDM and a high score indicating a high level of anxiety around DDDM. As shown in Table 5, reliability within each domain of the 3D-MEA ranges from 0.84 to 0.92 as measured by Cronbach's alpha (Dunn et al., 2013).

Table 5

Reliability of the Data-Driven Decision-making Self-efficacy and Anxiety Inventory (3D-MEA)

Domain	Domain Reliability	Item Reliability	
Efficacy for Data Identification and Access	0.84	Item 1	0.67
		Item 2	0.91
		Item 3	0.89
Efficacy for Data Technology Use	0.91	Item 4	0.89
		Item 5	0.90
		Item 6	0.84
Efficacy for Data Analysis and Interpretation	0.81	Item 7	0.82
		Item 8	0.70
		Item 9	0.76
Efficacy for Application of Data to Use Instruction	0.92	Item 10	0.72
		Item 11	0.85
		Item 12	0.87
		Item 13	0.82
		Item 14	0.84
		Item 15	0.82
DDDM Anxiety	0.88	Item 16	0.74
		Item 17	0.82
		Item 18	0.84
		Item 19	0.72
		Item 20	0.81

Note. Internal consistency reliability (Cronbach's alpha) was calculated for each of the five scales by Dunn, Airola, Lo, and Garrison (2011).

Interviews

The next phase of data collection consisted of semi-structured interviews for participants who met the purposeful sampling inclusion criteria and consented to an interview. This phase of data collection began in early September 2024 and concluded in early October 2024. Semi-structured interviews are used when specific information is desired from all participants; they

allow the researcher to have flexibility in their responses and to respond to new ideas that emerge (Merriam, 2009). A semi-structured protocol allowed me to ask open-ended questions that generated possible data around this topic (see Appendix B). Interviews were conducted in person at a location of the interviewee's choosing. I facilitated interviews as primary researcher. Elwood and Martin (2000) indicate that the setting of qualitative interviews has an impact on the quality of the data collected. When participants are given choice of setting, they may feel empowered in interactions with researchers.

The interviews began with introductions, and participants were asked to sign a consent form. Permission to obtain an audio recording of the interview was also obtained with written consent, and interviews were recorded and transcribed using otter.ai. The interviews consisted of 6-10 questions across several categories and lasted between 22 and 32 minutes (see Appendix B). Categories of questions included experience and behavior, values and attitudes, and knowledge (Patton, 2014). A summary of the interview data collected is shown in Table 6.

Table 6
Interview Data Collection

Participant	Time of Interview	Duration	Word Count of Transcript
Shelly	12:07 pm	22:13	3,604
Carl	9:00 am	22:12	3,611
Robert	1:51 pm	32:22	4,083
Dylan	3:29 pm	22:28	3,611
Lucy	3:25 pm	27:22	4,475
Maria	4:11 pm	28:56	4,609

Note. Total Interview Duration Time: 155 minutes, 40 seconds, Total Length of Transcripts: 23,993 words.

The interview protocol underwent two steps during development to ensure it reliably captured the intended content. In the first step, experts in qualitative interview design gave feedback on the interview protocol. When experts collaborate and provide input in research design and instrumentation, the reliability of the study increases (Stahl & King, 2020). The second step to increase validity involved a series of pilot interviews with three teachers not part of the study. These pilot interviews were intended to allow refinement of the interview questions and ensure the questions captured the desired data. As part of this pilot process, teachers used a metacognitive strategy called a "think-aloud". Think-alouds have been shown to be a valid source of participant data and are an effective technique to illuminate thought processes (Charters, 2003). No changes were made because of the pilot interviews, as the think-aloud responses suggested that the interview questions were functioning as intended.

Observations

The second phase of data collection included observations of participants in a data team setting. Observations were competed in mid to late November, and five of the six participants participated in this round of data collection. Observations allowed data triangulation through comparison between the actions and behaviors of the participants to the data gathered through interviews. Conducting and documenting direct observations of the events and actions as they occur in a local setting is a critical part of a case study's data collection (Yin, 2013). The setting for observations was school data team meetings. Meetings occurred in a classroom during the regular school day as part of the regular teacher collaboration schedule and lasted between 28 and 52 minutes. The observation helped answer the research question about how the attitudes and beliefs of classroom teachers operate within the structures of data-driven decision-making.

After semi-structured interviews with participants to uncover themes related to DDDM, the observation gave additional data to show how the themes discovered in the interview part of the data collection showed up in practice. Interviews were intended to identify the attitudes and beliefs associated with DDDM. Participant observations were conducted to determine how the expressed attitudes and beliefs of each participant informed participation in a data team setting. In addition to considerations around access, there were some potential ethical concerns and other implications. Using this meeting for a specific data gathering purpose required informing the teacher that the researcher would be gathering data. Emerson et al. (2011) states that being open and honest about intent can help avoid "the risks and sense of betrayal" that can come with taking data in a setting with an established personal relationship to the participants (p. 185). The presence of the researcher increased the risk of having the researcher perspective mixed with the observational data, which could decrease objectivity (Emerson et al., 2011). Additionally, researcher presence has had a "contaminating effect" on the participants, which means the way they talked and behaved could have been influenced by the observational nature of the researcher's attendance at their meetings (Emerson et al., 2011, p. 78).

The methods for data collection during the observation included jottings (see Appendix C). Emerson et al. (2011) suggests several key points for researchers using jottings to capture data during observations. Any form of notetaking during observations requires reduction of the actual events, and the choice of method reflects the assumptions of the researcher about how to best capture the situation. Including direct quotes in the jottings can be a way to record exactly what was said. Jottings can capture the events and impressions of the participants. Jottings took place on paper, and were a form of open jotting, which means the notes were taken in the presence of the participants. This is an acceptable approach given the setting of a classroom

where notes are generally taken as part of the regular process of data team meetings. Data captured in the jottings included key components of interactions, concrete sensory details of the setting and interactions, short quotes, emotion expressions, and general impressions and feelings This level of observation was intended to yield trustworthy and recurrent patterns of data which would allow me to compare the stated attitudes and beliefs from the interview data with behavioral data from the observation.

Data-Analytics Strategies

A six-stage thematic analysis approach to data analysis was implemented. This method of thematic data analysis was developed by Braun and Clark (2006) and is intended to systematically uncover themes from qualitative data (see Figure 4).

Figure 4

Stages of Thematic Analysis

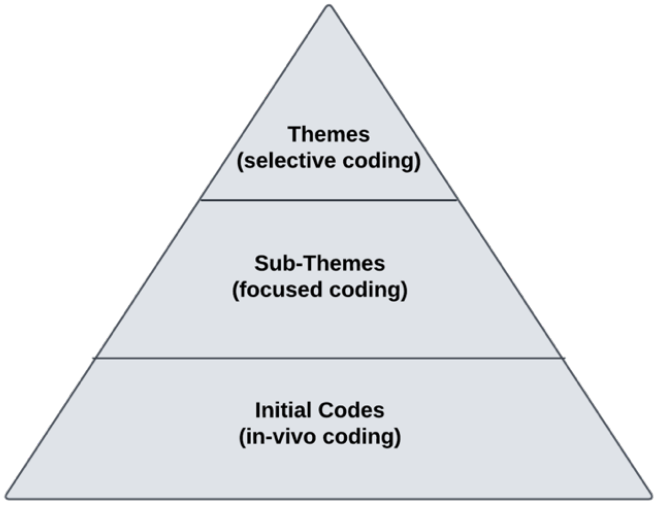
Note. Adapted from Braun & Clark (2005)

The first stage of this data analysis included reading and re-reading of the transcripts from the interviews and observations. The purpose of this stage was familiarization with the data. The main purpose of going through all the data in such a way was to become fully immersed in the whole dataset and collect initial points of interest (Chamberlain, 2015). Multiple readings of transcribed data also allowed the researcher to check the transcripts against the original data to check for errors (Braun & Clark, 2006). Each interview transcript and each observation transcript were uploaded into Dedoose (version 9.2.005), a qualitative analysis software program. During the second stage of data analysis, Dedoose was used to develop initial codes based on the data.

Codes are ideas that appear interesting to the researcher and will form the basis of themes in the next step of the data analysis process (Braun & Clark, 2006). The three rounds of coding are represented in Figure 5.

Figure 5

Coding Rounds During Analysis



The initial analysis of the data employed in vivo coding. In vivo coding is a form of inductive coding where codes are derived from the data themselves (Saldaña, 2013). In vivo coding is used to capture the exact wording used by participants in the form of excerpts and is used to generate initial codes.

In the third stage, codes were combined into themes and sub-themes using focused coding. Focused coding, according to Saldaña (2013) allows researchers to group similarly coded data together and create initial sub-themes. Additionally, focused coding was used at this stage to look for patterns across data as well as analytic memos intended to organize the thinking process as sub-themes were generated from the initial codes. Analytic memos are "sites of conversation with ourselves about the data" (Saldaña, 2013, p. 40).

Then, themes were further refined and linked back to research questions. The fourth and fifth stages of thematic analysis were combined to reduce data to a set of final themes. Selective coding served as the third and final round of coding. Selective coding combines all developed codes from previous stages into the final codes, or themes, of the qualitative data. All codes and sub-themes become combined into themes that "appear to have the greatest explanatory relevance for the phenomenon" (Saldaña, 2013, p. 224).

During the third, fourth, and fifth stages of data analysis, codes were converted into themes as patterns began to emerge. As Braun and Clarke (2006) point out, "a theme captures something important about the data in relation to a research question and represents some level of patterned response or meaning within the data set" (p.10). As the initial codes collapsed into sub-themes, excerpts in each code were examined to seek patterns and repeated key phrases and words. Naeem et. al (2023) identified the use of patterns of excerpts from data to establish a rationale for sub-themes. This is essentially a second round of coding intended to sharpen and focus the initial codes from in-vivo coding. Focused coding was used to develop initial themes. Focused coding can be used after in-vivo coding and compares data across participants (Saldaña, 2013). Grouping codes into sub-themes relied on rich and repeating excerpts.

Member checks were used during two distinct phases of data analysis. McKim (2023) emphasized the importance of participants as experts, suggesting that they should be asked to provide input into the findings. The first member check happened after phase one. During phase one of data analysis, all interviews were transcribed verbatim and read several times to ensure researcher familiarity with the data. Participants reviewed the transcriptions of their individual interviews for accuracy. All case study participants agreed the transcripts were accurate and reflected the interview experience. The second member check occurred between the fourth and

fifth stages of thematic analysis. Participants were presented with themes surfaced during data analysis. By reviewing themes and findings, participants can clarify quotes or summaries from their interviews (McKim, 2023).

