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Teacher's Self-Efficacy for Data Driven Decision Making

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TEACHER'S SELF-EFFICACY FOR DATA DRIVEN DECISION MAKING

by

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ABSTRACT

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The present study used a sequential mixed method design to compare special education and general education elementary teachers' self-efficacy for data-driven decision making. Participants were 127 teachers from several school divisions in a mid-Atlantic state in the United States. Dunn et al.'s (2013a) *The Data-Driven Decision Making Efficacy and Anxiety Inventory* (3D-MEA) was used for this study along with Tschannen-Moran and Hoy's (2001) *The Teachers' Sense of Efficacy Scale* (TSES), specifically the subscale on the efficacy of instructional strategies. According to the quantitative findings, there was a statistically significant difference between special education and general education teachers' *efficacy for application of data to instruction scale.* The study did not reveal any statistically significant difference between special education and general education elementary teachers' beliefs about self-efficacy for DDDM in the five other factors examined in the survey. The structured qualitative interview revealed that special education and general education elementary teachers had experience with student data in pre-service classes or on-the-job training. Further, the interviews revealed that the teachers exhibited self-efficacy for DDDM in their area of certification.

***Keywords**:* Self-efficacy, data-driven decision making, special education teachers, general education teachers.

I dedicate my study to the elementary school teachers who teach our children and meet their diverse needs. I also dedicate my study to my children Monique, Nichole, and KJ and daughter in-law Alicia who have been on this journey with me from the beginning to the end. I want them to know that it doesn't matter how old you are—nothing is impossible when you have a goal and a dream!

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CHAPTER I

INTRODUCTION

Educational Policies

In the United States, the use of student data has been on the rise over the last two decades. Specifically, several policies formed the basis of using student data to document increased achievement of special education students in the United States (Handler, 2006). The No Child Left Behind Act of 2002 (NCLB), the Individual with Disabilities Education Improvement Act of 2004 (IDEIA), and Every Student Succeeds Act of 2015 (ESSA) include educators' collection of student data as "a critical feature of evidence-based educational practice" (Ruble et al., 2018, p. 177). Petersen (2016) emphasized that NCLB "required educators to consider how a student with a disability would access and participate in general education curriculum and statewide accountability systems" (p. 19). In particular, NCLB focused on the accountability of teachers in regard to closing the achievement gap between special and general education students (van Geel et al., 2016).

IDEIA is a reauthorization of the Individuals with Disabilities Education Act (IDEA). IDEIA continued the policies of IDEA including the concept of least restrictive environment (LRE). LRE provides that special education students are to be placed in classrooms with the general population of students to the maximum extent possible. Lipkin and Okamoto (2015) stated that the LRE "is to preserve interactions with typical children and to ensure exposure to educational material and interactions that may not be found in a more restrictive placement" (p. 1654). Students with disabilities were no longer automatically placed apart from regular students and teachers for the entire school day. In addition, IDEA required that every classroom where core subjects were taught be staffed by highly qualified teachers and that special education teachers be accountable for the progress of their students within the context of the general education curriculum (Gehrke & McCoy, 2011).

In 2002, the Elementary and Secondary Education Act (ESEA) was reauthorized as NCLB which launched the US education sector into an unprecedented 'Age of Accountability' with states holding teachers and schools accountable for student performance through policy tools such as learning standards, high-stakes standardized tests, and teacher evaluation systems (Burkhauser & Lesauz, 2017). NCLB projected "the importance that all students reach some standard of excellence [this] was placed at the top of the national education agenda" (Cybulski et al., 2005, p. 440). NCLB regulated the use of accountability standards through formal testing to compare students and groups. The federal policy of NCLB focused on the educational gaps of minority students, students with disabilities, English-language learners, and students who were in a low socio-economic range (Klein, 2015). According to Yell and colleagues (2006), NCLB "requires that states implement a statewide assessment system that is aligned to the state standards in reading/language arts, math, and eventually science" (p. 6). Yell and colleagues (2006) further stated that the purpose of the statewide testing was to "measure how successfully [targeted groups of] students are learning what is expected of them and how they are progressing toward meeting these important academic standards" (p. 6).

Conversely, ESSA—the authorization of NCLB that followed 13 years later—included formal and informal testing of students (Young et al., 2017). State and local governments regained their past responsibilities for determining their own policies of success and accountability. Under ESSA, formal and informal testing are used to glean achievement status of the students to detect the individual students' performance. Formal assessments included "developmental or academic screening tests, achievement tests, readiness tests, diagnostic assessments, or teacher-made tests" (Gullo, 2013, p. 417). Standardized testing data are only one part of the data-driven decision making (DDDM) process determining student successes and teachers' accountability (Franquiz & Ortiz, 2016). Informal assessments include the students' "performance assessments, academic or developmental checklist, or anecdotal and running records" (Gullo, 2013, p. 417). NCLB and ESSA directly affected the required assessments of special and regular education students. The major differences between the mandates of NCLB and ESSA are highlighted in Table 1 (Murphy & Warren, 2015, p. 1).

Table 1

Major Differences of NCLB and ESSA

	NCLB	ESSA
Testing	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.
Accountability	Defined progress primarily on test scores; provided 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 place on each measure, but a majority of the weight must be on academic indicators (test scores, graduation rates, etc.).
School improvement	Schools that did not make progress toward the federal goals were labeled failures; states were instructed to intervene in specific ways to address failing schools.	Does not specifically authorize new money, but allows states and districts to direct a portion of Title I dollars for school interventions.
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 I dollars for school interventions.
Teacher evaluation	Not officially part of the NCLB but the Obama administration required states to establish teacher evaluation systems based in part on student test scores, in order 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.

Two notable changes in the federal mandates that directly affect teachers were the areas of accountability and evaluations. No longer are there punitive measures placed on teachers due to their students' achievement scores from one summative test (Dennis, 2017). Under ESSA, teachers are able to use several aspects of the student's academic performance to determine a student's progress. Therefore, it is important that teachers understand the premise of DDDM and feel confident in that process to effectively assess students' academic achievement in areas that are not based on a particular test score. Reviewing several of the federal mandates and their progression of requirements for states and teachers puts inherent emphasis on special and regular education teachers' ability to critically gather, assess, and evaluate student performance. The process of DDDM is an important factor when considering how to effectively address the academic needs of students.

Problem Statement

The purpose of this research is to fill the gap in the literature on general and special education teachers' self-efficacy in gathering and analyzing student data under the framework of DDDM. The self-efficacy of teachers is affected by their beliefs about the difference between accountability and data use that led to some misunderstanding, threatening discussions about data, and pressure to show student improvement (Datnow & Hubbard, 2016). General and special education teachers need to acquire a confidence in their ability to not only assemble and gather data, but they also need to interpret its impact on their teaching and the students' learning (Rea-Dickins, 2001). In this regard, it is speculated that teachers will be able to use the student data retrieved through the process of DDDM to affect the instructional changes that promote increased achievement and reduce the gap among groups of students. Researchers have yet to extensively study the self-efficacy of special education teachers in DDDM with a comparative model of general education teachers' self-efficacy for DDDM (Leyser, 2002). Therefore, the educational community could benefit from an empirical study on the following questions:

1) To what extent do special education and general education teachers use DDDM to gauge student performance?
2) What is the difference between special and general education teachers' self-efficacy in using data to plan instruction?

3) How does self-efficacy in DDDM differ between special education and general education teachers?

In the next section, I will examine teachers' accountability and DDDM.

Accountability and Data-Driven Decision Making

Educators are held accountable for student achievement, and their ability to be successful is contingent upon their appropriate engagement with the DDDM process. The collection and analysis of student data is based upon the educator's effective and systematic ability to maneuver through the DDDM process (Carlson et al., 2011):

> Standards-based accountability generally includes attainable benchmarks that specify what children in school are expected to know and what skills they should be able to demonstrate. It also includes measures of attainment of these benchmarks as well as a set of consequences for schools or classrooms based on these data. (Gullo, 2013, p. 415)

It is important for educators to precisely analyze student data to make well-informed choices for students (Newman & Newman, 2013). When enacted properly, DDDM can result in schools making changes that will bring about improvement regarding "teacher quality, curriculum development, and student performance" (Gullo, 2013, p. 418). In addition, teachers can use DDDM to respond to student performance in hopes to improve student outcomes and instructional planning in the school (Demchak & Sutter, 2019). Gullo (2013) wrote that DDDM "can be a powerful tool for revealing needed change, and for questioning long-held assumptions, as well as for facilitating communication with and among students, families and other colleagues" (p. 415). Figure 1, referenced in van Geel and colleagues (2016), depicts an overview of teachers achieving accountability performance on DDDM based on pre-determined goals and various approaches. I am including this figure here because it gives a broad picture of the process involved in DDDM when the teachers work along with school personnel to examine the students' data. As a by-product of the analysis of data, school personnel are able to set goals, map out strategies for instruction, and determine if the performance goals were achieved.

Figure 1

Schematic Overview of Data-Based Decision Making

Effects of Data-Based Decision Making

In the ideal of the schematic overview, van Geel and colleagues (2016) asked, "whether all teachers can master the professional skills needed to implement [DDDM] in daily practice and whether they are all able to adapt their instruction to the needs of *all* students in their classroom?" (p. 388). It is important that teachers know that they are accountable for their students' performance levels as soon as they enter the classroom. Teachers' self-efficacy in DDDM relies on their ability to confidently analyze student data, set goals, determine and execute strategies for instruction, and determine students' performance. Formal and informal assessments guide teachers through the process of student achievement.

Self-Efficacy

Ruble and colleagues (2018) explained that "self-efficacy is not a general trait, meaning that it varies across different domains and activities" (p. 180). Teachers who have positive self-efficacy tend to be considered successful in addressing the needs of their students (Klassen et al., 2011). Perera and John (2020) stated that “teachers’ self-efficacy beliefs were found to be associated with their work satisfaction and classroom levels of interaction quality and achievement” (p. 10). It is evident by the research that there is a relationship between teacher self-efficacy and student achievement. Next, I provide a brief overview of the construct of self-efficacy—particularly as it pertains to DDDM.

Self-Efficacy and Data-Driven Decision Making

Ruble and colleagues (2018) postulated, “In the teaching profession, self-efficacy encompasses beliefs about one’s capabilities to deliver content, manage classroom environments, and engage students” (p. 180). Van der Scheer (2016) explained that teachers are able to affect the performance of their students when their self-efficacy is high. On the other hand, Datnow and Hubbard (2016) stressed that if a teacher possessed even a minute amount of anxiety, they would have problems analyzing student data. Ruble and colleagues (2018) found that the self-efficacy of teachers was an indicator of how and when teachers collected student data.

Teachers’ motivation to follow state, district, and school policies related to student data is based on their belief system that fosters flexibility, modeling, training, and interactions with seasoned professionals who are proficient in the DDDM process (Datnow & Hubbard, 2016). Some teachers are lacking in self-efficacy and have a difficult time engaging in collecting and analyzing student data which can affect the way DDDM is implemented (Walker et al., 2018). It is also problematic for some teachers to connect the student data to the curriculum objectives (Datnow & Hubbard, 2016). The process of engaging in DDDM, according to Gullo (2013), requires that student data are confidently collected. Teachers are a part of the data retrieval process and must use their knowledge of DDDM to determine the effectiveness of their instructional presentation and their students' performance. Improving teachers' self-efficacy in DDDM may require that teachers acquire basic knowledge of statistics to analyze the assessments of students and to increase students' performance and make connections to the curriculum (Dunn et al., 2013b; Newman & Newman, 2013). Franquiz and Ortiz (2009) suggested that state and local agencies under ESSA will determine "what must happen when groups of students are consistently underperforming, advocacy groups, teachers, and communities ought to get together to ensure our most vulnerable students and their teachers succeed" (p. 2). Most teachers who get training based on students' data are generally shown how to retrieve data, but the training usually does not include information on apprehension and anxiety that affects the teachers' self-efficacy for DDDM (Datnow & Hubbard, 2016).

Special Education and General Education

Another major aspect of NCLB and ESSA was to combine the content knowledge expertise of general education teachers with special education teachers' knowledge of addressing academic challenges (Handler, 2006). The performance in a general education classroom focused on the mastery of the state objectives as they are written in the districts' curriculum. The special education teachers focused on the state objectives as they relate to the Individual Education Program (IEP) of the student (Handler, 2006). Brownell and colleagues (2005) found that "Exemplary programs in general teacher education placed heavy emphasis on subject matter pedagogy, whereas special education programs tended to focus on more generic pedagogy (e.g., instructional methods, assessment, individualized education plans)" (p. 248). The parameters that define student mastery of concepts in general education classes may differ from the purpose of a special education teacher's observation of students' ability to master a concept. Brownell and colleagues (2005) found that general education teachers were exposed to evidence-based data to effectively determine student performance. These programs are written in support of the state standards. Special education teachers have to impart the DDDM grade level curriculum state standards to their students, as well as social learning goals and objectives (Handler, 2006).

General and special education teachers make sense of data by knowing the students' abilities and eliciting and maintaining student data. Additionally, teachers need to know their subject in relationship to the state standards' emphasis (Datnow & Hubbard, 2016). For general education teachers there is an emphasis on "subject-matter pedagogy (e.g., reading, mathematics, science)" (p. 248) which is lacking in the preparation for special education teachers (Brownell et al., 2005). Despite the federal mandate and state policies, according to Carlson and colleagues (2011), "student assessments, accountability programs, and the use of associated data systems" (p. 378) some general and special education teachers lack self-efficacy in DDDM. Special education teachers are required to collect data on their students, but many find it difficult to gather daily data on all their students (Ruble et al., 2018). DDDM is essential for special education teachers to be cognizant of the student data needed for the purposes of accountability and documentation on the student's IEP. The progress shown on the IEPs include the data on special needs students who receive services in the special education classroom or receive services in the general education classroom (Handler, 2006). The data collection for special education students is left up to special education teachers to determine avenues to align with DDDM (Ruble et al., 2018). Ruble and colleagues further elaborated that special education teachers' abilities to gather the IEP data are crucial to their self-efficacy. Special education teachers' self-efficacy is related to their ability to successfully provide their students with appropriate instruction based on the special education students' needs. Special education teachers require more instruction on DDDM to meet the mandates of the IEPs and to simultaneously reflect the state standards. Services offered to students who are considered for special education are based on the analyzed data from professionals in the field (e.g., psychologist, social workers, school administrators, and teachers). Special education teachers are required to use the data to determine IEP goals and objectives that will satisfy the needs of the students, as well as merge the state standards with the students' needs. Special and general education teachers are encouraged to have confidence when identifying students' areas of need, differentiating the lesson, and engaging in DDDM at the class level (Morgan et al., 2013). General and special education teachers have an obligation to the students and the teaching profession to make sure that class instruction is focused on increasing students' knowledge and performance (Rea-Dickins, 2001).