CHAPTER IV

RESULTS

The research questions addressed the relationship between teacher attitudes and beliefs and their behavior in data teams:

RQ1: What teacher attitudes and beliefs serve as barriers to data-driven decision-making?

RQ2: What teacher attitudes and beliefs serve as facilitators of data-driven decision-making?

RQ3: How do the professed attitudes and beliefs of classroom teachers manifest in situations involving data-driven decision-making?

Ultimately, the answers to these questions are highly dependent on the nuance of the individuals involved. The themes developed during data analysis were both barriers to and facilitators of DDDM. Data from each participant informed the research questions and identified elements of each theme. This chapter presents research results, starting with the initial coding process followed by each of the major themes and results of data analysis through each of the steps completed during the case study.

Initial Codes

During the first stage of data analysis, the researcher read through each interview transcript and observation field notes, and data from the interviews was used to place data into initial codes. Although only five participants out of six were observed, the interview data from the sixth participant was included because it informed the research questions identifying teacher attitudes and beliefs. No *a priori* codes were used but research questions were central to inform the first round of coding. Key words and phrases in the case study data gave insights into barriers and facilitators to DDDM. In vivo coding was chosen for this initial analysis to capture how

participants resolved their approach to using data as suggested by Saldaña (2013). In vivo coding of the interview transcripts yielded 14 initial codes (see Table 7).

Table 7

Codes from In-Vivo Coding

Code Label	Number of Excerpts
Efficiency barrier	3
Time barrier	15
Relevance and reliability barrier	15
Unreliable or irrelevant data	22
Teacher autonomy	31
Teacher intuition	37
Effectiveness facilitator	10
Time facilitator	4
Relevance and reliability facilitator	7
Reliable and relevant data	26
Support and resources	19
Teachers feel bad	11
Teachers feel good	2
Collaboration	21

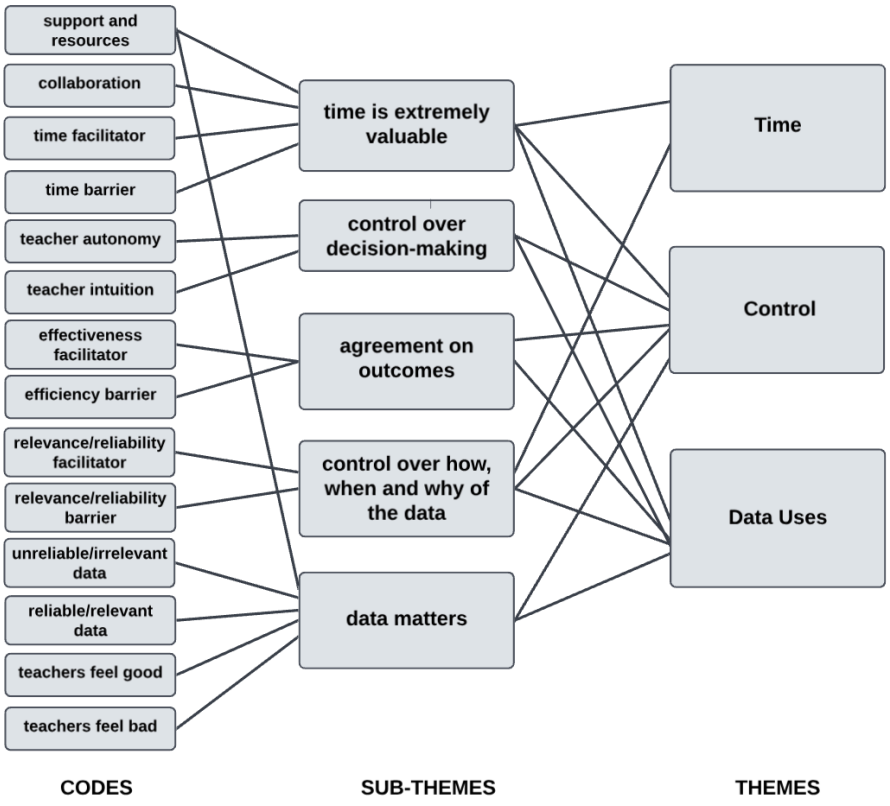
Theme Development

The 14 codes were combined into five sub themes and then into three final themes as shown in Figure 6. The sub-themes were (a) time is extremely valuable, (b) control over decision-making, (c) agreement on outcomes, (d) control over how, when, and why of data, and

(e) data matters. The final themes suggested by data analysis from both interviews and observation are: (a) time, (b) control, and (c) data.

Figure 6

Code, Sub-theme, and Theme Development



Interview Results and Themes

Three major themes were identified from participant interviews and a discussion the results of each theme as well as the sub-themes used to develop them is presented in Figure 6. The three themes include more than one sub-theme, and the interconnected nature of the themes will be discussed later in this chapter.

Time

Time was a prevalent theme, and during interviews several participants expressed concerns related to time. The data suggests time as a major barrier for teachers as they were

using data for decision-making. During interviews, nearly all participants (83%) indicated concern over the amount of time it took to participate in data driven decision-making, including the amount of time it takes to collect data, the time it takes to analyze data, and the amount of time it takes to come together as a team and collaboratively discuss data and make decisions. Although most teachers identified DDDM as a needed component of teaching, they had concerns about devoting time to data because it took away from other tasks deemed more important and critical to the job of teaching. Shelly, a high school science teacher, expressed concern about taking time to collect and look at data.

> I can't just take a week off of school or a week out of that class to stop and look at the data and make those decisions, and so it always just feels like it lags. I don't know how you support that. I mean, we've had people that would come in and do those data team meetings with us, and we were able to do them with ourselves and reasonable capacity, I felt like, but then you're still always just like one step ahead or one step behind kind of where you need to be, that balance between moving forward but staying where you are until maybe your data says that it's time. But you also can't, like, it's, it's a push and pull, yeah, there's, I mean, there's an infinite amount of time to, or non-infinite amount of time to the semester or the quarter or the unit, or the next test that you have to kind of be ready.

Lucy, a teacher with over 20 years of experience in the classroom, stated the following in response to a question about limitations of DDDM:

> I think the big limitation is it's just a huge time suck, huge amount of time, if we really own how much time it takes to get every kid through all those tests, especially when you have kids that have, I mean, you know all those reasons, attendance, avoidance, whatever, and I'm not convinced that us knowing that you're real.

Although time was identified as primarily a barrier to DDDM, two participants identified time as a facilitator. Carl, a high school math teacher with more than 20 years of classroom experience made the following statement when asked about efficiency of DBDM:

> The thing where administrators and teachers don't align on is the efficiency of it. You can't be spending you can't be spending a long time making data dives. The data has got to be quick and apparent, like when I put my quizzes in and like the thing that the part of the power of proficiency grading, I have those quizzes graded five minutes after the kids are out of class, whatever it's got it, and then my data is ready".

Carl's sentiment was echoed by Lucy, who said she wanted "more formative assessments as ways to do effective, quick, formative, quick formative assessments" when asked about supports and resources to help support teachers with DDDM. "I think there's going to be more opportunities for me to just grab something and say, I'm going to use that as a formative it's going to take five minutes".

Time Sub-theme Development. Time emerged as a major theme from one primary sub-theme: time is extremely valuable. This sub-theme described how teacher participants felt time (positively and negatively) impacted their willingness to engage in DDDM. Teachers find time to be an asset and during interviews participants primarily stated concerns around the (limited) amount of time DDDM requires to collect and analyze data as well as the time required to collaborate with colleagues.

Time was also mentioned as a resource that could increase teacher participation in collaborative DDDM. When participants were specifically asked what supports and resources would be helpful for this endeavor, four of the six participants referenced time. Keywords and phrases in this sub-theme were selected from the data if they were mentioned in the context of data collection, time to meet with colleagues, time to analyze data or other references to time and are shown in Table 8.

Table 8

"Time is Extremely Valuable" Sub-theme Keyword Examples

Code	Source Type	Excerpt Keyword/Phrase
Collaboration	Observation	No time to look at anything ahead of time
	Interview	Don't have a common prep
	Interview	We have time to check in
	Interview	Checking in daily
Time facilitator	Interview	Take 5 minutes
	Interview	Quick data
	Interview	Graded in 5 minutes
Time barrier	Observation	I had no time
	Observation	Not enough time
	Interview	Huge time suck
	Interview	Finite amount of time
	Interview	Scrambling

Control

A second major theme identified was control, which describes how participants expressed the need for control when it comes to data-driven-decision-making. As a theme, control encompasses the need for autonomy and the importance of teacher intuition. As suggested by the interview data teacher intuition refers to the ability of educators to make informed, instinctive judgments or decisions in the classroom without relying on data or data analysis and stems from a combination of experience, professional knowledge, and an understanding of students' needs, behaviors, and learning processes. Teachers also indicated wanting control over the type of data

collected and the timing of the data collection. A strong belief in their individual control over their own instruction and what is best for students, as well as control over what data is collected and analyzed, is a major barrier to DDDM. Two teachers had similar responses during interviews when asked about the interplay between teacher autonomy and DDDM. Shelly said,

> Well, you know, like, if I wanted to teach from a box, then I would, you know, I wouldn't have done this. I want to be able to do it with my personality and my autonomy and those types of things. And so sometimes data can lead to decisions being made that feel like that wasn't necessary, or I don't really want to do that.

Lucy reported similar sentiments about autonomy. "I think when you really start taking away autonomy of you must do this and only this. You're going to, it's not good, because one of the powers of education is you've got people that are passionate about their subjects".

Four of the six teachers in the study had feelings about autonomy and its importance in their professional decision-making. A special education teacher, Dylan, expressed some concern that teacher autonomy without data has some disadvantages. In response to a question about how data may impact teacher autonomy, Dylan noted:

> When you shut the door, teachers can do what they want, and not all decisions are good ones and so the data, then is really important to do that, because you can say, well, the class is really happier. The students are really happy, and they enjoy being here, and it's such a relaxed environment, but nothing's really being accomplished.

In addition to the relationship between teacher autonomy and DDDM, teacher intuition was another way in which control becomes a barrier. When teachers are presented with data, or are asked to make decisions using data, participants conveyed resistance when their feelings about their students and their progress were ignored. Teachers were asked about the effectiveness of DDDM for improving student outcomes. Maria is a general education teacher with more than two decades of classroom experience. She had feelings about her autonomy around decision-making and feels student attitudes are important.

> I believe in testing fatigue too very much. We test our kids way too often, and they never see the results of it. So, if they're not invested in the state testing or the Easy CBM testing, and if it really doesn't matter to them, how is that data valid? But we use it to make decisions. And I get challenged with that.

Maria continued to indicate concern about ignoring her intuition. "At my stage my career, with the amount of experience I have, I think the teacher intuition trumps the data, because the data captures a number and doesn't capture everything that surrounds it".

Carl indicated his feelings about the role intuition plays with DDDM.

> Some of the data that's in my head is me walking around the classroom and seeing what they're that's, I mean, that's, it's not pen and paper data, but it's informing my intuition. Well, I think I know I can tell. I can just tell instead of… I don't have any… I don't actually know, but I can tell, and that's fine.

Robert, an experienced specialist at the middle school level, cautioned against reliance on intuition during his interview.

> I think in ways, it probably plays too, too much. In into it, in, in ways, like, where people will say, like, I know, I know. So, people's judgment sometimes are they think they're correct, but they're not. So, they may not believe what the data is telling, but they may believe what they feel, and in reality, the data is what should be, what is driving the decision.

Control Sub-theme Development. During analysis of the participant interview data, control emerged as a theme most connected to three sub-themes using selective coding: (a) control over decision-making, (b) agreement on outcomes, and (c) control over how, when, and why of data. The first sub-theme was identified as control over decision-making. All teacher expressed they were willing to look at data, but this came at the cost of both teacher autonomy and teacher intuition. This sub-theme is comprised of the initial codes of teacher autonomy and teacher intuition. These two codes captured the references participants made to the control they wanted or had over their own decision-making and the statements participants made about what they knew to be true about student achievement not captured by quantitative data. Together these two codes were placed into a sub-theme titled "control over decision-making". Table 9 shows

keywords and phrases from initial in-vivo coding used for this sub-theme of control over decision-making.

Table 9

"Control Over Decision-making" Sub-theme Keyword Examples

Code	Source Type	Excerpt Keyword/Phrase
Teacher autonomy	Observation	I don't think this fits at all
	Interview	You have this goal that isn't mine
	Observation	Timing doesn't work
	Interview	Teachers can do what they want
Teacher intuition	Observation	My class works at a lower level
	Observation	The reasoning level is too high
	Interview	Teacher intuition trumps the data
	Interview	Some of the data is in my head

The second sub-theme identified from the data was "agreement on outcomes". Although teacher participants generally agreed that DDDM can be effective for improving outcomes for students and instruction, they did not feel the process was efficient. Sample sources and keywords and phrases are provided in Table 10.

Table 10

"Agreement on Outcomes" Sub-theme Keyword Examples

Code	Source Type	Excerpt Keywords/Phrases
Effectiveness facilitator	Interview	Powerful
	Interview	Opportunity
	Interview	Helpful
Efficiency barrier	Interview	Disagreement
	Interview	Don't align
	Interview	Not beneficial
	Interview	Not efficient

The final sub-theme was teacher control over the how, when, and why of data collection and use. This sub-theme is informed by two primary initial codes, which describe teacher participant thoughts on the relevance and reliability barriers and facilitators of DDDM. Teachers are much less likely to engage in data use when the process feels irrelevant or unreliable, and expressed interest in DDDM when they were given lots of choice in the data process. Examples of relevant sources and keywords and phrases for the sub-theme of control over how, when, and why of data are provided in Table 11.

Table 11

"Control Over How, When, and Why of Data" Sub-theme Keyword Examples

Code	Source type	Excerpt Keywords/Phrases
Relevance/reliability facilitator	Interview	Use the data myself
	Interview	I wrote the assessment
	Interview	Consistent over time
	Observation	Fits with my unit
Relevance/reliability barrier	Interview	Lost credibility
	Interview	This data doesn't matter
	Interview	Lack of student effort
	Interview	Invalid

Data Uses

The final theme emerging from the study was data uses. This theme describes how participants feel and think about the kinds of data collected and used for DDDM. Data was found to be both a barrier and a facilitator, and during interviews teachers indicated that quick, formative classroom data were more important, more relevant, and more reliable that other kinds of data they were required to use. Analysis also suggested that participants have primarily negative emotions when they look at their classroom data.

When Lucy was asked how data analysis looked in her team setting, she stated "I will be honest, and I'm not a big fan of like, oh, we have to look at those state test scores". A follow-up question about what types of data she wanted to look at revealed a preference for "formative assessments, or the assignments that I give, that I do, either from my curriculum, or ones that I've created. That really informs me how my science students are doing in my classes."

Reliance on formative assessment data over state tests was also preferred by Robert. In response to a question about what type of data he likes to look at, Robert had a negative view of standardized tests.

> So, I feel like the data, the daily data is, I feel like it's a better measurement, opposed to, like, your state test, where, like student effort may not be the best for that state test. Or like, I think, like the iReady diagnostic, where I'll have students perform really well throughout the year, and then take a diagnostic, and then just not, not do as well.

Maria echoed similar feelings as those of Lucy and Robert when it came to reliable and relevant data. "So, if they're [students] not invested in the state testing or the Easy CBM testing, how is that data valid? But we use it to make decisions". Shelly also indicated a preference for data connected closely to "classroom instruction, like how they're doing on that type of work", and even supports looking at standardized test data "if you can get one that feels like it's connected to your content".

Several participants talked about negative emotions connected with data analysis. Dylan, a middle school special education teacher, summed up his experience with data teams.

> People were frustrated, because all of a sudden, they had to look at data, and they had to talk about it, they had to see what was going on, and they didn't like that, because your data could be low. So, then what do you then you're responsible? If you don't know who's low, you think they're all doing great".

This sentiment was also conveyed by Maria, who mentioned "getting injured over and over" in data team meetings. Lucy said one of the limitations of data and data analysis is that it "really makes you feel bad about yourself and that you don't, like, feel good". Only one teacher, Lucy, expressed a positive association with data and DDDM which occurred when she communicated that data analysis felt effective.

> I can't remember... it was a while ago, so, but that was fun, and that was a part of data that it was, like engaging to me as a teacher. It was because I felt like we weren't just looking at numbers, but we were actually thinking [about] what these kids need.

Data Uses Sub-theme Development. The theme of data uses includes the sub-themes: (a) time is extremely valuable, (b) control over decision-making, (c) agreement on outcomes, and (d) control over how, when, and why of data. Teachers in the study also identified training and professional learning on data and data-analysis as a needed resource to increase educators' skills and engagement in DDDM. The code "support and resources" is included as part of this sub-theme development.

During the interviews, participants had many thoughts and feelings about data. Taking time to collect, analyze, and discuss data was a concern (time is extremely valuable). One participant stated she "needed the time and space to think". Another teacher said they liked the idea of DDDM, but "teachers can't be spending a lot of time looking at data". Teachers also want control over the kinds of data collected and analyzed (control over how, when, and why of data) and control over what is done with the data (control over decision-making and agreement on outcomes).

The final sub-theme from the interview and observation data was data matters. This sub-theme described all the ways participants expressed thoughts and feelings about data, either as a facilitator or a barrier to DDDM. Sample sources and keywords and phrases for the sub-theme data matters is shown in Table 12.

Table 12

"Data matters" Sub-theme Keyword Examples

Code	Source type	Excerpt Keywords/Phrases
Unreliable/irrelevant data	Observation	Material didn't work
	Interview	Challenged
	Interview	Not a big fan
	Interview	Not useful for me
Reliable/relevant data	Interview	90% formative
	Interview	Quick formative assessments
	Interview	From my curriculum
	Interview	Daily
Teachers feel good	Interview	Really rewarding
	Interview	Fun and engaging
Teachers feel bad	Observation	Defensive
	Interview	Suffering
	Interview	Stifling
	Interview	Emotionally attached

Observation Results

Five of six participants across five different teams were observed during school based DDDM setting. One participant, Lucy, did not complete the observation phase of data collection. The initial codes were developed by using the interview data, then applied to analysis of the observation data. The results of the observations across these participants are presented in the next section followed by reporting of data from individual participant's interview and observation. The same codes applied to the interview data were applied to the observation data to

determine if the identified themes of time, control, and data use were observable in the participants' behavior during a data team meeting. Table 13 shows the observation code presence and application.

Table 13

Code Presence and Application for Participant Observation Data

Code	Presence	Application
Collaboration	3	8
Time barrier	3	5
Irrelevant/unreliable data	4	7
Teacher autonomy	3	6
Teacher intuition	5	17
Reliable/relevant data	2	2
Data makes teachers feel bad	1	1

Note. $n = 5$. Code is the number of times a code appears in the data set. Application is the number of times a code was used across the data set.

The most frequent code identified across observations was teacher intuition, with 17 applications across all five teacher participants. One participant, Shelly, had nine instances of teacher intuition during her 52-minute observation which represented 53% of applications for this most frequent code. Irrelevant/unreliable data was a code that was present in all but one observation. Application of irrelevant/unreliable data was evenly applied across the remaining four teacher participant observations ($M = 1.75$). The consistent presence of both teacher intuition and irrelevant/unreliable data across teacher participants aligns with themes of control and data uses.

Each teacher participant's thoughts and feelings about DDDM was compared to data collected during a data team meeting to determine how those thoughts and feeling would manifest in a collaborative setting. These data suggests a lack of convergence between the interviews and observations across all five participants. Using codes developed with interview data, analysis of observations demonstrated a disconnect between the thoughts and attitudes expressed by the participants during interviews and observable behaviors and statement during the observations. Initial coding showed that some codes were more frequent in the data than others. Association of code frequencies in relation to data type is provided in Table 14.

The most frequent code that was identified in both interview and observation data was teacher intuition representing 37 out of 223 code applications (17%). This code was applied at least once across each of the six interviews and all five observations. Teacher intuition captured how teachers felt about student achievement in their classroom settings. For example, Shelly stated during her interview that "a kid was nervous during the re-do because the question was worth so much" when discussing why a student's score was considered low. In her interview Maria said, "at my stage my career, with the amount of experience I have, I think the teacher intuition trumps the data, because the data captures a number and doesn't capture everything that surrounds it".