Significance

The significance of the research is in examining the self-efficacy of special and general education teachers through the process of DDDM (Dunn et al., 2013a). The collection of formal and informal data form the bases of special and general education teachers' DDDM accountability under the auspices of ESSA. Teachers need to have confidence in their ability to gather and analyze student data to direct their instructional lessons for improved student outcomes. Due to the limited research on comparing special and general education teachers' self-efficacy in the area of DDDM (Leyser, 2002), this research will focus on comparing the self-efficacy of special and general education teachers through their surveys and interview on their ability to gather and analyze data for instructional and student improvement. A mixed methods approach will be utilized. According to Fetters and colleagues (2013) "the qualitative data [in a mixed method design] can be used to assess the validity of quantitative findings. Quantitative data can also be used to help generate the qualitative sample or explain findings from the qualitative data" (p. 2135). Cronholm and Hjalmarsson (2012) state the importance of using a mixed model in that it strengthens the conclusions that are made from quantitative and qualitative data. The use of a quantitative model along with a qualitative model helps to "transparently bridge theory and phenomena … to dispel some of the concerns about bias, vagueness, imprecision, and distortion of direct observation" (Malina et al., 2011, p. 60). Another reason for using a mixed model is the flexibility of the researcher to reexamine qualitative data and repeat the statistical data when necessary.

Definition of Terms

Self-efficacy: The following definition of self-efficacy beliefs from Takahashi (2011) will be used in this study, "teachers' understandings of their own capability and their beliefs about whether and to what degree teachers are responsible for the outcome that students produce" (p. 735).

Data-driven decision making: Gullo (2013) defined DDDM as decisions made using student data to improve student achievement and teacher instructional outcomes.

Special education teachers: Special education teachers are defined as teachers who instruct students who have been identified as having at least one disability that may limit their access to the educational process. Instruction is based on the information presented in the student's IEP.

General education teachers: General education teachers are defined as those teachers who instruct students in public or private schools based on the instructional curriculum of the local or private school system.

Summary

The federal policies of NCLB, IDEA and ESSA laid out the premise of teacher accountability for student outcomes that drive teachers' use of data today. Teachers' self-efficacy for DDDM is a factor when determining teacher accountability and student performance. General and special education students' implications for graduation are dependent upon their teachers' abilities to assemble, understand, and disaggregate the student data. In some respects, the students' future depends on their teachers' self-efficacy in DDDM.

In the next section, I will examine the literature pertinent to the research including literature on educational reform, the definition of DDDM, DDDM issues, comparisons of special and general education teachers, teachers' accountability and bias, as well as the theoretical framework, and teachers' self-efficacy. Self-efficacy is further explained in connection with DDDM and student achievement.

CHAPTER II

LITERATURE REVIEW

When I was a math support teacher, I—along with two other resource teachers—were given the job to assist elementary school teachers with the math program. I was directed to demonstrate math concepts to teachers and work with small group of students in the area(s) of their math weaknesses. In my position, I made 4th grade semester math assessments. The assessments covered state math standards that were given annually to the students. I shared the assessments with the 4th grade teachers to administer to their students. The students' responses were disaggregated by a software system located at the administrative offices. I analyzed the student disaggregated data and presented it to the schools' administrators and 4th grade teachers each semester to determine which students required review on particular math concepts. When preparing the assessments, I Googled information on who, how, and why particular questions were being asked on the annual math assessments. To my chagrin, I found one person who said he wrote a particular question because he thought it was good for 4th graders to know. My first thought was "What the…!"

I mention this because, while preparing this literature review, I realized that as a math support teacher I was just as ignorant as the person who wrote questions for the math standards. I knew nothing about what the data should reveal concerning an assessment instrument prior to it being nationally administered to students. The use of tests' validity and reliability was only referred to when ordering school materials per federal mandate. Despite the fact that I made up formative assessments for preparation for the summative assessment, formative or summative assessments were not a part of my vocabulary. Popham (2011) asserted that "the more that teachers understand about assessment, and especially the requisite features of tests that can trigger sensible instructional choices, the more likely it is those teachers will know what to look for when identifying tests able to bolster the caliber of their instructional efforts" (p. 271). The most interesting fact about my lack of knowledge of the assessment process is that other educators have also expressed their ignorance in the area. Popham expressed his sin as a teacher educator in that he "overlooked the expanding importance of educational assessment in a teacher's day-to-day responsibilities" (p. 267). In the next section, I will expand on the educational mandates that pushed educators to become more efficacious in the data use process.

The purpose of this research is to examine the self-efficacy of special education and general education elementary teachers in the process of data-driven decision making (DDDM) and student achievement. The influence of teacher self-efficacy in DDDM may provide confidence in their ability to gather and analyze student data. Through self-efficacy in DDDM, teachers will be able to inform instructional curriculum that specifically meets the needs of their students. This study will add to the research base on teachers' self-efficacy for DDDM and student achievement for special education and general education teachers. In the literature review below, I will scrutinize scholarly literature on the national reforms that provided insight on issues of teacher self-efficacy for DDDM and its impact on student achievement.

The literature review will comprise ten sections after the initial examination of the United States' national reform movement in education. In the next two sections, I define data and DDDM. DDDM will be examined which includes the process of gathering and analyzing student data. The issues with DDDM are examined in the fourth section. Special education and general education teachers' issues with student data are explored in section five. In the sixth section—accountability, bias, and data—I will examine teachers' involvement with policies focused on accountability for student learning. Additionally, I include information on teacher bias that affects teacher decision making and teachers' knowledge of DDDM. Section seven comprises the theoretical framework and includes Bandura's (1977) self-efficacy theory which relates to the teacher's belief in their ability to confidently manage the process of DDDM. Self-efficacy for teaching is explained in section eight. Teacher self-efficacy is further explained with an emphasis for DDDM in section nine. In section ten, teacher efficacy, DDDM, and student achievement, I examine the relationship of teacher efficacy to DDDM and how it affects student achievement.

National Reform

Educational reform in the United States has shaped the instructional dynamics of special and general education. Specifically, the national school reform movement emphasized that school districts include all students in their improvement plan of closing the gap in academic improvement (Mintrop & Sunderman, 2009). This was especially a concern for students who were identified as having an exceptional disability. For the purposes of the current study, two of the federal mandates will be emphasized here because of their influence on the US educational system (Datnow & Hubbard, 2015; van Geel et al., 2016): the No Child Left Behind Act (NCLB) and the Every Student Succeeds Act (ESSA) of 2015. The former mandated school districts in the United States to expand teaching and learning for general and special education students (Ruble et al., 2018). And the latter provided more control over annual student assessments to the states (Murphy & Warren, 2015).

Under NCLB, determining the progress of students in reading and mathematics was based upon the results of end-of-the-year summative standardized assessments (Datnow & Hubbard, 2016). NCLB mandated states examine differences across groups, and maintain high expectations for all, in order to provide more equitable outcomes for their students (Garner et al., 2017). Collecting data from all students through assessments formalized the action to increase the achievement level in public schools (Carlson et al., 2011). State assessments were geared toward the federal policies that stressed the improvement of instructional output for special education students (Handler, 2006). NCLB mandated that states allow students with disabilities to receive instruction within the same environment as general education students to the extent possible (Handler, 2006; van Geel et al., 2016). Cybulski and colleagues (2005) found that all students needed to show a level of improvement on state assessments as directed by federal policies.

ESSA updated the guidelines that were established by NCLB. According to Darrow (2016), ESSA was reauthorized to replace the "widely criticized NCLB Act" (p. 41). ESSA continued some of the mandates of NCLB such as students' end-of-the-year assessments (Dennis, 2017; Grissom et al., 2017). In contrast to NCLB, Mandinach and Gummer (2016a) asserted that "ESSA notes the need to use assessment data of all sorts (not just summative results) and goes further to include many sources of data such as behavior, motivation, attitude, attendance, and climate, among others" (p. 44). According to the mandate of ESSA, states were required to assess students' performance on end-of-the-year assessments (Garner et al., 2017). The accountability programs ushered in by NCLB and ESSA put pressure on public schools to perform well on state assessments (Carlson et al., 2011). ESSA also focused on the need for teachers to be competent in the use of educational data (Mandinach & Gummer, 2016a). In the next section, I will define data and describe how teachers gather and use data within their daily practice.

Defining Data

For the purpose of this research, data will be defined according to Reeves' and colleagues' (2016) definition,

> Pieces of information, [including] assessment data (e.g., state or district benchmark test scores, student performance on classroom-based formative and summative assessments such as running records, and student work) as well as other types of data such as student attendance and demographics. (p. 8)

These researchers found that the utilization of data varied among teachers. Teachers "regularly describe test data as one data point among many, they acknowledge that it gets more attention than much of the other, less public, data that they gather every day" (Beaver & Weinbaum, 2013, p. 497). Teachers gather student data throughout the year that includes weekly quizzes, unit tests, district assessments, and teacher observations (Marsh & Farrell, 2015). Mandinach and Gummer (2016a) emphasized that "more than its predecessor, ESSA calls on teachers to integrate data into their practice for the good of students" (p. 43). No longer are data viewed as the end of a destination but rather they "[equip] teachers and leaders with the knowledge and skills needed to engage in data-informed practice" (Jimerson & Childs, 2017, p. 587). Data derived from the students during the year help guide teachers' instructional foci. Additionally, school-level data are interpreted and compared with state data (Wachen et al., 2018). However, teachers "in high-performing schools, felt that test [data] did not provide information about what they are trying to do with their students" (Beaver & Weinbaum, 2013, p. 496). The teachers noted this discrepancy when they compared their students' abilities to use creative thinking skills to answer the test questions. To increase the learning of students, "teachers must have access to the data regarding student learning process and outcomes" (Chen, 2019, p. 503). Jimerson and Childs (2017) presented two reasons to analyze educational data: “1) Educational data use continues to be at the forefront of policymaking efforts to improve schools and 2) Effective data use can make a positive difference in equity and learning outcomes” (p. 586). The variety of information that is gleaned from students’ data is essential to the development of a more equitable educational system (Mandinach & Gummer, 2016b).

In order to understand data, however, it’s also important to recognize that data have been misused. Dennis (2017) wrote that “students who perform poorly—and their schools and teachers—are presented as deficient or defective, without acknowledging systems of oppression that may have limited their learning opportunities, hampered their performance, or created assessment bias” (p. 410). Thus, school systems became consumed by interpreting data to determine the effectiveness of their curriculum and instructional strategies (Cybulski et al., 2005; van Geel et al., 2016). Dennis (2017) stressed the importance of school systems surpassing the required pass rate for all students on annual tests to avoid sanctions. These sanctions could be a problem because schools could lose their state accreditation. Beaver and Weinbaum (2013) wrote, “The irony is that because the [test] scores are collected (and later reported) at a single point in time each year, they cannot reasonably be expected to inform the ongoing instructional decisions that compose the daily work of teaching” (p. 498). Datnow and Hubbard (2016) argued that accountability policies do not specify how one might organize, synthesize, and summarize multiple data points, either within or across student groups. The need to analyze “what educators actually do with data adds needed nuance to the field’s understanding of accountability policy” (Garner et al., 2017, p. 412).

There has been much variation in how teachers and administrators use student assessment data in schools and how proficient they are in using the data (Mandinach & Gummer, 2016b).

According to Beaver and Weinbaum (2013) “teachers should be equipped with (and trained on) sophisticated data-warehousing technology that allows them to share multiple types of assessment with new teachers…on student performance” (p. 500). Jimmerson and Childs (2015) stressed the need to equip “educators and school leaders with an ability to understand, utilize, and implement school, district, and state education data well so that they can assist in eliminating gaps and avoid exacerbating them” (p. 606). Datnow and Hubbard (2016) disclosed two important points in their meta-analysis. The first point is that it is important for teachers to be able to identify and analyze students’ strengths and weaknesses, “teachers need [to] deeply understand the subject matter, the curriculum standards, and how students learn” (p. 23). The second point is that teachers need to identify their biases to address their:

> pre-existing schemas about teaching and learning, assessment, data, and data use. Sometimes these belief systems prevent teachers from seeing the utility of data use, or conversely they may predispose teachers for being excited about using data, depending on their prior experiences. (p. 23)

Teachers need to be aware of their thoughts on the purpose of data, and the benefit to their accountability role in instruction, assessment, and student achievement. The DDDM process will be examined in the next section.