Table 14

Code Application and Frequency

Code	Interviews (n = 6)	Observations (n = 5)	Total
Efficiency barrier	3	0	3
Time barrier	10	5	15
Relevance/reliability barrier	15	0	15
Unreliable/irrelevant data	15	7	22
Teacher autonomy	25	6	31
Teacher intuition	20	17	37
Effectiveness facilitator	10	0	10
Time facilitator	4	0	4
Relevance/reliability facilitator	7	0	7
Reliable/relevant data	24	2	26
Support and resources	19	0	19
Teachers feel bad	10	1	11
Teachers feel good	2	0	2
Collaboration	13	8	21

Teacher autonomy was the second most frequently identified code (n = 31; 14%) and appeared across all six interviews and three of five observations. Teacher autonomy described how teachers felt about their own level of control over their classroom with regards to DDDM. One interview participant described using data as being "chained down in a set to where you

can't move" and that "data limits creativity". Another participant, when talking about using data in a team setting, stated "when you shut the door, teachers can do what they want".

Relevant and reliable data was the third most common code in the data and represents 12% of the code application. During interviews, participants identified instances of the data itself as a barrier to decision-making. One participant identified the curriculum map as "out of date", another said they were "not a big fan of state test scores", and a third teacher also referenced summative state tests by stating "it's not useful information for me". Approximately 43% of codes are represented by (1) teacher intuition, (2) teacher autonomy, and (3) relevant and reliable data.

Two codes represent the emotional impact of data and the association with positive and negative emotions. Negative associations with data was identified 11 times across five participants: 10 times during interviews, and once during an observation. Positive associations with data were only identified twice. Teachers used words such as "injured", "defensive", "frustrated" and "suffering". The only teacher who used words to represent positive feelings with data said, "kids showed a lot of growth, and that was really rewarding to me".

Convergence of Interviews and Observations

The following sub-sections organize results by teacher participant in terms of convergence between interviews and observations.

Carl

Analysis of Carl's interview demonstrated three dominant codes: (a) collaboration, (b) teacher autonomy, and (c) support and resources. A fourth code, relevance and reliability factors, was also significant. When speaking about collaboration, Carl mentioned the lack of formal time to meet six times and that a "more formal" schedule would be helpful. Carl gave his thoughts on

teacher autonomy, saying he "gets to pick the data that matters" and that teachers should be able to choose how data looks in their own classroom. Carl believed that quick formative assessments were optimal, particularly ones he could write himself. When asked about support and resources needed to improve DDDM, Carl referred to the need for administrators to show teachers how to use data four separate times, and that administrative support for implementation is "powerful". Coding from Carl's observation showed the dominant codes as (a) teacher autonomy, (b) teacher intuition, and (c) irrelevant/unreliable data. There was not a strong connection between Carl's interview data and his observation data. The three dominant codes that appeared in Carl's interview (n = 18) did not have a comparable frequency during his observation (n = 3). A comparison of codes is shown in Table 15.

The data team meeting had a distinct lack of structure. No agenda, note-taking, roles, norms, or other meeting structure was observed. As the team discussed an upcoming formative assessment, Carl lamented that his classroom instruction did not really match the assessment, and that the curriculum map the team was required to follow was incorrect. This frustration aligns with Carl's need for data that is more closely aligned to his classroom and reflects the data theme, particularly in the areas of teacher autonomy and relevant and reliable data. It appeared the goal of the meeting was to create a rubric for the upcoming test, but there was no student data present to support the discussion, and Carl was often mentioning the difficulty of the test items and how they were "too abstract", and that students would struggle. In the end, no rubric was created for the test that was scheduled for the following week. Although Carl emphasized the importance of formative assessment, teacher intuition, and time for collaboration, the informal nature of the meeting and the disagreement about test items yielded an unproductive meeting.

Table 15

Code Frequency Comparison for Carl

Code	Interview	Observation
Teacher autonomy	6	2
collaboration	6	1
Support and resources	6	0
Teacher intuition	3	2
Irrelevant/unreliable data	1	2

Carl's interview indicated a desire for formal collaboration to "stay on the same page", but the lack of data present at the meeting, absence of formal meeting structures, and lack of agreement on outcomes hindered the process. The lack of productivity may reinforce Carl's frustration with the limited time to meet and his "constant scrambling to get ready for class", data that shows up often in the theme of time.

Shelly

Analysis of Shelly's interview data showed teacher intuition as the most used code with seven applications. There was also a strong emphasis on time as a barrier and data as both a barrier and a facilitator, with five applications each of these initial codes. Shelly expressed being "disappointed" when data shows students don't do well and her plans are required to shift, and that her teacher intuition informs her as much or even more than what the data indicates. During her interview, Shelly expressed frustration with the timing of data collection, analysis, and collaborative problem solving, saying it "is a little bit off and a little bit slow", and isn't useful at that point. Her feelings about data were shown by references to daily classroom assessments, identifying exit tickets as "pretty helpful" in terms of information.

The focus of Shelly's data team observation was an end of a unit test, the culmination of 10 weeks of classroom instruction. As with Carl's data team meeting, there was no agenda, formal roles, or notes. Shelly had the results of her students' assessments as did the other teachers present in the meeting.

Analysis of data collected during Shelly's observation showed strong alignment of codes with teacher intuition as the most prevalent and time as a barrier and collaboration as the second most prevalent as shown in Table 16. Throughout the observation, Shelly made several references to her intuition. She stated the "reasoning level was too high" and that if kids "took more time" they would have done better. She also felt there was a lack of student engagement during the assessment, stating there "were only 2 kids who were actually engaging that still failed". Shelly's statements during the observation echo her comments made during her interview and demonstrate her need to rely on intuition to explain data. This attitude supports the theme of control, which describes the ways teachers want to interact with data and DDDM.

Table 16

Code Frequency Comparison for Shelly

Code	Interview	Observation
Teacher intuition	7	9
Time barrier	5	5
Collaboration	2	4

Shelly's observation data also supports the theme of time. She referred to lack of time to look at materials ahead of time, to teach the required skills, and to re-write the assessment. Shelly's statements about time as a barrier were similar during her interview, identifying not enough time to "dig into information". She also expressed concern about taking time to "look at data and make those decisions".

Robert

Robert's interview data represented a more balanced code application. Of the 10 initial codes applied to Robert's interview transcript, six of them were used twice and another three were used three times. Robert also took a balanced approach during his interview with regards to the themes of time, control, and data and expressed these themes in terms of both barriers and facilitators. He stated that "consistency over time" should be used when collecting and analyzing data, but that time for collaboration and his current experience with the infrequency of collaborative data analysis were barriers. Data that is formative and contains "curriculum-based measures" is helpful, but that data can be unreliable because "we don't get the students' best effort". In terms of control, Robert indicated that teacher intuition plays "too much" of a role, but at the same time believes he knows his students and he should be able to decide for "the students he works closely with".

It is interesting to note that the code used most often during Robert's observation was collaboration (n = 3), which was not applied during analysis of the interview data. Code comparison for Robert's interview and observation are shown in Table 17. Due to number of variety of codes present in the interview and the overall lack of codes from the observation, data is presented by number of codes that overlap.

Table 17

Code Frequency Comparison for Robert

Code	Interview prevalence	Observation prevalence
Irrelevant/unreliable data	2	1
Teacher intuition	2	1
Reliable/relevant data	3	1

This was the only team meeting for all the participants observed that had a formal structure. The meeting starting promptly on time, had an agenda projected on the screen, had a designated note-taker, and Robert was the meeting facilitator. Data was not the focus of this team meeting, but there were moments when the team presented some school-wide data. Instead of using the data as presented, the discussion was full of reasons the data was unreliable. Robert stated that although there was data present, the "overall lack of data makes a decision difficult" making the data "unreliable doe to the small amount of information per student". Most of the conversation around the data, which lasted three minutes out of the entire 29-minute meeting, was anecdotal and not based on the actual data on the screen. This supports the findings in the data theme. When teachers find the data to be unreliable it is a barrier to DDDM. Robert, when asked about support and resources needed to improve teacher engagement in DDDM in his interview, mentioned that more time would be beneficial. He indicated his data team meets "quarterly". Although 30 minutes was set aside for the observed meeting, 10% of this time was spent talking about data or using it for decision-making. This suggests a disconnect between the desire for time and the actual use of that time, demonstrating the overlap of time and data as themes.

Maria

Coding of Maria's interview yielded two dominant codes: (a) relevance and reliability barrier and (b) teacher autonomy. Across interview data, Maria mentioned thoughts and feelings about her autonomy in the classroom and with DDDM most frequently, with eight references in her interview. She also had feelings about the data itself, with eight mentions of data during her 29-minute interview. Maria used the words "testing fatigue" or "test fatigue" seven times when she was asked about what kind of data teachers should use for DDDM, and that this testing

fatigue makes the data unreliable and invalid. She also mentioned the data source itself, saying that if she is not the one choosing the data to analyze then "they've lost credibility with me". This sentiment is echoed in her comment about administrators choosing data for teams to look at, stating they "used to be knowledgeable about the classroom, but are very far from that now".

Interview data indicate that autonomy is important to Maria. She expressed data "limits creativity" and it makes her feel "chained down". Maria feels using data to make decisions and set goals can be in direct opposition to her professional autonomy. When the data-based goals are not directly related to what Maria feels her classroom needs, she feels "challenged", and that if she disagrees with both the data and the decision she will "shut my door". Maria was observed in a team setting focused on planning for an upcoming unit. There was no formal agenda or other structures, but Maria was taking some notes and most of the speaking during the meeting. The instructional decisions made during the meeting, which included one other teacher, did not include any student data but were based on Maria's intuition about what students needed. This was reflected in the analysis of Maria's observation with two primary codes: (a) teacher intuition and (b) relevant and reliability barriers. Code comparison between Maria's interview and her observation are shown in Table 18. Although there were 19 applications of three dominant codes during Maria's interview, analysis of her observation yielded only five applications.

Table 18

Code Frequency Comparison for Maria

Code	Interview	Observation
Relevance/reliability barrier	8	0
Teacher autonomy	8	1
Teacher intuition	3	4

The discussion about instructional adjustments and future planning were not based on student data but were based on Maria's intuition. Comments such as "my afternoon class works at a lower level", and "students struggle with this" reflect Maria's use of her knowledge of student needs as the basis for decision-making. Maria also expressed concern over the materials she was required to use for future instruction, saying it didn't "fit at all with the unit and that's my complaint". This mirrors her statement about autonomy made during her interview regarding decisions made by others. She also expressed concern about the teaching materials in general, stating that it has "major gaps", and "it didn't teach it well". This attitude is reflected in the team setting, with a lot of the discussion centered around other materials that would be better for Maria's students.

Data from Maria's interview, combined with her observation, demonstrate the themes of control and data. Control over materials, selection of data, need for autonomy, and a reliance on intuition for decision-making can be seen in Maria's data. Reliance on intuition and the absence of students' data during Maria's observation align with the theme of data. Maria's feelings that data collected by others, disconnected with her instruction, and given at times that increase "test fatigue" is invalid can be seen in her observation as she designs instruction and makes decision based on her intuition and need for autonomy. For Maria, data needs to be very closely aligned to her classroom instruction and her current students, and the decision-making using the data needs to be within her control and centered on an outcome she agrees with.

Dylan

Dylan's interview yielded the smallest number of coded excerpts at 21. Data from his interview is clustered in codes that represent attitudes and beliefs that are considered facilitators rather than barriers to DDDM. The most common codes for Dylan's interview data were (a)

relevant and reliable data, (b) support and resources, and (c) effectiveness of DDDM as a facilitator.

Dylan identified reliable and relevant data as connected to classroom instruction, collected frequently, and identifies deficits in student learning. Given that the data meets these qualifications, Dylan believes you "should be able to see student progress" and is a necessity if teachers are to make sure students "are getting what you think is brilliant" in terms of your instruction. According to Dylan, when data is used by teachers to make decisions it can be quite effective because "you have to have a starting point, a midpoint, and an ending point, so you can see what's going on. Otherwise, you're just kind of flying along and you don't know. Are they really learning?". It is interesting to note that Dylan identified the main support and resource for data-driven decision-making as enforcement of the process by the administrators and "that if isn't enforced it will just go away". He wants there to be a requirement to collect and analyze data along with follow-through by the school administrators to ensure it is happening. When asked, Dylan did not feel this would be a threat to his autonomy, saying "when you shut the door and teachers can do what they want not all decisions are good ones and nothing is being accomplished". Analysis of Dylan's interview showed data across four codes with a frequency of 15 applications. Dylan's observation data, however, showed only application in one code.

Dylan's observation did not yield much data as codes were applied four times. This data team meeting had the largest attendance of all observations conducted and Dylan was one of several teachers as well as administrators present. There was an absence of a formal agenda, designated roles, or notes. There was also no student data present even though the group was making a goal for the approaching grading period. This lack of data and the absence of any structure, along with Dylan's expressed desire for administrative supported data meetings with

reliable student data may explain Dylan's low level of participation in the meeting. The most prevalent code applied to Dylan's observation was teacher autonomy; applied only twice to Dylan's interview.

A summary of code prevalence for Dylan's data is in Table 19. Only two codes were applied to Dylan's observation data: almost all of it associated with teacher autonomy. He responded only when directly addressed and did not participate in the conversation without prompting. He did indicate "there's room for improvement" when asked about his students, but this was not a data-based statement. When asked directly about using a particular strategy in his classroom, Dylan responded with "I don't focus a lot on the critique part, which isn't good. This is an area I need to work on". These statements were coded as teacher autonomy as this represents how teachers view their own decision-making when it comes to DDDM. Dylan's positive support of using data for decision-making that surfaced in his interview was not reflected in his observation, primarily because the discussion was not data centered. Dylan held back and only responded when addressed directly but was agreeable to decisions made during the meeting.

Table 19

Code Frequency Comparison for Dylan

Code	Interview	Observation
Effectiveness of DDDM as a facilitator	3	0
Relevant/reliable data	5	0
Support and resources	5	0
Teacher autonomy	2	3

Interview and Observation Analysis

Across the five participants, the interconnected themes of time, control, and data use emerged consistently, with varying degrees of alignment between interview responses and observed behaviors. Thoughts and attitudes expressed in the interviews were generally not present in the observations. Maria, Shelly, and Carl indicated through their interviews a desire for control over the data they engaged with, particularly in how it informed instructional decisions. Their stated skepticism toward mandated data tools and preference for professional judgment often shaped their engagement in DDDM processes. During observations, Shelly and Carl exhibited the strongest alignment with their interview responses, as both had voiced concerns over the reliability of data and its usefulness in guiding instruction. Shelly's suspicion of the data results during her observation mirrored her earlier interview statements about the need to have control over what data was collected, while Carl's stated resistance to data he deemed unreliable was evident in his dismissal of the tool's validity and his reliance on personal intuition noted during his observation. Maria, though also expressing in her interview a need for autonomy, demonstrated a more flexible approach during her observation and adapted data-driven processes in ways that fit her instructional style rather than outright rejecting them. Across cases, time served as both a barrier and an enabler—participants frequently cited the challenge of dedicating time to data collection and analysis in interviews, and they also exercised control over how they prioritized and engaged with the process during observations. The expression of thoughts and attitudes on DDDM is nuanced and is dependent on each individual participant.

CHAPTER V

DISCUSSION

The purpose of the research study was to examine teacher attitudes and beliefs associated with data-driven decision-making and the impact of those attitudes and beliefs on teacher engagement in a data team meeting. Data collected from semi-structured interviews informed research questions about communicated beliefs and field observations informed the research question regarding how behaviors connected to communicated attitudes and beliefs may manifest in a data team setting. The results of the key findings of the research are discussed along with limitations, implications for practice, and recommendations for future research.

Summary of Key Findings

The findings of this study, revealed as attitudes and beliefs expressed during interviews, show that time constraints pose a significant barrier to effective data-driven decision-making among teachers. Additionally, analysis of interviews indicated control as a crucial concern, with teachers feeling limited in their ability to influence how data is collected, interpreted, and applied to instructional decisions. Many participants also expressed skepticism about the relevance and reliability of data, noting that standardized assessments and other external measures often fail to capture the complexities of student learning, leading to a disconnect between available data and actual classroom needs.

Furthermore, the data highlights the interconnected nature of these challenges, illustrating how time constraints, lack of control, and concerns about data quality collectively shape teachers' attitudes toward data-driven decision-making. Limited time exacerbates frustrations over irrelevant or unreliable data, as teachers feel that the effort required to analyze such data does not yield meaningful instructional insights. Similarly, a lack of control over data usage

intensifies skepticism, as teachers are often expected to make instructional adjustments based on metrics that they neither trust nor find useful. These findings suggest that for data-driven decision-making to be more effective, systemic changes must address not only time and control issues but also the alignment between data collection methods and authentic teaching and learning experiences.

Interpretation of Results

The data across interviews and observations suggest that the themes of time, control, and data related to quality can serve as both barrier to and facilitators of DDDM. The findings are interpreted within the scope of existing empirical literature.

DDDM and Time

The findings from this study reinforce the well-documented challenge that time presents for teachers engaged in data-driven decision-making (DDDM). During interviews, participants in this study overwhelmingly identified lack of time as a significant barrier, describing the data-use process—including data collection, analysis, and application—as cumbersome and often infeasible within the time constraints of their daily responsibilities. This feeling of infeasibility surface throughout the participant interviews as time was identified as “finite” and “limited”, and taking time to collect and analyze data did not seem to be something the participants felt was useful. These findings align with existing literature that highlights the persistent struggle teachers face in integrating data use into their practice due to time limitations (Ikemoto & Marsh, 2007; Schildkamp & Datnow, 2022; Schildkamp et al., 2017). While DDDM is often positioned as a mechanism for improving instruction to improve student outcomes, its effectiveness is contingent on whether educators have adequate time to engage meaningfully with data which aligns with research by Abrams et al. (2021). All participants work in a school that dedicates

time for data analysis in a collaborative team setting but the use of this time for DDDM was still seen as a negative. Participants identified grading papers, lesson planning, and other classroom related tasks as priorities within their limited time. Participants mentioned the dedicated time set aside for collaboration with colleagues around DDDM, but still expressed lack of time to complete all the tasks related the process (collecting, organizing, analyzing, synthesizing, and implementing) as identified by Mandinach et al. (2006).

Ikemoto and Marsh (2007) emphasize that DDDM is not a singular process but rather exists along a spectrum, from basic data use to more sophisticated, inquiry-driven approaches. The latter, which involves deeper analysis and reflection, requires significant time investment—time that teachers often lack. The participants echoed this sentiment, indicating that while they recognize the value of data-informed instruction, the practical reality of limited time restricts their ability to engage beyond surface-level interpretation. This tension between the perceived importance of DDDM and the practical constraint of time is a recurrent theme in the literature.

More recently, Schildkamp and Datnow (2022) stress that time for data use is not just about individual teacher capacity but also about systemic support. They argue that school and district leaders play a critical role in designing schedules that facilitate data use rather than impede it. The findings from this study across both interviews and observations suggest that without intentional efforts to embed data use into the school day—such as through dedicated professional learning communities (PLCs) or structured data meetings—teachers will continue to perceive time as a major barrier. Moreover, when time is not allocated explicitly for data use, teachers may view DDDM as an extraneous burden rather than an integral part of instructional decision-making.

Participants' expressed frustration about time aligns with the attitude and beliefs component of the Theory of Planned Behavior (TPB). Ajzen (1991) stated that when an individual does not believe a particular behavior is beneficial, they will be less likely to engage in that behavior. In the context of this research, most study participants did not believe the time spent participating in DDDM was beneficial, making engagement less likely. Despite structures and systems dedicated to DDDM at each participant's school, the teachers still felt that time could be better spent with classroom related tasks. This lack of engagement was seen during observations. Participants did not spend the dedicated time engaged with data but spent time with other tasks such as lesson planning, activity exploration, and looking at materials.

Control in DDDM

The findings from this study indicate that teachers desire greater control over the types of data they collect and use in data-driven decision-making (DDDM). Participants expressed concerns during interviews that mandated or standardized data sources, such as state summative tests or externally created interim assessments, often failed to capture the nuances of student learning, and they preferred to incorporate their professional judgment and contextual knowledge in the data-use process. These findings align with research by Hora et al. (2017), who argue that effective data use is not merely a technical process but also a deeply situated practice influenced by teachers' pedagogical beliefs, experiences, and professional autonomy. Similarly, Means et al. (2010) found that when teachers perceive data as externally imposed and disconnected from their instructional needs, they are less likely to use it in meaningful ways. The teachers in this study echoed these concerns, emphasizing that data use should be teacher-driven rather than dictated by top-down accountability structures (i.e. district interim assessments such as curriculum-based measures, state summative assessments, and national assessments including the National

Assessment of Education Progress). References to daily assessment like exit tickets and teacher-created quizzes as well as personal knowledge of their students emphasize the importance participants placed on their own classroom data over outside assessment.