Defining Data-Driven Decision Making

Teachers’ use of data has been defined as data literacy for teachers, DDDM, and assessment literacy. Mandinach and Gummer (2013) defined data literacy as “the ability to understand and use data effectively to inform decisions ... composed of a specific skill set and knowledge base that enables educators to transform data into information and ultimately into actionable knowledge" (p. 30). Mandinach and colleagues (2015) further defined data literacy for teachers as:

> The ability to transform information into actionable instructional knowledge and practices by collecting, analyzing, and interpreting all types of data (assessment, school climate, behavioral, snapshot, longitudinal, moment-to-moment, etc.) to help determine instructional steps. It combines an understanding of data with standards, disciplinary knowledge and practices, curricular knowledge, pedagogical content knowledge, and an understanding of how children learn. (p. 3)

Ebbeler and colleagues' (2017) mixed method research focused on the satisfaction of teachers' data use and the improvement of literacy skills. The researchers found that "data literacy skills are built using data from the teachers' own context and that teachers collaboratively use data" (p. 101) by following the steps in the process. It's important that teachers share their data with others within the school to show improvement in data literacy. Reeves and Chiang's (2017) quantitative research focused on pre-service teachers using a data literacy intervention. The researchers described data use: "[it] entails asking a variety of categories of questions about teaching and learning in order to draw conclusions (e.g., about student strengths and weaknesses, status and growth) and make decisions (e.g., about instructional strategies to use, next instructional steps)" (p. 157). The researchers concluded that preservice teachers needed to be exposed to a variety of questions to ascertain student data to get a more accurate consensus of the generated ability levels of students. According to Carlson and colleagues (2011) their study "provides the best evidence to date that data-driven reform efforts, implemented at scale, can result in substantively and statistically significant improvements in achievement outcomes" (p. 394). Buzhardt and colleagues (2020) posited that "DDDM helps educators identify children not responding to intervention, individualize instruction, and monitor response to intervention" (p. 74). Mandinach (2012) postulated that "educators must begin to use data-driven practices but first must become data literate in order to use data effectively" (p. 73). Teachers becoming data literate is an essential component of a teacher's knowledge of student data and a necessary conduit into the DDDM process.

Teachers' instructional formats and procedures are based on the process of DDDM (Dunlap & Piro, 2016). DDDM was referred to as the ability of teachers to utilize student data as a result of combining students' strengths and weaknesses with teachers' curriculum and learning knowledge (Datnow & Hubbard, 2016). Ezzani (2015) expressed that "the purpose behind DDDM is that analysis of student data will enable schools, districts, and states to target areas where progress is needed" (p. 3). No longer can educators rely on their gut feelings about a student to determine the student's performance within a classroom (Mandinach, 2012). A primary element of DDDM required teachers to use their professional ability to pivot their instructional approach based on student assessment data (Walker et al., 2018).

Dunn and colleagues (2013b) argued "that DDDM is an educational reform that goes far beyond standardized summative testing, in fact, when enacted properly, DDDM should affect teachers' classroom decision making and subsequently student success" (p. 233). When practicing DDDM, educators "will collect a variety of data, interpret those data and develop hypotheses about how to improve student learning, and then make appropriate modifications to instruction to test the hypotheses and increase student learning" (Mandinach, 2012, p. 74). Datnow and Hubbard (2016) speculated that teachers' knowledge of rudimentary higher-order analysis was necessary to manipulate and apply student assessment data. Gullo (2013) concentrated on DDDM in relationship to early language and literacy. The researcher noted that, “Due to the high-stakes nature that is frequently associated with data-driven decision making and federal mandates, student test scores represent the most common types of data that are collected and used” (p. 416). In this regard, schools are contingent on DDDM to make advances in school curriculum, teacher quality, and student achievement. Dunn and colleagues (2020) postulated that teachers involved with DDDM:

> Use learning and assessment activities to produce classroom data, close to the learning and the learner, to uncover students’ conceptual understanding and develop competencies specific to learning objectives which may be discrete content standards or more complex and interdependent competencies across multiple subject areas. (p. 2)

Chen’s (2019) mixed method research focused on science and math teachers’ use of a data mining protocol in DDDM. The research revealed advantages in the area of improvement in student learning and the ability of teachers to be able to determine the proficiency skill level of students.

To compare and contrast DDDM and data literacy is like determining what came first in nature: the chicken or the egg? Taking a position for the chicken or the egg would require one to support their premise. Within that frame of thought, I take the position that confidently navigating through the process of DDDM is the result of a framework of knowledge in data literacy. It is essential for teachers to understand the parameters and purposes of data to meander through the DDDM process. DDDM and data literacy involve teachers being able to “identify, collect, organize, analyze, summarize, and prioritize data” (Mandinach & Gummer, 2013, p. 30). DDDM and data literacy bolster teachers’ confidence in the area of interpreting data for instructional decisions and assisting stakeholders in making policy decisions for school divisions and states. The difference between the DDDM process and data literacy is that data literacy provides the knowledge base of data concepts and the process of DDDM provides the action of that knowledge (Mandinach & Gummer, 2016a). Prior to state and federal mandates on DDDM, some form of data literacy was a component of teachers' professional repertoire. Teachers taught their subject pedagogy and in turn gave formal and summative assessments that determined grades and achievement levels of their students. Teachers' knowledge of data literacy transformed as they became more responsive to changes in educational policies. The transformation of data literacy knowledge is the gateway into making educational and policy decisions in DDDM (Mandinach & Gummer, 2016b). Mandinach and Gummer (2013) stressed that DDDM "is a fundamental process that will bring about continuous improvement within the education system" (p. 31). Teachers executing the parameters of the DDDM process, the egg, depended upon the conception of knowledge gained from data literacy, the chicken.

To further explain the components of DDDM, Popham (2011) explained assessment literacy as "an individual's understanding of fundamental assessment concepts and procedures deemed likely to influence educational decisions" (Popham, 2011, p. 267). Xu (2016) argued that teachers need to have an extensive knowledge base of assessment literacy which includes:

> The knowledge of content pedagogy, knowledge of purposes, content, and methods of assessment. They also need to know the rationale and the process of grading. They need to be able to identify and use the different types of feedback to support their students. They need to know the process of communicating assessment results to stakeholders. (p. 155)

Kim and colleagues (2020) emphasized the importance of educators being able to understand the type of assessments that are being given to the students. Educators should be able to interpret the statistical data generated from the assessments to determine the level of the students' performance. Garner and colleagues (2017) found that "teachers acted as though they accepted questions at face value, without considering other factors that may reduce the validity of assessment items (e.g., students' comprehension of the wording of the items)" (p. 415). Assessment literacy requires that educators' knowledge is based on data literacy and the utilization of the DDDM process. Assessment literacy goes further in its reach of educators' knowledge of DDDM as it not only involves gathering and interpreting data, but also involved the ability of the educator to determine the appropriateness of the assessment in relationship to what it is assessing.

This research focused on the self-efficacy of teachers in the area of DDDM. Student instruction is enhanced by teachers' effective use of DDDM (Datnow & Hubbard, 2016). Educators' knowledge and ability to traverse through the process of DDDM is important to the status of the schools, teachers, and curriculum. Gullo (2013) projected that DDDM can "result in schools making changes that will drive improvement in the areas of teacher quality, curriculum development, and student performance" (p. 418). Chen (2019) contended that the focus on student learning was the central goal of DDDM. Teachers' confidence in DDDM "can result in substantively and statistically significant improvements in achievement outcomes" (Carlson et al., 2011, p. 394). In the next section, I will examine issues when executing the DDDM process.

DDDM Issues

The national focus is on implementing DDDM and declaring its benefits to stakeholders (Carlson et al., 2011), but there appears to be issues with DDDM. Datnow and Hubbard (2016) reported on several issues with the process of DDDM that included teachers complaining about having limited time to review the student data which can hinder their analysis. Additionally, delayed administrative posting of the students' assessments scores was an issue. A troubling issue that continued to arise was the mass amounts of data being collected on students, and teachers' feelings of inadequacy in analyzing the data. Chen (2017) also mirrored some of the same issues with DDDM. Teachers expressed their lack of time to analyze the data, the delay in data retrieval, and the limited use of data for specific instruction. Ezzani (2015) posited that in order to have impartial student outcomes, DDDM required sustainable professional learning. The author's intent in their qualitative study was to "offer evidence of productive and effective professional development in DDDM and to provide those involved with educational reform with an example of how to implement an evidence-based culture in their schools" (p. 18). Similarly, Ezzani suggested that "sustainable professional learning in DDDM through structures and processes is critical to how district reform takes place to achieve equitable student results" (p. 2). Despite the issues with DDDM, the benefits for stakeholders outweigh any issues that arise from data retrieval, data analysis, or training. Next, I will explore general and special education teachers' DDDM.

Special Education and General Education

In this study, I investigated the self-efficacy of elementary school special and general education teachers in the area of DDDM. Specifically, special education and general education elementary teachers were compared in their ability to manage the particulars involved with DDDM. Bandura (1997) addressed comparative studies as a good predictor of motivation and action for self-efficacy. Prior to the passing of federal mandates that assured equal access and quality of education to all students, special education teachers were excluded from the assessment process of their students' performance on school wide and national testing. The special education teachers' collection and analysis of student data was used specifically to write and prescribe a plan of action for an individual student's mode of instruction based on their needs within the classroom setting. General education teachers, prior to federal mandates, were not privy to their students' scores on school-wide or national testing unless deemed necessary by their administrator(s). Since the passing of federal educational mandates in the United States, there has been an enormous burden placed on special education and general education teachers to be not only actively involved with collecting and analyzing student data, but also confident in their ability to make instructional decisions based on DDDM.

The focus on DDDM increased the fluctuation of special education students served in general education classrooms (Dunlap & Piro, 2016). Due to the increased services of special education students in inclusive general education classrooms, it was imperative that general education teachers serving special education students were confident in their instructional abilities and the DDDM process (Jordan et al., 2019). Special and general education teachers are tasked with giving educational services to students who require a multitude of strategies to engage with the academic curriculum. Beaver and Weinbaum (2013) found that teachers and other specialists who worked with special education students expressed their frustration in gathering data from state tests that were ineffective for the particular needs of the students. The DDDM process can be challenging to special education and general education teachers due to the resulting data that coincide with other identifying groups (e.g., male, female, black, white, poor) (Park & Datnow, 2017). It is the teachers' knowledge of DDDM that helps them identify the various levels and needs of their diverse students.

Stan (2019) compared special education and general education teachers' psychological distress. In their research they found that special education teachers were "more dissatisfied regarding the fulfillment of the need for competence [in their jobs] by comparison with teachers for general education" (p. 66). Kuronja and colleagues (2019) conducted a quantitative study on the self-efficacy of special education and mainstream primary teachers. The researchers found that special education teachers perceived a higher sense of self-efficacy in the area of improving students' comprehension ability and classroom management. Conversely, Kuronja and colleagues (2019) revealed that mainstream teachers had higher self-efficacy in the area of sharing knowledge from different socio-pedagogical areas. In addition, they found that special education teachers "lack the knowledge required to implement demanding educational processes for pupils needing efficient and extensive support" (p. 46). The cooperation between general and special education teachers is essential to plotting data and improving outcomes for all students (Handler, 2006). In general terms, teachers' data collection and analysis can determine the type and amount of support that a student requires to be proficient in a subject (Dunn et al., 2013b; Reeves et al., 2016). The confidence of special education and general education teachers appropriately executing DDDM can open avenues of collaborative support for all of their students.

Evidence-based processes are the cornerstone to teachers' accountability for DDDM. Ruble and colleagues (2018) wrote that "data collection is a necessary prerequisite for the accurate implementation of evidence-based practices in the classroom" (p. 186). Gable and colleagues (2012) explored special education and general education teachers' perceived knowledge of evidence-based processes when working with special education students. The results of the study, "indicated that many special education teachers and general education teachers lack the necessary preparation to implement a number of evidence-based classroom practices effectively" (p. 499). The federal policies beginning with NCLB directly focused on closing the achievement gap between special education and general education students by using evidence-based procedures. Handler (2006) stressed the importance of special and general education teachers working in partnership to close the achievement gap between special and general education students.

Special education and general educations teachers' perspectives on the DDDM process are noted in the following studies. Ruble and colleagues' (2018) examination of special education teachers' views of DDDM extracted evidence that special education teachers believed that collecting data from students was beneficial and necessary for students to meet their IEP goals. Copp's (2017) empirical study revealed that general education teachers believed that the collection of data were an important part of the DDDM process that determines student and teacher accountability. Ruble and colleagues (2018) suggested that "self-efficacy may be critical in understanding special education teachers' beliefs about their own abilities to collect data" (p. 187). They found that the main predictor of gathering IEP data was teachers' self-efficacy in the DDDM process. Brady and Woolfson (2008), through their comparisons of special education and general education teachers, found that general education teachers expressed that special education "teachers with a higher sense of efficacy have more confidence in their ability to influence student performance" (p. 42). Brady and colleagues' (2008) study findings were contrary to other research like van der Shear's (2016) and Carlson and colleagues' (2011) revelation that teachers who exhibited a higher self-efficacy had a positive effect on student performance. Brady and colleagues examined special education and general education primary school teachers' sense of self-efficacy and attitudes toward special education students in Scotland. The researchers found that "teachers with a higher sense of efficacy attributed the children's difficulties more to external factors than those with a low sense of efficacy" (p. 539). Bandura (1997) stressed that teachers' self-efficacy is increased when they succeed in the endeavor they are undertaking. Bandura (2000) perceived that "self-efficacy contributes significantly to level of [teachers'] motivation and performance accomplishments" (p. 17). Teachers' (special education and general education) self-efficacy in the area of DDDM is dependent on them faltering in the face of difficulties or overcoming their difficulties when they view them as challenges (Bandura, 2000). In the next section, I will elaborate on the issues of accountability and bias that plague teachers' ability to affectively service their students.

Accountability and Bias

State annual assessments are the primary accountability tool used to measure improved student outcomes (Ingersoll & Collins, 2017). Therefore, teachers' instructional accountability continues to be the catalyst by which students' achievements are measured. According to Garner and colleagues (2017) "teachers have little control over the content of assessment items selected at the state and district levels" (p. 419). Teachers are pressured to yield an increase in student assessment scores through their instructional practices (Dennis, 2017). Garner and colleagues (2017) stressed that "test-based accountability policies place pressure on teachers and schools to increase test scores, particularly for students from historically marginalized groups" (p. 407). Under NCLB (2002) and ESSA (2015), accountability systems allowed states to amass disaggregated data on subcategories of students according to their racial identity, bilingual status, socioeconomic status, or special education status in order to examine the educational disparities and close gaps between students (Garner et al., 2017; Mintrop & Sunderman, 2009). Park and Datnow (2017) investigated how teachers in elementary language arts and math classes used student data to determine ability groupings in their case study. The researchers indicated that elementary school teachers used their interpretation of student data to assign class ability groupings. The researchers "witnessed some instructional trends that suggest the use of student-performance data and the accountability context may have led to a rise in ability grouping" (p.

281). Park and Datnow argued that data are a formidable tool that allow teachers to confront the status quo of narrow suppositions about students' capacity for learning. These accountability policies lacked specific directions for teachers to accumulate and analyze student test scores (Datnow & Hubbard, 2016). Ingersoll and Collins (2017) found that the cause of poor performing schools was due to the inadequate teaching staff. This may be due to teachers who have a problem with identifying and using proper accountability standards and formative testing. Grissom and colleagues (2017) suggested that "test-based accountability systems created incentives for schools to improve student outcomes and sanctions for schools that fail to do so" (p. 1082). Carlson and colleagues (2011) found the teachers were positive about the information that was gleaned from the student accountability data, but their instructional strategies were not affected. Ingersoll and Collins (2017) further noted that when teachers' accountability was generated from persons in authority, it rarely produced successful outcomes. When persons in authority omit the incentives along with the obligations for teachers, the accountability outcomes are affected. Teachers' perspectives and issues should be considered when discussing their role in accountability in order for them to commit to the instructional process.

The accountability of teachers directly connects student data with student instructional performance. Garner and colleagues (2017) centered their research on teachers' instructional decisions that are based on their interpretation of student data. The researchers contended that there are problems with the accountability policies that teachers are mandated to adhere to, "Test-based accountability policies do not compel educators to use data to address the deeper issues of equity, thereby inadvertently reinforcing biased systems and positioning students from marginalized backgrounds at an educational disadvantage" (p. 407). The researchers noted that basically teachers disavow the thinking of the students in place of the standards presented on the multiple-choice test items on assessments. Gullo (2013) found “evidence of schools responding to accountability pressure by differentially reclassifying low-achieving students as learning disabled to exclude their scores from the formula that determines schools’ accountability ratings” (p. 1082). However, teachers' use of data to determine the instructional focus and student achievement is an important factor in determining the teachers' accountability capacity (Schildkamp et al., 2017).

Teachers’ focus on student data need to include a self-reflection on their biases and assumptions about students and make corrective moves (Park & Datnow, 2017). Teachers are charged with making decisions on students' futures based on the idea that unbiased data are generated from observations gleaned in the classroom (Schildkamp et al., 2017). Lorenz’s (2021) study on German elementary school teachers examined their bias of achievement expectations. They found that “stereotypes among teachers cause bias in their evaluation of ethnic minority students” (p. 21). Copur-Gencturk and colleagues (2019) found that if teachers identified a group of students as deficient in the area of mathematics the teachers were more apt to be biased against any ambiguous answers given. Also, Quinn’s (2020) study revealed that when teachers are not given specific criteria to grade a student’s assignment there is more opportunity for the teacher to be biased toward specific students. Mandinach (2012) maintained that student “data can provide invaluable information about the learning strengths and weaknesses of students, as well as clues about how to structure instructional strategies to meet those needs” (p. 79). Teachers’ instructional decisions should be based on unbiased interpretation of student data.

Garner and colleagues (2017) submitted that “test-based accountability policies do not compel educators to use data to address the deeper issues of equity, thereby inadvertently reinforcing biased systems and positioning students from marginalized backgrounds at an educational disadvantage" (p. 407). Making teachers accountable for their students' instructional and learning outcomes focused the biases they possessed that may have been directed at specific students. In the next section, I will lay out the theoretical framework which is grounded in Bandura's (1977) construct of self-efficacy under the premises of the social learning theory.

Theoretical Framework

Bandura's social learning theory (1977) on self-efficacy relates psychological measures to personal efficacy and will be used to guide the current study. Bandura (1997) explained that "self-efficacy theory provides explicit guidelines on how to enable people to exercise some influence over how they live their lives" (p. 10) The theory of self-efficacy specifies that driven people will attain their strongest optimistic beliefs because that is where their major focus resides (Takahashi, 2011). Dunn and colleagues (2013b) argued that "Individuals' beliefs about how well [people] will or will not perform profoundly affect their pattern of thought, emotion, and behavior" (p. 224). In other words, according to van der Scheer and Visscher (2016), "teachers with a high sense of efficacy have more confidence in their ability to influence student performance" (p. 42). Figure 2 (Tschannen-Moran & Hoy, 2007) depicts the person's outcome after a change in behavior has been experienced. The outcome will be experienced if the person had confidence that it will occur (Bandura, 1977). It will take a significant experience to alter a person's thoughts about self-efficacy once the new beliefs have been rooted (Tschannen-Moran & Hoy, 2007). According to Bandura (1977), questions arise that a person's self-efficacy will affect their ability to perform a task. Self-efficacy expectations can be changed according to Bandura (1977) when:

> a) It creates additional exposure to former threats, which provides participants with further evidence that they are no longer adversely aroused by what they previously feared. Reduced emotional arousal confirms increased coping capabilities,
>
> b) Self-directed mastery provides opportunities to perfect coping skills, which lessen personal vulnerability to stress,
>
> c) Independent performance, if well executed, produces success experience, which further reinforce expectations of self-competency. (p. 212)

Bandura (2000) further refined his statement that self-efficacy included a cognitive, motivational, emotional, and selection process focus, as well as our beliefs in these processes. These efficacy beliefs refer to:

> Cognitive processes - The stronger the perceived efficacy, the higher the challenges people set for themselves and the firmer their commitment to meet them.
>
> Motivational processes – Courses of action likely to produce positive outcomes tend to be adopted and used, whereas those that bring unrewarding or punishing outcomes are usually discarded.
>
> Affective Processes (Emotional states) – People's beliefs in their coping capabilities also affect how much stress and depression they experience in threatening or taxing situations.
>
> Selection processes – By choosing their environments, they [people] can have a hand in what they become. (p. 17-20)

Teachers' self-efficacy in their personal and professional lives do not isolate these processes as one area of their lives is intermingled with the other area (Bandura, 1997). In the professional life of teachers, their self-efficacy can be diminished by varies occupational duties. Bandura (1997) declared that "educational systems are strewn with conditions that can erode teachers' sense of efficacy and occupational satisfaction" (p. 244) (e.g., following instructional standards, managing student subject needs, and determining instructional focus).

Figure 2

Efficacy Expectations and Outcome Expectations

Note. The diagrammatic representation of the difference between efficacy expectation and outcome expectations.

The focus of self-efficacy of individuals is the major driver of a person's self-worth. Self-efficacy determines an individual's view of their confidence, influence, and their task ability. A focus on the cognitive, motivational, affective, and selection processes explains a person's self-efficacy. In the next section, I will examine teachers' self-efficacy.

Self-Efficacy for Teaching

In education, when teachers are not able to cope and lack self-efficacy, they stop trying to understand the process and will sabotage their teaching experience (Bandura, 1977). At that point, teachers don't believe that they can change the student's outcome (Jennett et al., 2003). Bandura (2000) wrote that "It is not all that difficult to produce veridical self-appraisal in which people's beliefs in their efficacy match their current performance, but they do not strive for something higher" (p. 22). Takahashi (2011) argued that "If teachers believe that they can positively affect student learning, they are more likely to put forth the effort to implement different pedagogical strategies, and to keep trying even when faced with setbacks" (p. 732). Brady and Woolfson (2008) commented that "Teaching [self]-efficacy is another potentially important variable with regard to teaching learners with learning support needs. Teaching [self]-efficacy relates to a teacher's feelings of his/her own capacity to successfully facilitate learning" (p. 529). Takahashi's (2011) qualitative research focused on the self-efficacy of four junior high school teachers. The author concluded that when teachers are able to identify purpose, responsibility, and meaning to their commitment to students' learning, it will structure their self-efficacy viewpoints in a positive direction. In the next section, I will examine teacher self-efficacy for data-driven decision making.

Teacher Self-Efficacy for Data-Driven Decision Making

Self-efficacy for DDDM, in particular, has been defined as "teachers' beliefs in their abilities to organize and execute the necessary courses of action to successfully engage in classroom-level DDDM to enhance student performance" (Dunn et al., 2013a, p. 87). For a teacher to use student data successfully "he or she must be technologically, statistically, and pedagogically savvy" (Dunn et al., 2013b, p. 223). Bandura (1997) referred to the use of technology as a component of self-efficacy. The use of technology is important for teachers to be able to manage and analyze student data within the DDDM process. Teachers' effectiveness in DDDM requires that their self-efficacy is associated with their ability to confidently maneuver through the data process (Dunn et al., 2013a). Mandinach (2012) posited that there are two main avenues of DDDM that should be utilized in the educational setting: "Technical tools…to support data inquiry process [and] for educators to use data effectively, they must acquire skills and knowledge of data literacy" (p. 76). DDDM can be challenging for teachers to manage the collection and analysis of student data on a daily basis (Chen, 2019). Teachers' self-efficacy in analyzing and interpreting data was imperative to understand the process of DDDM (Dunn et al., 2013b). Walker and colleagues (2018) stated that teachers frequently do not engage in DDDM due to their poor self-efficacy. According to Chen (2017), “in the real-world educational setting, both teachers and students are often at a loss of what to do when their data becomes accessible” (p. 504). Stress and anxiety can overwhelm teachers' ability to confidently analyze student data to make instructional decisions (Dunn et al., 2013b).

There is a need for school leaders to provide more training, specifically in the area of DDDM, to increase teachers' confidence in data use (Demchak & Sutter, 2019). Dunn and colleagues (2020) investigated the relationship between pre-service teachers’ self-efficacy and anxiety for DDDM. Jordan (2019) postulated that:

> If teachers do not leave teacher education programs with a high sense of self-efficacy, or do not quickly achieve it in their workplace, then they are less likely ever to experience high self-efficacy, and their students are more likely to experience the negative effects of a low self-efficacy teacher. (p. 186)

One suggestion to address teachers who require assistance with self-efficacy in DDDM was for teachers lacking in self-efficacy in DDDM to seek out teachers who are proficient in DDDM to model (Mintrop & Sunderman, 2009). Ezzani (2015) claimed that “the efficacy in the use of DDDM…has to be comprehensively and systematically taught and learned, using the best professional learning practices” (p. 3). Training for DDDM should take place before teachers step foot in a classroom and when they are professionally practicing their craft. In the next section, I will associate DDDM, self-efficacy, and student achievement.

Teacher Data-Driven Decision Making, Self-Efficacy, and Student Achievement

How does teachers’ self-efficacy in DDDM affect students’ achievement? The empirical research varies. On the positive side, Carlson and colleagues’ (2011) empirical research revealed that, when teachers used DDDM, student gains were made in mathematics and reading achievement. Their research was a year-long process with over 500 schools, including fifty-nine school districts that covered seven states. DDDM was required to improve student achievement and adapt instructional lessons that increased student outcomes (Demchak & Sutter, 2019; Marsh & Farrell, 2015). Teachers' self-efficacy for DDDM highlighted the ability of the teachers to confidently manage through the process to increase student achievement (Walker et al., 2018). Carlson and colleagues (2011) noted that their large-scale research revealed a significant relationship between DDDM and student achievement. Gathering student data, according to van Geel and colleagues (2016), should not be difficult for teachers to retrieve, analyze, or compare with national standards. Teachers are the primary agents who connect the data to student instruction and achievement (Datnow & Hubbard, 2016).

The pressure on teachers to change instructional strategies based on DDDM and student achievement has left some teachers with self-doubt about their abilities. Marsh and Farrell (2015) postulated that despite the amount and type of data that teachers compiled on their students, teachers were not confident in their ability to associate instructional changes that affect student achievement (Dunn et al., 2013b). Datnow and Hubbard (2016) wrote that teachers' use of data was not commensurate with their exposure to data training and application. As a result, teachers continued to lack confidence in their capacity to analyze student data to determine student achievement. Teachers' lack of self-efficacy will happen when "failures occur before a sense of efficacy is firmly established" (Bandura, 1997, p. 80). Teachers' self-efficacy for DDDM and student achievement is not a perfect process for teachers who have difficulty connecting the components.

The results of several empirical studies offered teachers ways to improve their self-efficacy for DDDM to assist them with determining information for students' achievement.

Beaver and Weinbaum (2013) stressed that retrieval of student data is a starting point for teachers. They further stated that “analysis and interpretation of state data can encourage further inquiry, which in turn can inform those efforts at targeting remediation/instruction at the student level and aligning content at the school level” (p. 499). Both elementary and secondary school teachers participated in their study. Chen (2017) explored math and science secondary teachers’ perceptions of the information system used to collect student data and their ability to use the system. The results conveyed the need for teachers to apply what they learned about collecting and analyzing data and plan lessons based on the student data to improve student achievement. Dunn and colleagues (2013b) found that teachers who collaborated with their peers increased their self-efficacy in the area of DDDM. Further, “elementary settings tend to support collaborative DDDM opportunities through a variety of activities such as grade-level team meeting, professional learning communities, and data team meetings” (p. 237). Teachers who specifically establish purposeful inquiry into the DDDM process, plan lessons based on the data, and work with other teachers can improve their self-efficacy for DDDM and student achievement.

Summary

The government mandates of NCLB and ESSA changed the focus of teaching and learning in the United States. State learning standards were required as a template for school districts and teachers to follow (Galluci, 2008). The literature review included definitions of data, data literacy, and assessment data to give a detailed account of DDDM. Issues with DDDM were examined and the critical importance of DDDM in making equitable student discissions (Ezzani, 2015). The section on special education and general education teachers focused on some areas of comparison and data responsibilities. Teachers’ accountability and their responsibility for the results of student performance was examined. Teacher biases revealed areas of biases that may affect a teacher's judgment of students. The theoretical framework for this study is based on Bandura's (l977) social learning theory of self-efficacy to give credence to the dilemma of teachers who have a lack self-efficacy in an area of their practice. I specifically related self-efficacy for teachers and their capacity to support learners. Teacher self-efficacy for DDDM revealed that the commitment to student learning can put a focus on their self-efficacy. The last section on teacher DDDM, self-efficacy, and student achievement was examined to show how a teacher's self-efficacy in DDDM can make a difference in student achievement. Therefore, the research on DDDM could be enhanced by including an empirical study that addresses the following questions: 1) To what extent do special education and general education teachers use DDDM to gauge student performance? 2) What is the difference between special and general education teachers' self-efficacy in using data to plan instruction? 3) How does self-efficacy in DDDM differ between special education and general education teachers? In the next section, I will reveal the methods and procedures for the study.