Similarly to time, an individual's belief in their ability to influence an outcome which in turn affects their motivation and likelihood of engaging in a behavior, is reflected in the results. Ajzen (2002) identified perceived control as one of the primary influences of behavior. In the context of this study, teachers' willingness to engage in DDDM was strongly linked to whether they felt they had control over the data they were required to use for DDDM. This idea of control surfaced during participant interviews. When teachers were required to rely on standardized assessments or district-mandated metrics that did not align with their instructional goals, they expressed frustration and disengagement. Conversely, when they had the flexibility to use data from formative assessments, student work samples, and other qualitative indicators, they felt more empowered and invested in the process. These findings align with research by Hoogland et al. (2016), who found that teachers' engagement with data is significantly shaped by their perceived autonomy in selecting and interpreting data sources.

Schelling and Rubenstein (2021) further argue that teachers' sense of ownership over data is a key determinant of whether DDDM leads to meaningful instructional change. When teachers perceive data as something imposed upon them rather than as a tool to inform their practice, they are more likely to engage in superficial compliance (i.e., skimming through assessment scores or attributing low scores to external factors) rather than deep analysis. The teachers in this study echoed these concerns during interviews, stating that they felt most effective in using data when they had the ability to determine what data mattered most for their students. Data collected during observations support this belief. When data was present during

meetings, participants were observed downplaying its significance or dismissing the data with statements about external influences. This perspective aligns with Schildkamp and Datnow's (2022) assertion that successful DDDM requires a balance between external accountability and professional autonomy. They argue that for data to be actionable, teachers must see it as relevant and useful rather than as an instrument of external control. These findings highlight the importance of designing data-use policies and practices, particularly at the district level, that respect teachers' professional judgment and provide them with greater agency in the data collection and analysis process. Without such autonomy, teachers may perceive DDDM as a rigid, bureaucratic exercise rather than as a tool for enhancing student learning. District policies that require dedicated time for data analysis, allow teachers to select classroom data to contextualize district and state assessment data, and create a collaborative and transparent data culture would encourage effective and meaningful DDDM.

Data Use: Validity, Reliability, and Accountability

Another central theme that emerged from the data was teachers' skepticism toward the reliability and validity of the data examined during collaborative data team meetings. This theme emerged both in interview and observation data. Participants expressed frustration during observed data team meetings that the data did not accurately reflect student learning, citing issues such as student effort, misalignment between assessments and instruction, and external factors affecting performance. These findings align with prior research that highlights the widespread perception among educators that data, particularly standardized assessment results, are often unreliable indicators of student ability and instructional effectiveness (Hora et al., 2017; Means et al., 2010). Means et al. (2010) found that when teachers perceive data as untrustworthy or disconnected from their classroom realities, they are less likely to engage with it

meaningfully. Participants in this study echoed these concerns during interviews, arguing that data discussions often felt performative rather than substantive, as the data itself was seen as flawed or unhelpful in guiding instruction.

This skepticism is further reinforced by the participant's association of data with accountability rather than instructional improvement. During interviews, most teachers in the study identified DDDM as something they were required to do, and that often the goals and types of data selected were not something they got to have control over. Mandinach and Schildkamp (2021) identified that teachers often view data, primarily data such as student test scores, as a mechanism for external oversight rather than as a tool for refining their practice. In the present study, participants expressed concern that the data being examined in team meetings was not being used to support student learning but rather to meet administrative mandates. This accountability-driven focus contributed to a sense of disengagement, as teachers felt that data use was more about compliance than about meaningful instructional decision-making. When data is framed in this way, teachers may resist engaging with it critically, particularly if they believe it does not accurately reflect their students' abilities or needs.

Another key factor influencing teachers' engagement with data is their reported existing beliefs and assumptions about data in connection to student learning. Research has shown that when data contradicts teachers' expectations or prior experiences, they may dismiss or ignore it rather than adjusting their instructional practices (Hannaway, 1989; Ingram et al., 2004; Young & Kim, 2010). This phenomenon was evident in the present study and surfaced during interviews, as teachers frequently reported disregarding data that they felt did not align with their professional judgment. For example, some participants noted that when standardized test scores suggested students were struggling in areas where they appeared proficient in class, they were

more likely to question the validity of the data than to reconsider their instructional approach. This finding underscores the cognitive and emotional dimensions of data use—teachers are not neutral consumers of data, but rather, they interpret it through the lens of their experiences, values, and expectations.

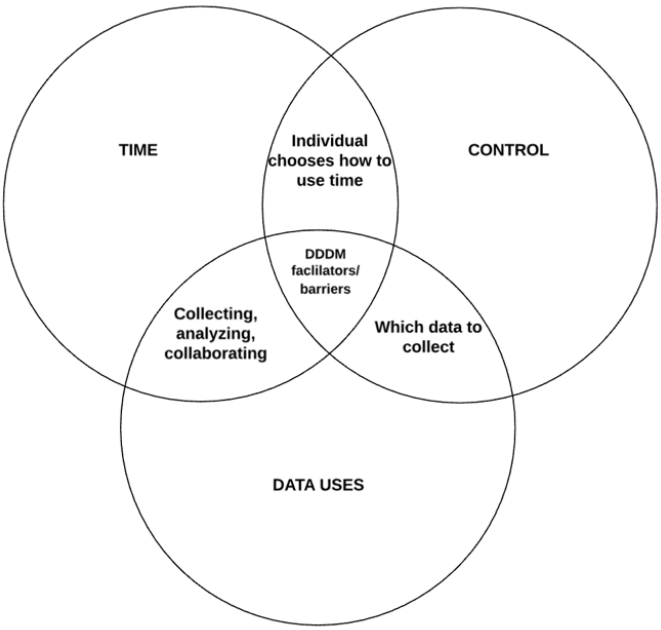
Taken together, these findings highlight a critical tension in DDDM: while student data is intended to inform teachers' instruction, its perceived validity and purpose significantly shape how teachers engage with DDDM. Addressing these challenges around the intersection of perceived usefulness and engagement requires not only improving the quality and alignment of assessments with instruction but also shifting the culture around data use so that teachers see it as a valuable and trustworthy tool rather than as an imposed requirement. Without such shifts, efforts to promote data-driven instruction may continue to face resistance and skepticism from educators who feel that the data does not accurately capture their students' learning or their own instructional impact.

Relationships Between Themes

Three distinct themes were identified across the interviews and observations: (a) time, (b) control, and (c) data use. Although each of these themes identify differing thoughts and attitudes from teachers around DDDM, the themes also demonstrate a meaningful degree of interconnection, given that each theme can serve as both a barrier and a facilitator of DDDM as shown in Figure 7. The connections between time, control, and data are examined in the following section.

Figure 7

Intersection of Themes



Time, Control, and Data Use

The theme of time describes teacher attitudes and beliefs about how time influences engagement in DDDM. As shown in Figure 7, the intersection of time and control relates the need for participants to choose how to spend their time. During the interview one participant pointedly said, “unless you’re willing to spend a huge amount of time digging into information, which we don’t always have, something that we don’t have that control over, it doesn’t feel as relevant to me”.

Participants recognize that time is limited, and expressed frustration when they feel data may dictate how that time is used. During one observation of a data team meeting, one teacher noted that although the student data showed gaps in understanding, this would have to be addressed the following school year because “I don’t have time to change things now”. This same teacher also identified a field trip as a reason her students may not have done well on a

recent assessment. An observation of another participant also showed this conflict between time and control. The teacher mentioned a discussion about how there was a previous decision made that there was not enough time to write a new test even though the questions were perceived as lacking quality.

The data suggests that teachers are willing to spend time using data for decision-making if the process is quick and ongoing. Time spent collecting, analyzing, and collaborating about data was met with resistance by the teachers in this study. All participating general education teachers mentioned data collection that was “quick”, done on a “daily” basis, and is “consistent over time” is the most relevant and reliable.

Data analysis was the area where themes of time and data use intersected. Nearly all participants identified the amount of time required to look at the data as a major barrier, both in terms of individual and data team analysis. Tension between time and data thus becomes a balancing act: on one hand, educators are encouraged to respond to data swiftly to ensure that students are making progress; on the other, they may not have the time or resources to delve deeply into the data to uncover underlying trends, patterns, or insights. Several participants identified the value of analyzing data to improves student outcomes but felt that the lack of time prevented useful insights.

Analyzing data in a team setting, and the time required for it, were problematic for most of the participants. Interestingly, during most of the data team observations, student data was available, but teachers did not engage in decision-making using the data. Although each participant accessed the dedicated time with their team to collaborate, this time was spent with other tasks, such as planning future lessons, setting goals not based on data, and discussions about student attendance, behavior, and effort.

Control and Data

The intersection of control and data in the context of teacher attitudes and beliefs around DDDM is evident in the data. Participants' feelings of control—or lack thereof—over data can significantly shape their beliefs about its value and utility in the classroom. At the heart of this issue is the tension between teachers as autonomous professionals and the external pressures they face from administrators, policymakers, and accountability systems. When data use is mandated through top-down directives, tied directly to high-stakes evaluations, or restricted to standardized assessment results in ways that feel imposed or prescriptive, teachers may perceive it as a tool for surveillance or compliance, rather than a means of enhancing their practice. In these situations, teachers may resist or disengage from DDDM, viewing it as something that takes away their professional autonomy and decision-making power. The perception of control over data is often shaped by how data is collected, analyzed, and used in the school environment. Teachers who feel that they have little say in the types of data collected or how it is interpreted may be more skeptical of DDDM. This skepticism is reflected in interview data by several participants who reported they felt powerless and dismissed as professionals during DDDM discussions where principals or district leaders selected the data and directed the outcomes. When teachers are involved in the process of data collection and analysis, have the freedom to make decisions based on their professional judgment and knowledge of their students, they may be more likely to embrace data as a valuable tool for improving teaching and learning. These findings may indicate that school and district leaders should prioritize teacher involvement in the data collection and analysis process to foster a sense of ownership and relevance. Additionally, the findings suggest that providing teachers with greater autonomy in interpreting data and making instructional decisions could enhance their engagement with data-driven practices.

Control and data intersect not only with collaboration and analysis but also is dependent on the type of data collected. All participants identified the desire for data that is tied directly to their daily teaching, is short and easy to collect, and is teacher-created. Participants expressed a need for autonomy when collecting data in their classrooms to ensure that the information they gather is relevant, accurate, and reflective of their students' learning needs.

Ultimately, the intersection of lack of feeling control over the use of data influences how teachers perceive the value and potential of DDDM. When participants perceived data as something that they control and can use to improve their practice, their attitudes toward DDDM tended to be more positive. However, when data was viewed as something imposed upon them teachers viewed it as a burdensome or punitive practice.