CHAPTER III

METHODOLOGICAL APPROACH

The purpose of this study was to compare the self-efficacy of special education and general education elementary school teachers in the area of data-driven decision making (DDDM). Further, the purpose was to examine special and general education teachers' self-efficacy in determining the instructional needs of their students. The rationale for using a mixed method model for this study is reviewed next.

Strength of Mixed Model Research

I employed a mixed method design for the study. The strengths of a mixed model over an independent quantitative or qualitative model were evident in the literature. Cronholm and Hjalmarsson (2012) stressed the benefit of using a mixed model as it increased the suitability and fidelity of the research. They further indicated the importance of using a mixed model to strengthen the conclusions made from the quantitative and qualitative data. The use of a quantitative model along with a qualitative model helped to "transparently bridge theory and phenomena, as does a publicly available statistical dataset, to dispel some of the concerns about bias, vagueness, imprecision, and distortion of direct observation" (Malina et al., 2011, p. 60). Venkatesh (2013) claimed that mixed model research progresses the understanding of the issues researched through a gestalt lens. In a mixed model, the researcher counteracted the boundaries that limit the processes of quantitative and qualitative research (Almeida, 2018). The value in using mixed methods research, according to McKim (2017), is the combination of using both methods to fill in the weakness of the other. For example, in the survey that was used in this study, the participants rated themselves based on the set parameters of the tool. In the interview, the participants gave more insight into their feelings and actions when answering the questions about their self-efficacy regarding DDDM and instructional processes.

When researchers use mixed methods, one design is usually dominant in the study; in this case, the quantitative component (i.e., the survey) was dominant (Fetter & Molina-Azorin, 2019; Östlund et al., 2011). The survey measured the efficacy of general and special education teachers with a focus on DDDM and student achievement, as noted in the research questions (Ponce & Pagán-Maldonado, 2015). Bailes and Nandakumar (2020) stressed the importance of using a survey for its quick response rate of participants and the ability for researchers to review the data in a timely fashion.

The administration of the interview gave me a clearer understanding of the reason why the participants responded the way they did in the survey (Malina et al., 2011). Almeida (2018) submitted, "Qualitative research has a fundamental objective: the understanding of certain behaviors and the collection of opinions and expectations of the individuals in a population" (p. 138). The structured interview of the participants gave more details about the participants' perceptions (Caruth, 2013). The survey and interview were administered online. In response to McKim's (2017) question, "Is mixed methods going to add more value than a single method?" (p. 202). Within this research study, the use of mixed methods, which includes a survey and the opinions conveyed by the interview, added more value to this study than a single method.

The value of mixed methods was apparent, despite the time and effort to complete the process. The participants in McKim's (2017) study listed the values of mixed methods in attaining "confirmation of results, deeper meanings, multiple perspectives, and rigor" (p. 213). Besides, mixed methods, due to the components of the process, directed relevant professional discussions on the topic of the research (Molina-Azorin & Fetters, 2019). Leech and

Onwuegbuzie (2010) postulated that mixed methods differ from single method researchers "in mixed methods, researchers do not believe in a one-size-fits-all approach to research" (p. 77). In this case, a separate quantitative or qualitative study did not complement any research questions that better fit a mixed model (Ponce & Pagán-Maldonado, 2015).

Study Design

Based on the research questions and the strengths of a mixed model approach, the current research was based on the sequential model parameters of a mixed method study (Cameron, 2009). The research questions were:

1) To what extent do special education and general education teachers use DDDM to gauge student performance?
2) What is the difference between special and general education teachers' self-efficacy in using data to plan instruction?
3) How does self-efficacy in DDDM differ between special education and general education teachers?

The quantitative and qualitative approach to the research was necessary to examine the entire phenomenon being studied (Fetter & Molina-Azorin, 2019). The approach and comparative mixed method research followed a sequential explanatory design (Almeida, 2018). A sequential explanatory design was provided to collect the data with the quantitative instruments administered initially. The research was based on a descriptive and comparative mixed method design. Afterward, the qualitative interview was conducted to add to the quantitative data of the questionnaire (Caruth, 2013; Rapanta & Felton, 2019).

Sampling and Participants

I sent emails to Region 1 and Region 2 division administrators in a mid-Atlantic state to request permission to execute the research in their division (Ponce & Pagán-Maldonado, 2015). Thirty divisions were invited to participate in the survey. The superintendents and the persons responsible for elementary school research in the system were contacted using the information retrieved from the official state's department of education website. After sending repeated requests, six divisions gave permission to implement the study. The divisions' responses that did not participate in the study ranged from no response, to "I am not interested," to a very thoughtful response, "We have discussed and considered your request, however, due to prior commitments, teacher time requirements, a continuation of online instruction for some students, and a shortage of teachers, we cannot support your proposal." After procuring authorization from six school divisions, I used a purposive sampling technique to acquire a comprehensive mix of general and special education elementary school teachers.

An online invitation and survey link were sent out to either the division administrator in charge of research protocols or sent directly to general and special education elementary school teachers responsible for teaching academic courses in elementary schools. The procedure used to contact participants who received the invitation and survey link was directed by the division administrator who oversaw the research. A $15 gift certificate incentive was raffled off for every 50 participants who consented to participate in the study. The participants received their incentive after the completion of the survey. The invitation and survey were sent as soon as the research application was approved. The survey was completed by 134 participants. Several participants were excluded from the study. Four participants were middle school teachers, one was a high school teacher, and one did not complete the survey. As a result, the total number of participants was 127. Thirty-five special education elementary teachers and 92 general education elementary teachers participated in the study. The percentage of special education teachers to the total number of participants in the study was higher than the number of special education teachers represented in each of the participating divisions' total elementary school teachers. The reference to the total elementary school teachers is those teachers who teach in grades K-6 in an elementary school setting. The percentages of special education teachers compared to the total number of elementary teachers in the participating divisions ranged from a low of 16% to a high of 26%. The average percentage of special education teachers in the 6 divisions was 20% of the elementary teachers. My study revealed that 28% of the participants were special education teachers. Therefore, my study represented more special education elementary teachers in relationship to the total number of participating elementary teachers than in the 6 divisions studied. An online survey was implemented because it was less time consuming than pencil and paper surveys for both the participants and the researcher (Elswick et al., 2016).

I informed the participants about their "confidentiality, anonymity, and informed consent" (Mertens, 2010, p. 11). The sample of volunteer teachers was informed that they could end their participation at any point during the study. The teachers were told that their names and any identifying information about them were hidden from view except for the researchers' use only for general demographic reporting purposes. They were given the option of choosing another name as identification for the researcher's purpose only. All data, including demographic and survey responses, were on password-protected computers in encrypted online drives with no other person having access to the information except the research team.

The participants were treated with respect and informed that no harm would be levied on them due to their responses to the survey, except for a potential breach of confidentiality

(Merten, 2010). I shared the research results with the participating school divisions, where teachers had access to the findings. The benefit of this study was identifying areas for improvement for general and special education teachers' self-efficacy in the area of DDDM and student achievement (Merten, 2010).

The teachers were given the option to participate in a web-based, recorded, semi-structured interview at the end of the survey. The researcher contacted the teachers to make arrangements for the qualitative interview. The researcher made several attempts to procure the nine participants for the semi-structured interview. The consent form was presented to the teachers before the survey and interview.

Data Collection and Measures

The *Data-Driven Decision Making Efficacy and Anxiety* Inventory (3D-MEA) (Dunn et al. 2013a) was sent to the teacher participants via email through a Google Form survey. The 3D-MEA consists of 20 questions with a 5-point Likert scale, ranging from 1 = *strongly disagree* to 5 = *strongly agree*. The 3D-MEA measures teachers' anxiety and self-efficacy and its relationship to DDDM (Dunn et al., 2013b). The 3D-MEA was a validated and reliable instrument (Walker et al., 2018). Dunn and colleagues (2013b) "rigorously evaluated the 3D-MEA scores' internal structure through exploratory factor analysis (EFA) and confirmatory factor analyses (CFA)" (p. 480). Walker and colleagues (2018) revealed a high score internal consistency for all 5 scales in 3D-MEA. The 3D-MEA 5 scales specifically denote questions of teacher efficacy in DDDM as follows:

[1] Efficacy for Data Identification and Access (Identification) Scale included 3 items (Items 1 through 3) that assessed a teacher's self-judgment of their ability to identify, access, and gather appropriate reports needed for DDDM.

> [2] The Efficacy for Data Technology Use (Technology) Scale included 3 items (Items 4 through 6) that assessed a teacher’s self-judgment of his or her ability to utilize and navigate district and state level technology tools to access information for DDDM….
>
> [3] The Efficacy for Data Analysis and Interpretation (Interpretation) Scale included 3 items (Items 7 through 9) that assessed a teacher’s self-judgment of his or her ability to analyze and interpret basic components of student performance data.
>
> [4] The Efficacy for Application of Data to Instruction (Application) Scale included 6 items (Items 10 through 15) that assessed a teacher’s self-judgment of his or her ability to connect and apply what was learned from data interpretation to instruction in order to improve student learning.
>
> [5] The fifth Scale, DDDM Anxiety (Anxiety) included 5 items (Items 16 through 20) that assessed a teacher’s self-judgment of his or her sense of trepidation, tension, and apprehension related to their ability to successfully engage in DDDM. (Dunn et al., 2013, p. 92)

The entire 3D-MEA survey can be found in Appendix A. A distribution of part of Tschannen-Moran and Hoy's (2001) The Teachers' Sense of Efficacy Scale (TSES) long-form was utilized as a part of the survey. The TSES consisted of three subscales: efficacy for instructional strategies, efficacy for classroom management, and efficacy for student engagement. I used the eight-question subscale on the efficacy of instructional strategies which “addresses to the strategies teachers use in order to help their students learn a specific material” (Cocca & Cocca, 2022, p. 40) found in Appendix B. The authors based their scale on Bandura's (1977, 1997) self-efficacy beliefs (Fives & Buehl, 2010). Tschannen-Moran and Hoy’s (2001) factor analysis of the instrument found three areas of correlation: efficacy in student engagement, efficacy in instructional practices, and efficacy in classroom management. The participants responded to a 9-point Likert scale that ranged from "1 (nothing) to 3 (very little) to 5 (some influence) to 7 (quite a bit) to 9 (a great deal)" (p. 796). Dunn and colleagues (2013b) found that the 3D-MEA inventory connected with the TSES shared discriminant validity evidence. Tschannen-Moran and Hoy (2001) postulated that the TSES "could be considered reasonably valid and reliable" (p. 801). The demographic data were collected on the participants for future management and reference as needed for the research. The participants' demographic information was used to identify their status as current general education or special education teachers, the grades and subjects they were currently teaching, and the number of years they had been teaching. The teachers' race and age range questions were included but made optional (Scotland, 2012). At the end of the 28-item survey, the participants were given the opportunity to participate in a structured interview that focused on the teachers' perspective of their self-efficacy for DDDM in the classroom. I contacted all participants who agreed to join in the interview part of the study and set up convenient days and times to conduct the interview. The 15-question, structured interview was conducted after the completion of the survey. The complete interview guide is located in Appendix C.

Data Analyses

I analyzed the quantitative data using descriptive statistics and a *t*-test to determine the significance of the collected data (Rouder et al., 2016). Before inputting the data into the SPSS data software, the survey data was separated to denote the open-ended questions and responses. The remaining questions and responses were also separated to distinguish the references to DDDM and self-efficacy. Mishra and colleagues (2019) noted that a *t*-test is "used to test whether mean difference between two groups is statistically significant" (p. 408). A t-test was utilized for the 3D-MEA survey and the TSES. The *t*-test was used to compare responses from special education and general education teachers. The independent *t*-test or the unpaired *t*-test "is an inferential statistical test that determines whether there is a statistically significant difference between the means in two unrelated (independent) groups" (Mishra et al., 2019, p. 408). The research question, methods of data collection, and methods of analysis are shown in Table 2. The participants were similar in that they were all teachers but regarded differently in their denotation as special education teachers or general education teachers. The number of participants who completed the instrument increased the power of the research and determined the significance of the study.

Table 2

Methods of Data Collection and Analysis

Research Questions	Methods of Data Collection	Methods of Analysis
To what extent do special education and general education teachers use DDDM to gauge student performance?	The Data-Driven Decision Making and Anxiety (ED-MEA) Inventory Interview	Descriptive Statistics *t*-test Descriptive Coding Focused Coding
What is the difference between general and special education teachers' self-efficacy in using data to plan instruction?	The Data-Driven Decision Making and Anxiety (ED-MEA) Inventory Interview	*t*-test Descriptive Coding Focused Coding
How does self-efficacy in DDDM differ between special education and general education teachers?	Factor 1: Efficacy for instructional strategies Interview	*t*-test Descriptive Coding Focused Coding

I transcribed the interviews and determined the codes (Creswell & Poth, 2018). A descriptive analysis was implemented to report on the demographic particulars of the participants. Also, frequency tables were used to examine the accumulated themes of the qualitative study. Descriptive coding was used for the first coding to index the data contents. Descriptive coding "summarizes in a word or short phrase—most often as a noun—the basic topic of a passage of qualitative data" (Saldana, 2009, p. 70). The second coding I conducted was the focused coding. Focused coding "is appropriate for virtually all qualitative studies…and the development of major categories or themes from the data" (p. 155). In Table 3 there are examples from the codebook I used to record the codes for the qualitative responses in the study.

Table 3

Data-Driven Self-Efficacy Codebook

Codes	Definitions	Examples
Data Novice	Someone who is new at collecting and analyzing data.	"I'm learning to collect it now." "This year."
Confident	Feels sure of themselves in using data to inform their instruction.	"I was very aware of using student data to inform my instruction. "Yes, I feel very confident in using data and I before I didn't understand the importance of collecting it and setting goals to be able to collect it."
Practice analyzing data	Practicing the procedures of data collection, analysis, and interpretation.	"For me it's really just practice and having you know, continuing to practice collecting data and looking at it and analyzing it." "Continuing to practice collecting data and looking at it and analyzing it.

I found themes that connect to the quantitative survey findings (Ponce & Pagan-Maldonado, 2015). Creswell and Poth (2018) referred to themes as "broad units of information that consist of several codes aggregated to form a common idea" (p. 328). The goal of the qualitative part of the analysis added participant voices to the study. My adviser and I used negotiating codes to analyze the qualitative interviews. Berli (2021) shared that when using negotiating codes, "The participants in the data sessions do not primarily classify and assess what is good and what is bad. Rather they jointly develop and improve interpretations and ideas regarding their data" (p. 785). Twenty percent of the interview data were analyzed by negotiating codes.

Positionality

As a former public school special education teacher, data use was a necessary part of my job. It was crucial for the researcher, according to Mertens (2010), to be aware of "engaging in critical self-reflection and dialogue about the philosophical assumptions that underlie their positions as researchers" (p. 16). My job was to inform general education teachers about a student's academic abilities. It was important that I presented actual data that I collected on the student's subject knowledge. The data included classroom assessments, classwork, observations, and grades. The information was presented during an IEP conference that included the general education teacher, administrator, the parent, and other stakeholders when appropriate.

As a special education teacher, I was trained to gather student instructional data, meet the student's needs according to the data, and interpret the data for stakeholders. It was important to note that data can also be biased. Depending on the reason for data acquisition and the particular instrument used, it can and has been used to identify specific students in need of special education services. I found that data use was very valuable in determining the direction of student instruction in my classroom and pinpointing the areas for extra focus. This research aligned with my training as a special education teacher. My background as a special education teacher benefitted the research through my insight into using student data to plan instructional programs for students confidently.

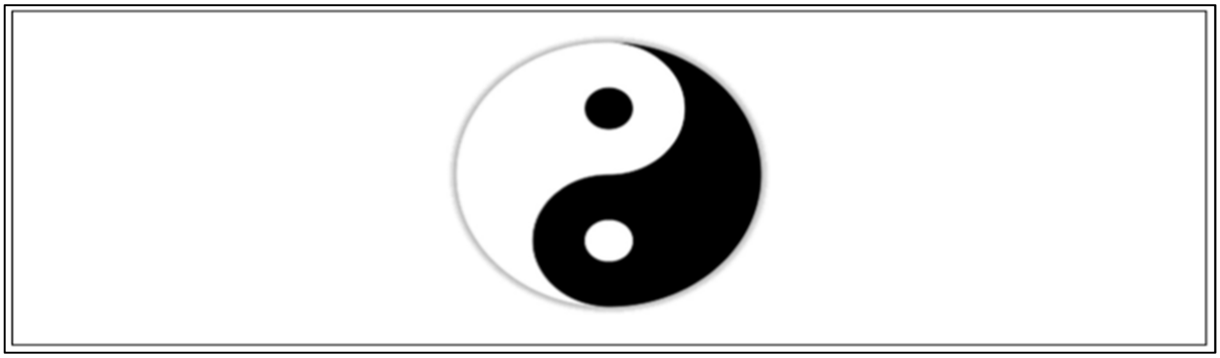
Practical and Pragmatic Concerns

Philosophically, the study results may not change the way general and special education teachers react when using DDDM. The issues may not lead others in education leadership to do anything about the significant results revealed between teachers' efficacy, DDDM, and the teachers' perspectives of student achievement. With this in mind, I reflected on Merten's (2010) information about making ethical decisions when working with human subjects: axiology. I considered the realities of people that may differ from my experience of reality or ontology.

In addition, I needed to make a connection "between researcher and participants; knowledge is socially and historically situated; power and privilege are explicitly addressed; development of a trusting relationship is critical" (Marten, 2010, p. 11). Leech and Onwuegbuzie (2010) further emphasized that the philosophical process should be intertwined throughout the study from the beginning to the conclusion of the mixed methods research. Fetters and Molina-Azorin, (2019) stressed the features of mixed model research by comparing it to the yinyang philosophy, which was identified by the picture of the *taijitu sign in* Figure 3.

Figure 3

The Taijitu Symbol



The different colors of the sign represent the parts of the mixed model research. Black represents the empathetic and delicate part of the qualitative research called the yin. The white represents the statistics, and the role of the quantitative research called the yang. The circles represent the thought that each qualitative and quantitative model was in the other (Fetters & Molina-Azorin, 2019).

Yinyang's philosophy also followed the premise of this research. Fetter and Molina-Azorin (2019) described the philosophy of yinyang as embracing both quantitative and qualitative research used in a study to complement each half of the whole: the ontology. They also believed that quantitative and qualitative information was needed for the study to have any meaning or epistemology. The axiological perspective of the yinyang philosophy allowed the researcher to reveal the value of the mixed model by their connection to each other. The researcher was aware that one aspect of the mixed model was a dominant presence in the study. The philosophical aspects of the research were guided by Merten's (2010) and Fetter and Molina-Azorin's (2019) complementary descriptions of the mixed model approach.

Limitations

Merten (2010) the relationship of the researcher and participants should be considered, the "methods would be adjusted to accommodate cultural complexity; power issues would be explicitly addressed; and contextual and historical factors are acknowledged, especially as they relate to discrimination and oppression" (p. 11). The methodological concerns of the research hinged on the sample number for the quantitative part of the study and engaging participants in the interview process. One of the limitations was that the study sample encompassed teachers in only one Mid-Atlantic coastal region of the United States and was not reflective of the national consensus of teachers' self-efficacy. Although, it was not my goal to generalize to other teaching situations.

Another limitation was that teachers were asked to complete the survey and interview during the COVID-19 state regulations, which directed some teachers to teach their students online. As a result, the teachers were overwhelmed with virtual and face-to-face instruction and may have refused to participate in an online survey and interview. Further, a limitation was presented when the research topic was revealed. It may have deterred teachers' participation in the study because of their schools' and districts' emphases on DDDM throughout the year. The participants may have hesitated to start or complete their responses on the survey due to their fear of repercussions from their division. To mediate any concern about their responses being used against them, I stressed the confidentiality of their responses in all reports. It was crucial for the researcher, according to Mertens (2010), to be aware of "engaging in critical self-reflection and dialogue about the philosophical assumptions that underlie their positions as researchers" (p. 16). During the interview process, I was aware of biases when interviewing general and special education teachers. The written questions kept my focus on the task at hand and deterred me from sharing my opinions. When necessary, I redirected the teachers interviewed to the questions being asked.

The benefits of the research outweighed the physical and philosophical limitations of the study. The data revealed deficits in the area of teacher efficacy in their ability to use data to determine instructional strategies to increase student performance, how to group students, and analyzing student data. Moreover, my findings informed divisions about training in the form of professional development for their special and general education teachers. The focus on professional development specifically centers on activities that increased the efficacy of teachers' abilities to use DDDM to improve student performance.

CHAPTER IV

FINDINGS

The purpose of the present explanatory sequential mixed methods study was to examine the self-efficacy of special education and general education elementary school teachers in the data-driven decision-making (DDDM) process. Data collection included a quantitative online survey and a qualitative structured interview with participants who were given the option to participate after filling out the online survey. The research design of this study was primarily quantitative. I aimed to answer the following research questions:

1) To what extent do special education and general education teachers use DDDM to gauge student performance?
2) What is the difference between special and general education teachers' self-efficacy in using data to plan instruction?
3) How does self-efficacy in DDDM differ between special education and general education teachers?

In this chapter, I focused on the results of the data analysis of the online survey and the structured interview. Dunn et al.'s (2013b) *Data-Driven Decision-Making Efficacy and Anxiety Inventory* (3D-MEA) in Appendix A and Tschannen-Moran and Hoy's (2001) subscale on the efficacy of instructional strategies from *The Teachers' Sense of Efficacy Scale* (TSES) in Appendix B were used for my study's survey—*Teacher's Self-Efficacy for Data-Driven Decision Making Survey.* The statistical data gleaned from the *Teacher's Self-Efficacy for Data-Driven Decision Making Survey* were calculated by the IBM SPSS Statistics (Version 28) predictive analytics software. To explore the DDDM process of special education and general education teachers, I presented the statistical findings of the survey, and I examined the verbatim quotes from the participants to give voice to the survey (Ogan-Bekiroglu & Suzuk, 2014).

The first part of the findings present the quantitative analysis of the special education and general education teachers' responses to the DDDM survey and the significance of the data. In the second part of the findings, the teachers' responses to the structured, open-ended questions were examined to investigate how they gave further detail to the responses in the survey. The quantitative and qualitative findings are presented under each research question in the next section.

Research Question 1

The first research question guiding this study was, To what extent do special education and general education teachers use data-driven decision making to gauge student performance? Below, I provide the quantitative results of the *t*-test first before incorporating the qualitative data by theme.

Quantitative Results

The statistical analysis of the *efficacy for data identification and access scale* included questions 1-3 of the 3D-MEA survey (see Appendix A; Dunn et al., 2013b). The focus of the questions was the teachers' *efficacy for data identification and access scale* and included information about accessing students' performance. The SPSS analysis in Table 4 showed that the mean for special education teachers was higher than the mean for the general education teachers (4.15 > 4.06). The special education teachers' *SD* was smaller than the *SD* for the general education teachers (.654 < .822). The designated *t* value in Table 5 was .649 with 76.88 *df*. The significance value was .259. I compared the significance value of .259 to the *p*-value of .05 (.259 > .05) and found that the significance value was greater than the *p*-value; therefore, I accepted the Null hypothesis. That meant that the mean scores were not significant. The mean difference was .091, so I can be 95% confident that the actual difference of the mean competency for special education and general education was between -.188 and .369, as reported in the 95% confidence interval of the difference. I cannot say there was a significant difference between special education and general education teachers in the factor *efficacy for data identification and access scale* that "assessed a teacher's self-judgment of their ability to identify, access, and gather appropriate reports needed for DDDM" (Dunn et al., 2013b, p. 239).

Table 4

Efficacy for Data Identification and Access Scale – Group Statistics

Factor	Teaching Area	N	Mean	Std. Deviation	Std. Error Mean
Efficacy for Data Identification and Access	Special Ed	35	4.15	.654	.110
	General Ed	92	4.06	.822	.086

Table 5

Efficacy for Data Identification and Access Scale— t-Test for Equality of Means

			Sig.			95% Confidence Interval of the Difference	
Variances	*t*	*df*	*One-sided p*	*Mean Diff*	*Std. Error Diff*	*Lower*	*Upper*
Equal variances assumed	.586	125	.279	.091	.155	-.216	.397
Equal variances not assumed	.649	76.878	.259	.091	.140	-.188	.369

The mean scores generated from the *t*-test in Table 4 included the factor *efficacy for data identification and access scale* revealed $M = 4.15$ for special education teachers and $M = 4.06$ for general education teachers. The teachers' *efficacy for data identification and access scale* was scored in the range of the “agree” anchor for “their ability to gauge student performance by using the necessary materials needed for DDDM” (Dunn et al., 2013b, p. 236).

Qualitative Findings

Theme: Identifying Student Data. Identifying student data for DDDM was addressed by several questions in the structured interview questions including, “How and when were you made aware of using student data to inform your instruction?” One of the participants expressed their awareness of using students’ data to inform instruction by attending professional development training provided by her district. Audrey, a special education teacher, said, “I’ve had it [data training] several different times in different professional development sessions. I had several sessions that I attended on how to analyze data and all of that.” She excelled enough in data analysis that she was able to provide professional development sessions on student data analysis to her peers. She shared, "I gave those professional development sessions to teachers on how to collect data, how to use what they have, and how to analyze that data.” Other participants like Jane and Carlene, both second-grade general education teachers, knew about data before it became a district policy to follow. Jane said, “I was very aware of using student data to inform my instruction. There was a program where you did a series of tests to determine whether they [students] were concrete in numbers or not.” Carlene said, "I've always, since the very beginning, had to collect data in some way." Carlene, who had taught for 15 years and was one of the more experienced participants interviewed, stated that:

> I would say not until probably halfway through, maybe like six or seven years ago, that I really realized it's not just another step or a process that we're doing, that you can really truly see where your students are and then guide your instruction, and differentiate it based on that.

Carlene couldn't remember a class at her university that instructed her on the aspects of student data. She explained, "I don't remember having anything specific." She learned about using student data through professional development. "You know, professional development really helped me understand what it means to collect data and use it in your teaching."

Unlike Audrey, Jane, and Carlene, some participants mentioned being exposed to student data in their pre-service years in specific teacher preparation classes. When asked, "How did your teacher preparation program prepare you to work with student data in the process of DDDM?" Barb, a special education teacher who was a career switcher, learned about analyzing student data when she went to several universities to earn her teaching certification. She stated that what introduced her to the DDDM process was "The specific coursework that I took to get my certification." She commented on a couple of particularly noteworthy classes on student data, "I had a class on instructional design and one on data-driven instruction from [several universities]." A general education teacher, Amani, could not remember the name of the class she took at the university that introduced her to DDDM. Still, she did remember some aspects of using student data. She recalled working with some student work samples during her pre-service courses. She had to, "Look at some work samples of students and then decide what would these students need next?" Lynn, a special education teacher, was introduced to the DDDM process at her university. She and her classmates were made aware of the process of analyzing student data by all their instructors. They were given profiles of students and asked to analyze the data to determine the students' current performance. Lynn said she was "definitely" introduced to students' data before her first teaching position. She reminisced about her university instructors, saying:

> All the teachers who teach specific special education classes always talk about data. Like even when it comes to behavior [they talk about] how to take data, different kinds of data, and how to analyze data? And I know at [university] they even say here's the student's profile, analyze it.