The relationship between time, control, and data use highlighted by the data reflects the complex and interconnected factors that shape teachers' engagement with data-driven decision-making (DDDM). Teachers' perception of time as a barrier, their desire for greater control over the data they use, and their skepticism about the reliability and validity of mandated data are not isolated concerns. Rather, these themes intersect to form a web of facilitators and barriers that influence whether and how teachers engage in DDDM. This interconnectedness aligns closely with the Theory of Planned Behavior (Ajzen, 1991), particularly in how attitudes, perceived behavioral control, and subjective norms collectively inform behavior.

Perceived behavioral control is especially relevant in this context, as teachers' observed engagement with DDDM is strongly influenced by their belief in their ability to navigate the process effectively within the constraints of time and autonomy. Teachers in this study reported during interviews they felt that their limited control over how time was allocated for data use and which data sources were prioritized undermined their ability to make meaningful instructional

decisions. Observed behaviors during data team meetings align with this belief as teachers were using dedicated time for DDDM to lesson plan, discuss materials, or other non-data related tasks. This lack of perceived control often led to disengagement, reinforcing Ajzen's (1991) assertion that individuals are less likely to perform a behavior if they feel unable to influence its outcomes. The overlap of time and control in the diagram underscores this relationship, as the allocation of time and the autonomy to determine how it is used are critical factors in enabling—or constraining—teachers' data use.

Furthermore, the overlap of data and control reflects the importance of teachers having agency in selecting and interpreting data. When data is perceived as externally imposed or misaligned with instructional practices, teachers are more likely to reject it, as previous research has shown (Hannaway, 1989; Ingram et al., 2004; Young & Kim, 2010). The data collected in this study reinforces these findings, as participants often ignored data they felt was invalid or unreliable, instead relying on their professional judgment and intuition. However, the central role of collaboration in DDDM highlights the potential for shared decision-making processes to address these concerns. By fostering collaborative environments where teachers can collectively decide how to use time, what data to prioritize, and how to align data with instruction, schools can strengthen teachers' perceived behavioral control and overall engagement with DDDM. Study findings demonstrate how tightly each of these are connected and highlights the complexity of DDDM in the classroom.

Implications

The findings of this study have significant implications for school and district leaders seeking to enhance the quality of teachers' engagement with DDDM. The themes of time, control, and data use suggest that systemic and structural barriers can hinder teachers' ability to

meaningfully integrate data into their instructional practices. School leaders at both the building and district levels must recognize that while data use is often framed as a technical process, it is deeply influenced by teachers' perceptions, professional autonomy, and available resources. Addressing these factors requires a strategic, teacher-centered approach that acknowledges the realities of educators' daily work and fosters a culture of meaningful, rather than compliance-driven, data use.

Implications for District Leadership

District leaders should evaluate the pacing of mandated data cycles, ensuring that teachers have adequate time not just to review data but to act on it in meaningful ways. Districts could space out mandated data review cycles to allow teachers sufficient time to implement instructional changes before the next cycle. Ideally, this would be on a quarterly basis and would align with curricular pacing guides to ensure data timing supports instruction. Instead of structuring data meetings solely around reviewing assessment results, districts could allocate dedicated time within these meetings for teachers to collaboratively plan instructional responses**.** This could involve incorporating lesson co-design, targeted intervention planning, or professional learning focused on instructional strategies aligned with data findings**.**

District leaders must also recognize the link between data use and accountability pressures. District leaders can shift the emphasis from high-stakes accountability to instructional improvement by adjusting how data is communicated and used in professional learning. Student growth measures, such as Lexile gains and formative assessment improvements, can be displayed alongside proficiency rates. Observable actions include revising district data policies to highlight growth metrics rather than just proficiency rates, providing professional development on using data for formative instructional decisions, and publicly celebrating schools and teachers

who use data to drive student progress and not just meet benchmarks. This study found that teachers often associate data discussions with evaluation, which can lead to skepticism or resistance (Mandinach & Schildkamp, 2021).

Additionally, previous research suggests that when data contradicts teachers' professional judgment, it is often ignored or dismissed (Hannaway, 1989; Ingram et al., 2004; Young & Kim, 2010). To shift the potential for this mindset, leaders must reframe data use as a tool for growth rather than compliance. This can be achieved by fostering a supportive culture where data is used for instructional improvement rather than punitive measures. For example, district leaders can shift the language used in district reports, meetings, and professional development to emphasize growth and instructional adjustments rather than accountability and sanctions. This could involve replacing punitive data labels (e.g., "failing schools" or "low-performing teachers") with growth-oriented language (e.g., "areas for instructional refinement" or "emerging strengths and needs"). Additionally, district leaders can highlight success stories where data-driven decisions led to student progress rather than just focusing on gaps. Sharing success stories in district newsletters, on district websites, and in board meetings helps to highlight how educators use data to adjust teaching and improve growth.

Another key implication relates to professional development and data literacy training. The findings of this study suggest that teachers want greater control over which data they use and how they interpret it, which aligns with research on perceived behavioral control in the Theory of Planned Behavior (Ajzen, 1991; Hoogland et al., 2016; Schelling & Rubenstein, 2021). Districts should provide opportunities for teachers to learn about data analysis paired with opportunities for teachers to critically evaluate the strengths and limitations of different data sources. This could include training on data triangulation, where teachers learn how to integrate multiple types

of data to get a fuller picture of student learning. Districts can provide a professional learning series where teacher learn how to analyze assessment, behavioral, and observational data together, use real case studies to practice identifying learning patterns across data types, and discuss scenarios showing how single data sources can be misleading. Additionally, embedding ongoing coaching and collaborative learning opportunities can help ensure that data practices are contextualized and meaningful, rather than perceived as externally imposed directives. Districts can provide coaches with protocols for leading data discussions with teachers, and encourage coaches to co-analyze student work, formative scores, and observation notes with teachers during coaching cycles.

By addressing these key issues—time, control, and the meaningful use of data—school and district leaders have a better opportunity to foster environments where DDDM is not just a mandated process but a valuable and sustainable practice.

Implications for School Leadership

One key implication is the need for principals to address time as a barrier to effective data use. Teachers in this study expressed frustration with the time demands associated with collecting, analyzing, and discussing data, aligning with prior research (Ikemoto & Marsh, 2007; Schildkamp et al., 2017; Schildkamp & Datnow, 2022). Principals should consider structural changes that provide dedicated and protected time for teachers to engage in DDDM. This could include embedding data meetings into existing professional learning communities (PLCs), streamlining the data collection process, or reducing redundant assessments that do not directly inform instruction. Specifically, principals can designate early release or late start time for data inquiry and rotate support staff including administrators and specialists to cover classes to allow grade-level teams uninterrupted time to collaborate. Faculty meetings can be redesigned once or

twice per quarter as instructional labs, where teachers bring student work or assessment data and work in small groups to analyze, reflect, and plan next steps.

Another critical implication addresses the desire for greater control over the data teachers use to inform their instructional decisions. Participants in this study expressed frustration with being required to use standardized or benchmark assessments that they felt did not align with instruction or accurately reflect student learning. This finding supports prior research showing that when teachers perceive data as unreliable or invalid, they are less likely to integrate it into decision-making (Hora et al., 2017; Means et al., 2010). School leaders can address this issue by giving teachers more agency in selecting, interpreting, and applying data. This may involve allowing teachers to incorporate formative, classroom-based assessments alongside mandated data sources, ensuring that the data used in collaborative discussions is both instructionally relevant and actionable. Restructuring PLC norms and protocols to allow teacher teams to analyze formative assessments and anecdotal data such as observational notes can increase teacher engagement in DDDM. Additionally, providing professional development and collaborative planning time for teachers to create common formative assessments that align with their instructional goals would allow them to generate more meaningful, context-specific data. Finally, allowing teachers to lead discussions and select the data that is most relevant to their current instructional challenges and student needs would increase teacher agency.

One critical area for improvement is how data meetings and collaboration structures are designed. The study's findings suggest that many teachers feel that the data they are required to analyze in collaborative meetings is unreliable or disconnected from instruction. This aligns with research showing that teachers are less likely to engage meaningfully with data if they do not see its relevance to their classroom practice (Hora et al., 2017; Means et al., 2010). To address this,

principals should consider shifting the focus of data meetings from compliance-driven analysis to teacher-led inquiry. For schools and school districts that have dedicated time for data team meetings this could involve allowing teachers to bring in multiple forms of data—including classroom-based assessments, student work samples, and observational insights—so that discussions reflect a more comprehensive view of student learning.

Finally, schools must consider the broader culture of data use and how it impacts teacher motivation and trust in the process. The findings indicate that many teachers associate data discussions with accountability pressures rather than instructional improvement, a sentiment echoed in previous research (Mandinach & Schildkamp, 2021). To shift this mindset, schools should cultivate a culture of inquiry and reflection, where data is used formatively rather than as a high-stakes evaluative tool. One approach is to normalize data use for professional learning, encouraging teachers to analyze data in low-stakes, collaborative settings where the focus is on growth rather than judgment. Principals can also schedule short, informal bi-weekly gatherings where teachers can bring a quick formative assessment and analyze it collaboratively without the need for formalized reporting or documentation to encourage conversation. Additionally, creating feedback loops—where teachers see how their insights lead to concrete instructional changes and student growth—can help reinforce the value of engaging with data meaningfully.

Recommendations for Future Research

While this study provides insights into teachers' perceptions of time, control, and data use in DDDM, further research is needed to deepen the understanding of these interconnections. Expanding on these themes through different research designs and contexts will help refine best practices for supporting teachers in effective data use. For example, a quantitative study to measure the relationships between time availability, teacher perceptions of control over data, and

data use effectiveness could determine how these factors interact and influence teachers' engagement with DDDM. Using a large stratified random sample of K-12 teachers from multiple school districts and utilizing a cross-sectional survey design could increase generalizability of study results and inferences.

Additionally, a longitudinal study following teachers over multiple years could provide insights into how these themes evolve over time, particularly as teachers gain experience with DDDM or encounter shifting policy and accountability structures. Studying these themes in diverse educational contexts—such as different grade levels, subject areas, and school types—could reveal variations in how teachers perceive and navigate these barriers and facilitators. Such research would provide a more comprehensive picture of the systemic and contextual factors that influence effective data use.

Another critical area for further investigation is the role of collaboration within DDDM. This study only included observations of teachers during scheduled data meetings with grade and content-alike colleagues, and more research is needed to determine how different models of collaboration impact teachers' engagement with data. For example, future studies could examine how professional learning communities (PLCs), peer coaching, or interdisciplinary data teams shape teachers' perceptions of data relevance and use. Additionally, research could explore how school leaders can foster trust and shared ownership in collaborative data practices, ensuring that teachers view these discussions as meaningful rather than compliance driven.