Lynn included that this process of analyzing student data continued throughout her undergraduate classes to her current university classes while earning her master's degree. She stated, "I'm now almost finishing my master's degree, and that's the same way, too. It's here, this profile we've [instructors] created it for you, analyze their test scores, and everything like that." Barb, Amani, and Lynn remembered some aspects of being taught about student data in the DDDM process at their universities. Special education and general education teachers learned about student data in a pre-service university program or professional development training. This increased their exposure to the DDDM process that focused on student performance.

In sum, the results of the *t*-test for the *efficacy for data identification and access scale* suggested that there was no statistically significant difference between special education and general education teachers' "self-judgment of their ability to identify, access, and gather appropriate reports needed for DDDM" (Dunn et al., 2013b, p. 239). The anchor scales of the means were presented for later discussion. Special education teachers and general education teacher participants were made aware of collecting and analyzing student data through their professional development training and in some cases through their pre-service university classes. They used their student data to inform and guide their instruction through the DDDM process.

Research Question 2

The second research question asked, What is the difference between special and general education teachers' self-efficacy in using data to plan instruction? I will present the findings of the *t*-test first before exploring the qualitative findings.

Quantitative Results

The factor *efficacy for data technology use scale* included questions 4-6 of the survey (see Appendix A; Dunn et al., 2013b). The focus of the questions was the efficacy of data technology use. The SPSS analysis in Table 6 showed that the mean for special education teachers was smaller than the mean for the general education teachers (3.36 < 3.58). The special education teachers' *SD* was smaller than the *SD* for the general education teachers (.891 < .988). In Table 7 the *t* value was -1.159 with 125 *df*. The significance value was .124. I compared the significance value of .124 to the *p*-value of .05 (.124 > .05), and I found that the significance value was greater than the *p*-value; therefore, I accepted the Null hypothesis. That meant that the mean scores were not statistically significant. The mean difference was -.221, so I can be 95% confident that the actual difference of the mean competency for special education and general education teachers was between -.600 and .157, as reported in the 95% confidence interval of the difference. I cannot say there was a significant difference between special education and general education teachers in the "self-judgment of his or her ability to utilize and navigate district and state level technology tools to access information for DDDM" (Dunn et al., 2013b, p. 239).

Table 6

Efficacy for Data Technology Use Scale—Group Statistics

Factor	Teaching Area	N	Mean	Std. Deviation	Std. Error Mean
Efficacy for Data	Special Ed	35	3.36	.891	.151

Technology Use	General Ed	92	3.58	.988	.103

Table 7

Efficacy for Data Technology Use Scale—t-Test for Equality of Means

			Sig.			95% Confidence Interval of the Difference	
Variances	*t*	*df*	*One-sided p*	*Mean Diff*	*Std. Error Diff*	*Lower*	*Upper*
Equal variances assumed	-1.159	125	.124	-.221	.191	-.600	.157
Equal variances not assumed	-1.214	67.729	.114	\-.221	.182	-.585	.143

The mean score on the frequency table exhibited in Table 6 for the factor *efficacy for data technology use scale* revealed $M = 3.36$ for special education teachers and $M = 3.58$ for general education teachers. The efficacy for data technology use was scored in between the ranges of *neither agree nor disagree* and *agree* anchors on the Likert 5-point scale regarding their ability to use technology tools to navigate assessment data (Dunn et al., 2013b).

Questions 7 through 9 of the 3D-MEA (Dunn et al., 2013b) survey are represented in the factor *efficacy for data analysis and interpretation scale* (see Appendix A). The SPSS analysis in Table 8 showed that the mean for special education teachers was higher than the mean for the general education teachers (4.15 < 3.98). The special education teachers' *SD* was smaller than the *SD* for the general education teachers (.747 < .879). The *t* value in Table 9 was 1.016 with 125 *df*. The significance value was .156. I compared the significance value of .156 to the *p*-value of .05 (.156 > .05) and found that the significance value was greater than the *p*-value; therefore, I accepted the Null hypothesis. That meant that the mean scores were not significant. The mean difference was -.221, so I can be 95% confident that the actual difference of the mean competency for special education and general education was between -.585 and .143, as reported in the 95% confidence interval of the difference. Because there was a chance that one group's competency score could be higher than the other, I cannot say there was a significant difference.

Table 8

Efficacy for Data Analysis and Interpretation Scale—Group Statistics

Factor	Teaching Area	N	Mean	Std. Deviation	Std. Error Mean
Efficacy for data interpretation, application, and evaluation	Special Ed	35	4.15	.747	.126
	General Ed	92	3.98	.879	.092

Table 9

Efficacy for Data Analysis and Interpretation Scale—t-Test for Equality of Means

			Sig.			95% Confidence Interval of the Difference	
Variances	*t*	*df*	*One-sided p*	*Mean Diff*	*Std. Error Diff*	*Lower*	*Upper*
Equal variances assumed	1.016	125	.156	.170	.168	-.162	.503
Equal variances not assumed	1.093	71.820	.139	.170	.156	-.140	.481

The mean for special education teachers in the e*fficacy for data analysis and interpretation scale* in Table 10 showed $M = 4.15$ and $M = 3.98$ for general education teachers. Both groups of teachers' scores were around the *agree* anchor on the 5-point Likert scale. This showed that the teachers felt they could improve students' learning by interpreting the student data and “assessed a teacher's self-judgment of his or her ability to analyze and interpret basic components of student performance data.” (Dunn et al., 2013b, p. 239).

The *efficacy for application of data to instruction scale* (Dunn et al., 2013b) included survey items 10 -15 (see Appendix A). The SPSS analysis in Table 10 showed that the mean for special education teachers was higher than the mean for the general education teachers (4.39 < 4.14). The special education teachers’ *SD* was smaller than the *SD* for the general education teachers (.554 < .695). I assumed the variances were equal and read the top numbers of the *t*-test in Table 11. The *t* value was 1.894 with 125 *df*. The significance value was .030. I compared the significance value of .030 to the *p* value of .05 (.030 < .05). I found that the significance value was less than the *p* value. I can be 95% confident that the actual difference of the mean competency for special education and general education was between .012 and .484 as reported in the 95% confidence interval of the difference. The factor *efficacy for application of data to instruction scale* showed the difference of the mean competency was statistically significant. Therefore, a statistically significant difference was suggested between special education and general education teachers in their “self-judgment of their ability to connect and apply what was learned from data interpretation to instruction in order to improve student learning” (Dunn et al., 2013b, p. 239).

Table 10

Efficacy for Application of Data to Instruction Scale—Group Statistics

Factor	Teaching Area	N	Mean	Std. Deviation	Std. Error Mean
Efficacy for application of data to instruction	Special Ed	35	4.39	.554	.094
	General Ed	92	4.14	.695	.072

Table 11

Efficacy for Application of Data to Instruction Scale—t -Test for Equality of Means

			Sig.			95% Confidence Interval of the Difference	
Variances	*t*	*df*	*One-sided p*	*Mean Diff*	*Std. Error Diff*	*Lower*	*Upper*
Equal variances assumed	1.894	125	.030	.248	.131	-.011	.507
Equal variances not assumed	2.095	76.621	.020	.248	.118	.012	.484

Quantitative data collected for this study supported the finding that the survey responses for the factor *efficacy for application of data to instruction* scale were statistically significant. The special education teachers' highest mean score was $M = 4.39$ compared to the general education teachers' $M = 4.14$. The range of special education and general education teachers was in the *agree* anchor. Special education and general education teachers rated themselves positively in areas that "assessed a teacher's self-judgment of his or her ability to connect and apply what was learned from data interpretation to instruction in order to improve student learning" (Dunn et al., 2013b p. 239). Special education teachers take their major data cues from the goals of the IEP. It needs to be noted that the academic goals are centered around the state's standards in which general education teachers take their major data cues. Petersen (2016) wrote that special education teachers:

> Must measure students' progress toward individualized educational outcomes, engage in formative and summative assessments to measure students' progress within the general education curriculum, and prepare and support students in participating in state accountability assessments. They must also understand how assessment is used to inform

> decision making, instructional planning, and classroom practice to ensure high expectations and rigorous learning opportunities. (p. 20)

Qualitative Findings

The interpretation of the responses to the interview questions from the special education and general education teachers have led me to the following themes for this section: tools for student assessment, planning instruction, interpreting student assessment, and next steps for instruction.

Theme: Tools for Student Assessment. In their interviews, participants responded to the question, “How do you use data to plan the instruction of your students?” The responses showed the participants' use of the DDDM process to gauge the students' performance. Most of the interview participants used pre-assessment tools to determine the students’ current academic performance level. The pre-assessment tools were used to place students in particular groups for instructional services. Jane used a pre-assessment before teaching a unit to the students. For Jane, the data process was helpful to determine how she would differentiate the lessons for her students. Jane began her introduction to the unit by involving the student in a pre-assessment. She expressed her rationale for following this procedure:

> Generally, when we begin a unit, you can do a pre-assessment. That's always helpful. I think because in the general education classroom of an elementary school, in general, you're going to have a lesson that you pitch to the whole group. And then you have a small group lesson where you are differentiating for students who either have gotten the objective and need enrichment. Or you need to give them something else to kind of dig into. Or you're going to have students who maybe are just about ready to get this concept.

Special education and general education teachers examined the students' data to determine how to differentiate their services based on their performance. Audrey, a special education teacher, examined the data to assess the students' benchmarks based on their Individualized Educational Program (IEP) goals and their responses to questions. She described how she begins her process:

> First, I look at how many of the questions were correct to see if they have at least 75% correct. That's the benchmark for saying that they mastered the target or the goal. And so I look at that to see what percent they got correct. Then of those that they did miss [the benchmark], I look at how they answered to give me insight on how they got to that conclusion.

Carol, a general education teacher, used pre-assessment tools but was not convinced as other interview participants were of their effectiveness in determining instructional strategies in a Title I school. She didn't see pre-assessments as a good use of instructional time. Carol shared that:

> I occasionally will do pre-assessments, although to tell you the truth, I'm in a Title I situation. So, I haven't found that pre-assessments really buy me a lot of time. I just don't find that I have a lot of children who pre-assess high enough to be able to buy me extra time for enrichment and acceleration activities. But what I've done instead is I teach everything, but I teach it sort of rapid-fire. And then I test it once. I refer to it as separating the goat from the sheep.

Based on Carol's teaching procedures, she separated the groups according to those who warrant accelerated activities and those who need reteaching of the lesson at a slower pace. Jane, Audrey, and Carol specifically mentioned pre-assessments as part of their responses on using the DDDM process to determine the next instructional step for their students.

Theme: Planning Instruction. Planning instruction was addressed by the teacher participants when they were asked, “How do you use data to plan the instruction of your students?” Shirley, a special education teacher, used data primarily to write and follow IEP goals for her students. Her initial assessments showed the current educational status of the students. Later assessments were used to determine the progression of the skills achieved or needed support to achieve goals in the IEP. Shirley stated:

> So, the data I take, most importantly, is writing their IEP goals. And we have to address the IEP goals all the time. And then we also have to collect data on those IEP goals, so I can kind of see where the data points are. And then take the data, and I am constantly reporting to make sure they're meeting their goals throughout the year.

Like Shirley, Kalyn’s data focus was also on student IEP goals. The data on the students’ goals were used to assess the ongoing needs of the students’ skills to differentiate the lessons. Kalyn reported:

> We use the data to differentiate the lessons. And when we're differentiating the lessons, we use the data that's collected to see if the goals are met or if the goals are not being met and then to see if we need to take a different approach while we're teaching the students that we’re working with.

Carlene and Amani responded to the question, How do you use data to plan the instruction of your students? Carlene talked about her data use in reading, “I collect data on sight words, and their reading abilities, their accuracy, their comprehension, and their reading skills. I then guide them into small group instruction based on what they already know and what they don't yet know.” Carlene collected her data for instructional strategies to use as she observed her students in the process of engaging in the lessons. A general education teacher, Amani, was using data to help her close the gaps in students' education caused by the school emergencies related to COVID-19. She said, "The big thing this year is trying to figure out where's the learning gaps?" Amani addressed the difficulty of determining where the gaps were in order to service the students. Amani stated how they used the data in her class:

> So, we've been using the data mainly to see what it is that they're still struggling with and how we can hone in on just those little pieces to close this two years gap for these kids. And just, what can we not skip but not waste too much time on, and then, what do we do next.

The teacher participants used several assessment tools in their arsenal of DDDM to determine students' instructional needs and the most appropriate strategies for their students' learning. Special education and general education teachers used pre-assessments to identify the current status of the students' learning. Shirley's and Kalyn's process of student data use was focused on IEP goals and reporting on them regularly throughout the year, and differentiating the lessons based on their goals. Carlene mentioned how she collected student data as she observed her students in the learning process. Amani used student data to identify learning gaps to guide her teaching to close the educational gaps due to COVID-19.

Theme: Interpreting Student Data. Interpreting student data was addressed when I asked the interview participants, "Do you find the use of student assessment data as beneficial for teachers and students? How is it beneficial for teachers? How is it beneficial for students?" Through this exchange, I learned that the participants found the use of data beneficial for teachers and students for several reasons. Special education teachers noted that using assessment data helped them to group students according to their needs. It showed the academic growth of the student and their ability to transfer and apply the knowledge that they learned. When using strategies to group students, Kalyn used “assessment data to determine strategies to group students for instruction, to meet IEP goals.” She further stated, "Basically, it helps identify areas of student growth in their understanding of concepts.” Audrey felt that a benefit of teachers using assessment data for instruction revealed, “What students have learned, what they understand, and what needs to be retaught or refreshed?” General education teachers like Jane used student data to pinpoint the students' present level and determine their ability to transfer their knowledge from the classroom setting to an assessment. Her stated benefits of student assessment data are:

> Teachers could know where their students are and if they're able to apply that and transfer it to something else. Or are they [students] able to do it in your classroom and not on your assessments? They need to figure out why.