Finally, future research should examine the impact of DDDM processes on student achievement. While much of the existing literature focuses on teacher attitudes and implementation challenges, there is a need for studies that link specific DDDM practices to student learning outcomes. Future studies could investigate how teacher-driven data inquiry—

where educators have greater autonomy in selecting and interpreting data—compares to top-down accountability-driven models in terms of student growth. Additionally, research could explore whether certain types of data use (e.g., formative assessments, real-time analytics, or adaptive learning tools) are more effective in improving instruction and closing achievement gaps. By addressing these areas, future research can provide a more nuanced and evidence-based understanding of DDDM, ultimately informing policies and practices that support teachers and improve student outcomes.

Limitations

Although findings can inform our understanding of DDDM, there are limitations that should be considered when interpreting findings, including several methodological limitations that should be acknowledged.

First, the study had a small sample size. While the in-depth nature of qualitative research allows for a rich exploration of individual experiences, it also limits the generalizability of the findings. Yin (2013) identified case study research as particularly susceptible to limitation due to the small number of participants which limits a broader application to the general population. Perspectives captured in this study may not fully represent those of a broader population of teachers, particularly those working in different school contexts or educational systems.

Next, the use of purposeful sampling, while appropriate for ensuring participants had relevant experience with DDDM, introduces potential bias. Participants were selected based on specific criteria meaning that their views may not reflect the full diversity of teacher experiences. For selection in the study, individuals must teach middle or high school, scored in either the top or bottom quartiles on the 3D-MEA screener, and have agreed to participate in both interviews and observations. Participants were selected from a pool of respondents to a screening survey,

and those who chose to participate may have had particularly strong opinions about DDDM which could skew the findings toward more polarized perspectives. All participants were experienced teachers, each with 20 or more years of classroom experience. This limited the viewpoints to only those of experienced educators and decreased the generalizability to the general population. The sample was from a single school district and did not necessarily represent the experiences and systems present in other school districts.

Semi-structured interviews also present limitations. While interviews provide rich, detailed narratives, they are inherently shaped by participants' self-reported perceptions, which may not always align with their actual practices. Social desirability bias may have influenced responses, leading teachers to present their engagement with data in ways they felt were expected or professionally appropriate rather than fully reflective of their daily practices. Semi-structured interviews lack the standardization of structured interviews, making it difficult to ensure consistency across different interviews. Variability in how questions are asked and how responses are probed can lead to differences in the data collected (Kallio et al., 2016). Participant responses were self-reported during the interviews, and responses may have been influenced by their perceptions of the interviewer, their mood at the time of the interview, or their desire to present themselves in a positive light.

Field observations were included to complement interview data, but this method also has limitations. Observations were conducted within a specific timeframe and context, which may not fully capture the complexities of teachers' interactions with data over time. Time constraints only allowed for one field observation for each participant and this limited observational data decreases the validity of the results. The presence of the researcher may also have influenced participants' behaviors, a phenomenon known as the *observer effect* (i.e., people alter their

behavior when they know they are being observed). As noted by DeWalt and DeWalt (2011), participants may become self-conscious or adjust their actions to align with perceived expectations, leading to discrepancies between observed behaviors and actual day-to-day practices. In this study, it is possible that teachers may have altered their behavior during observations, consciously or unconsciously modifying their typical practices. Despite these limitations, the findings of this study offer valuable insights into the complexities of DDDM, providing an important foundation for future research and practical improvements in how educators engage with data to inform instruction.

Conclusion

This research study investigated the teacher attitudes and beliefs around DDDM and how those attitudes and beliefs manifest in a data team setting and highlights the complex and interdependent nature of time, teacher control, and data use in data-driven decision-making (DDDM). The findings indicate that these themes can act as both barriers and facilitators, depending on how they are perceived by teachers. Time constraints often hinder teachers' ability to engage in meaningful data analysis, yet when provided with dedicated, structured time, teachers are more likely to see data use as beneficial. Similarly, teachers desire greater control over the data they use, particularly in selecting assessments that align with their instructional practices and professional judgment. However, when data is perceived as externally imposed or disconnected from the classroom, it is often met with skepticism. Furthermore, teachers' trust in data is influenced by how they experience collaborative data discussions, with a preference for instructionally relevant, teacher-led inquiry rather than compliance-driven analysis.

The interconnectedness of these themes underscores the importance of viewing DDDM as a holistic process rather than a set of isolated tasks. This study contributes to current research

by reinforcing the idea that successful data use is not simply a matter of technical proficiency but is deeply shaped by teachers' perceptions, autonomy, and available resources. By identifying the structural and cultural factors that influence DDDM, this study provides insights that can inform school leadership, policy development, and future research, ultimately supporting more effective and sustainable data practices in education.

APPENDIX A

DDDM SELF-EFFICACY AND ANXIETY INVENTORY (3D-MEA)

This questionnaire is designed to assess the teachers' beliefs in their abilities to effectively analyze and interpret student data to successfully connect or apply their interpretation of data findings to class- room instruction and to improve student learning. It consists of 20 behavioral statements that describe data-driven decision-making practices and behaviors. You are asked to consider each question in terms of your confidence and aptitude. To complete, read each statement carefully. Then select the choice that best fits the specific level of agreement during the past school year. For the response to each statement:

1 represents Strongly Disagree
2 represents Disagree
3 represents Neither Disagree Nor Agree
4 represents Agree
5 represents Strongly Agree

In some cases, these responses may seem awkward; use your judgment in selecting the most appropriate response to such questions. Please select only one number per question.

Data-driven Decision-Making self-efficacy and Anxiety Inventory (3D-MEA) (20 items)					
	Strongly Disagree	**Disagree**	**Neither Agree Nor Disagree**	**Agree**	**Strongly Agree**
1. I am confident in my ability to access state assessment results for my students	1	2	3	4	5
2. I am confident that I know what types of data or reports I need to assess group performance.	1	2	3	4	5
3. I am confident that I know what types of data or reports I need to assess student performance.	1	2	3	4	5
4. I am confident I can use the tools provided by my district's data technology system to retrieve charts, tables or graphs for analysis.	1	2	3	4	5
5. I am confident I can use the tools provided by my district's data technology system to filter students into different groups for analysis.	1	2	3	4	5

6. I am confident that I can use my district's data analysis technology to access standard reports.	1	2	3	4	5
7. I am confident in my ability to understand assessment reports.	1	2	3	4	5
8. I am confident in my ability to interpret student performance from a scaled score	1	2	3	4	5
9. I am confident in my ability to interpret subtest or strand scores to determine student strengths and weaknesses in a content area and weaknesses in a content area.	1	2	3	4	5
10. I am confident that I can use data to identify students with special learning needs	1	2	3	4	5
11. I am confident that I can use data to identify gaps in student understanding of curricular concepts.	1	2	3	4	5
12. I am confident that I can use assessment data to provide targeted feedback to students about their performance or progress.	1	2	3	4	5
13. I am confident I can use assessment data to identify gaps in my instructional curriculum.	1	2	3	4	5
14. I am confident that I can use data to group students with similar learning needs for instruction.	1	2	3	4	5
15. I am confident in my ability to use data to guide my selection of targeted interventions for gaps in student understanding.	1	2	3	4	5
16. I am intimidated by statistics.	1	2	3	4	5
17. I am intimidated by the task of interpreting students'	1	2	3	4	5

state level standardized assessments.					
18. I am concerned that I will feel or look ‘‘dumb’’ when it comes to data-driven decision-making.	1	2	3	4	5
19. I am intimidated by my district’s data retrieval technology.	1	2	3	4	5
20. I am intimidated by the process of connecting data analysis to my instructional practice.	1	2	3	4	5

APPENDIX B

SEMI-STRUCTURED INTERVIEW PROTOCOL

1. Interviewer Name	
2. Participant ID#	
3. Interview Date	____/_____/_____
4. Participant agreed to be digitally recorded	YES……☐ NO……..☐
5. Time Interview Began	
6. Time Interview Ended	

Pre-Interview Section

- **Introduce myself as the researcher**
- **Describe the research**
- **Remind participant that participation is voluntary… participant can skip questions or stop interview at any time**
- **Describe confidentiality process**
- **Ask permission to audio record interview**
  - **Notes will be taken if not given permission to record**
- **Give info about interview length (30-40 minutes)**
- **Ask of there are any questions**
- **Obtain consent to interview**

(BEGIN AUDIO RECORDING IF PERMITTED)

Interview Questions

1. What role do you think teacher intuition plays in conjunction with data-driven decision-making?

2. In your opinion, what are the most critical types of data that teachers should regularly collect and analyze to improve teaching and learning?

3. What do you see as the benefits and limitations of incorporating data into your teaching practices?

4. What factors do you consider when determining the relevance and reliability of the data you use to inform your teaching?

5. In what ways do you think data-driven decision-making can support or challenge your professional autonomy as a teacher?

6. What are your thoughts on the effectiveness of using data-driven decision-making in improving student outcomes?

7. What support or resources do you believe are necessary to effectively implement data-driven practices in education?

8. What role do you believe data should play in guiding instructional practices?

APPENDIX C

STRUCTURED OBSERVATION PROTOCOL

Meeting Title_____Observer_____ Participant_____

Date and Time _____ Duration of Observation_____

Overall atmosphere of the meeting:

Agenda and Objectives		Details:
Agenda present		
Stated objectives		
Data based goal		
Norms and roles		
Observations:		

Data presentation and analysis		
How data is presented		Details:
Types of data		
Depth of data analysis		
Observations:		

Collaborative Decision-making
Notes and Observations (Instances of collaborative problem solving or lack of problem solving, level of participation, etc.):

APPENDIX D

DISSERTATION TIMELINE

TASK	DATE
Proposal Meeting	June 6, 2024
Submitting IRB	May 15, 2025
Begin data collection	August 26, 2024
Finish data collection	December 15, 2024
Write/ complete results chapter	Jan 25, 2025
Send Chris a complete draft for review	Feb 13, 2025
Complete initial revisions	Feb 28, 2025
Apply for advanced degree	Feb 11, 2025
Send Chris full draft to review	March 10, 2025
Schedule dissertation defense	Feb 12, 2025
Send committee a final draft	March 21, 2025
Dissertation defense	April 18, 2025
Submit committee requested revisions	May 2, 2025
Receive revised final draft	May 2, 2025
Submit final dissertation to Division of Graduate Studies	May 2, 2025

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