The general education teacher participants also felt student assessment data was beneficial for teachers. They noted that when teachers examine the data, they can find the areas of strengths and weaknesses in a student’s ability and ascertain why specific responses were made on an assessment. Jane stressed that analyzing student data would benefit teachers because:

> It lets you know that if the majority [of students] did well, then they understood what you taught. If the majority did not do well, then it may not be the student, it may be the way you taught it, and you may need to reteach it and reteach it differently. They just didn't grasp it.

The participants expressed that looking at student assessment data can help to guide teachers’ instruction. To further explain, Carlene understood that the student assessment data could be used to guide the direction of the instruction and motivate students in their learning process. She commented, “I think as a teacher, I’m able to really guide that instruction and planning, making sure that the students can feel engaged, and empowered, and excited about their learning.”

Student assessment data are beneficial for teachers, according to Amani, because of the time factor of reteaching mastered concepts and pinpointing teaching where the kids are currently in their learning. Amani stated:

> I do think it is useful because it could save you some time—not reteach things they already know. I think it just helps. You're meeting the needs of your students, not just teaching to the textbook or teaching the objective. You're meeting them where they're at. Which ultimately is my goal to see progress, not just continually floundering because they don't know.

The participants expressed that the student assessment data were beneficial to special education and general education teachers, but they also expressed the benefits to the students.

The special education participants shared the student benefits of interpreting assessment data ranging from meeting IEP goals and the ability to monitor their progress throughout the year by charting their growth. Specifically, Kalyn focused on meeting IEP goals to address the benefit of how assessment data can benefit special education students. According to Kalyn, it benefits the students because, "It helps us to see if they've met these goals if we need to set new goals, or to see if we need to make changes to existing goals." Barb thought that assessment data are beneficial to students when they can visually track the progression of their efforts on a chart. “I think it's beneficial if a student is able to actually chart their progress in terms of mastery skills.” Similarly, Lynn followed this line of thought by graphing lines to show the students’ growth. She stated:

> They [students] like to see their growth. When you look at us now, we are here, but next time we'll get to here. That is our goal! And it's okay if you're not where your friends are,

> but your line is moving up. So, I think it's beneficial for them to see where they're going—just growth in general for growth.

General education teachers focused their comments on assessment data benefitting students by expressing the importance of students being able to self-monitor, detect their errors, determine growth, understand concepts, and experience opportunities for success. Carlene stressed the importance of students to self-monitor their performance by asking themselves, “Did I grasp this concept? Or did I not? Do I need to ask for help? Do I need to review? And especially as they move up in grade levels. I think that's very important for them to be able to self-monitor that learning.” It allows the students to see their growth when they can show their understanding of the concepts they missed. Carlene further pressed that assessment data are beneficial to students because:

> Obviously [it is] good for their grades, but it's also good for their overall understanding. Our skills are built on each other. And they need to have the first skill to be able to get to the second skill. And if I haven't gone back and retaught and brought them up to speed on the first skill, they’re going to struggle with the second skill.

Amani stated, “It helps them see what they understand even on the things that they may miss. It helps them sometimes see careless mistakes they've made. It also allows them to see their growth or not.” Jane shared that a benefit of assessment data for students was to make sure that the students were functioning at an appropriate level that allowed them opportunities for success. She argued:

> The more you can keep kids working at a level that is appropriate for them, and where they're experiencing success, or at least experiencing the sense that they're almost there, then your classroom learning is going to increase exponentially.

Theme: Next Steps for Instruction. The next steps for student instruction were gleaned from the responses of the special education teacher participants when they revealed that they used several forms of data to determine their students next steps of instruction. Shirley and Lynn described their process of analyzing the data and determining the needs of the students based on their IEP goals and mastery. Shirley explained:

> So, when I see the data that comes back from like the math testing from the district or anything like that, I take and analyze the data and say, okay, this is where their needs are, and that's what I'll do for their IEP goals or meeting goals in the classroom.

Lynn described the data process as collecting and analyzing data to determine student mastery, "You're collecting, you give some kind of assessment. You analyze that assessment to see what they mastered and what they still need help with." The data results helped teachers decide on ability groupings and the focus of the students' instruction. Audrey said she used the data to "group students by ability and understand what the students need. What were they supposed to get? What they actually got, and then what they still need to master?" The use of data to instruct students was evident throughout the focus of the participants' responses on their data process. Still, Barb questioned the type of data that teachers used to determine their instructional direction. She made a distinction between quantitative and qualitative data that was interesting:

> I think sometimes we use quantitative data instead of qualitative data. And I think sometimes it's more important for us to know, for example, not how many speech sounds the children have been able to master, but which speech sounds they have challenges with?

General education teacher participants named several programs that they used for data analysis to determine their students' instruction. Carlene talked about using running records to examine a student's reading behaviors. After reading about running records in more detail, Carlene increased her understanding of running records. She relayed:

> I just read this past summer a book about collecting data through running records and the purpose and why it's important, and how that can help you guide your instruction. Now, I'm looking at more of what their reading behaviors are as they are reading.

Carol used the computer-based literacy program called PowerUp Literacy (Lexia Learning, 2022), which is a literacy program that adapts its computer-based instruction to students' individual needs:

> We have a data table right there on the lesson plans, so we have to indicate what prior assessment we're using to take that data from. We have to put all the kids down. We have to give our criteria for how we selected the kids for the review group. Our criteria are usually any child who scored below 70 is coming in for review. If you have time at the end of the week, the children who scored between 70 and 80 might come in for a real quick review. Usually at the end of the week, we administer whatever that assessment is to give the kids another chance to make a better score now that they've reviewed the skill. That's a very straightforward, practical approach, and I really appreciate using it.

Jane mentioned that the validity and constant use of the Peer-Assisted Learning Strategies (PALS; University of Virginia, 2022) made it very useful for student data. She stressed:

> We use a program called PALS. I think the PALS data because it's been used, and tweaked, and tested, and analyzed, and reworked—I feel like much of the data that we get from that program is indeed valid, and that's very useful. I feel it is really good that data is very useful.

The factors *efficacy for data technology use* scale and the factor *efficacy for data analysis and interpretation scale* quantitative results were found to have no statistically significant difference between special education and general education teachers. The factor *efficacy for application of data to instruction scale* was found to be statistically significant and, therefore, there was a significant difference between special education and general education teachers' "self-judgment of their ability to connect and apply what was learned from data interpretation to instruction in order to improve student learning" (Dunn et al., 2013b, p. 239).

The *efficacy for data technology use scale* and the *efficacy for data analysis interpretation scale* were found to have no statistically significant difference between special education and general education teachers in the "self-judgment of his or her ability to utilize and navigate district and state level technology tools to access information for DDDM" (Dunn et al., 2013b, p. 239). In addition, there was no statistically significant difference in their "self-judgment of his or her ability to analyze and interpret basic components of student performance data" (Dunn et al., 2013b, p. 239). A statistically significant finding for the factor *efficacy for application of data to instruction scale* was reveal that showed a difference between special education and general education teachers "self-judgment of their ability to connect and apply what was learned from data interpretation to instruction in order to improve student learning" (Dunn et al., 2013b, p. 239). The themes *tools for student assessment, planning instruction, interpreting student data,* and *next steps for instruction* were discussed in this section.

Research Question 3

The third and final research question was, How does self-efficacy in DDDM differ between special education and general education teachers? The quantitative results are presented first followed by the qualitative findings with verbatim quotes from participants.

Quantitative Results

In the group statistics for the factor *anxiety: DDDM anxiety* in Table 12*,* the mean for special education teachers was slightly lower than the mean for general education teachers (2.03 < 2.28). I compared the *SD* and found that the *SD* for special education teachers was smaller than general education teachers (.774 < 1.022). The following steps revealed the result of the null hypothesis. I compared the significance value of .034 to my level of significance or *p*-value of 0.05 (.034 < .05) see Table 12; therefore, I rejected the Null hypothesis and assumed the variances were not equal. The bottom line of the data in the independent samples *t*-test was used to identify data points of the *t* - test (see Table 13). The *t*-test "assessed whether mean scores of two groups are statistically different from one another relative to an estimate of sample variability" (Rojewski et al., 2012, p. 264). I compared the *SD*s of the special and general education teachers and noticed that the values were not similar. The *t* statistic was -1.459 with 80.84 *df*, and the significance value was .074. I used the *p*-value of .05 (074 > .05), and I accepted the Null hypothesis, which showed that the mean scores between the groups were not significant. The mean difference was calculated by subtracting the first mean from the second mean (2.03 - 2.28) = -.246, and according to the confidence interval of the difference, I can be 95% confident that the actual difference of the mean competency for special education and general education teachers was between -.582 and -.090. I cannot say there was a significant difference.

Table 12

Data-Driven Decision Making (DDDM) Anxiety—Group Statistics

Factor	Teaching Area	N	Mean	Std. Deviation	Std. Error Mean
	Special Ed	35	2.03	.774	.131

DDDM Anxiety	General Ed	92	2.28	1.022	.107

Table 13

Data-Driven Decision Making (DDDM) Anxiety— t-Test for Equality of Means

			Sig.			95% Confidence Interval of the Difference	
Variances	*t*	*df*	*One-sided p*	*Mean Diff*	*Std. Error Diff*	*Lower*	*Upper*
Equal variances assumed	-1.289	125	.100	-.246	.191	-.624	.132
Equal variances not assumed	-1.459	80.836	.074	-.246	.169	-.582	.090

The quantitative data collected for this study supported the finding that the survey responses for factor *anxiety: DDDM anxiety* were not statistically significant. When I analyzed the frequency data for this factor, I noted that the highest mean score was the general education teachers' $M = 2.28$ compared to the special education teachers' $M = 2.03$. The range of special education and general education teachers was in the *disagree* anchor—the special education and general education teachers rated themselves similarly in the area of anxiety about their approach to data. They did not feel intimidated by the DDDM process.

Table 14 presents the statistical data for the *efficacy for instructional strategies-group statistics*. The mean for special education teachers was slightly higher than the mean for the general education teachers (7.85 > 7.56). The special education teachers' *SD* was smaller than the *SD* for the general education teachers (.921 < 1.031). The *t* value in Table 15 was -1.447 with 125 *df*. The significance value was .075. I compared the significance value of .075 to the *p*-value

(.075 > .05) and found that the significance value was greater than the *p*-value; therefore, I accepted the Null hypothesis. That meant that the mean scores were not significant. The mean difference was .288, so I can be 95% confident that the actual difference of the mean competency for special education and general education teachers was between -.106 and .682 as reported in the 95% confidence interval of the difference. I cannot say there was a significant difference in special education and general education teachers' *efficacy for instructional strategies* factor of the TSES (Tschannen-Moran & Hoy, 2001).

Table 14

Efficacy for Instructional Strategies—Group Statistics

Factor	Teaching Area	N	Mean	Std. Deviation	Std. Error Mean
Efficacy for instructional strategies	Special Ed	35	7.85	.921	.156
	General Ed	92	7.56	1.031	.108

Table 15

Efficacy for instructional strategies—t-Test for Equality of Means

			Sig.			95% Confidence Interval of the Difference	
Variances	*t*	*df*	*One-sided p*	*Mean Diff*	*Std. Error Diff*	*Lower*	*Upper*
Equal variances assumed	1.447	125	.075	.288	.199	-.106	.682
Equal variances not assumed	1.523	68.394	.066	.288	.189	-.089	.665

The factor *efficacy for instructional strategies* revealed that the mean for the special education teachers was $M = 7.85$ and the general education teachers' mean was $M = 7.56$ (see

Table 14). The ability to use data-driven decision making to gauge student performance was highly scored by both groups of teachers based on the 9-point Likert anchors which were between *quite a bit* and *a great deal*.

Qualitative Findings

Theme: Confidently Engage in DDDM Process. The special education and general education teachers responded to the interview questions that showed their ability to confidently engage in the DDDM process. Kalyn was an energetic novice special education teacher who showed her willingness to learn about the DDDM process from other school personnel. The assistance of her coach and administrator has influenced her increased confidence in DDDM. Kalyn stated:

> My coach and my building administrator over the special education department help me. So, between the two of them, I know with their support I will be more confident in my data-driven decision making.

Shirley had no problem claiming her definitive decision about her confidence in DDDM. She based her confidence on the fact that she worked with IEP goals daily and the constant reporting on the goals:

> Well, absolutely I do. I mean, I do it all day long. I'm just kind of what we've been hitting on all the other questions. I work with a special population, and I am a self-contained teacher, so all my students are with me the majority of the day. So, data is what I do in this room, so yeah, I definitely feel confident.

Shirley, a special education teacher, commented that "We have to address the IEP goals all the time." She continued to elaborate on the IEP process:

> And then, we also have to collect data on those IEP goals, so I can see where the data points are. And then, you know, take the data, and I'm constantly reporting to make sure they're meeting their goals throughout the year.

Barb also felt confident in the DDDM process as she stated, “Yes, I do feel confident in using the data, mostly because I feel that I can interpret the specific scores.” She gave an example of how she analyzed PALS (University of Virginia, 2002) student data when they are identifying rhyming words:

> So, for example, on our PALS testing with our students who have developmental delays. I can look and say, the amount or the number of items they got correct in the rhyming may be more of a reflection of whether or not they're hearing the ending sounds in words. I think some of the kids, for example, have the idea of rhyming, and they understand the concept. They just are not hearing all of the sounds in the rhyming words.

Barb observed the how and why students responded to determine the meaning of their responses to rhyming words. Barb had been working in education for 40 years and had noted changes in student data:

> Since then, there’s been several changes in the type of data gathered and how they reflect the needs of the student. But because, in special education, we are required to use it, and I mean, it just makes sense to use data-driven instruction.

In Amani's general education class, she gathered data about her students because it is a duty she has to do as part of her job. When asked if she felt confident in the DDDM process, she answered, "I do, I mean, I have to, so I do!” She viewed data as a clear-cut procedure based on a simple premise:

> You know, people say data doesn't lie, and it just takes the emotion and feeling part out of that. And you can really see this is the few things they're focused on out of this many attempts. Did they get it or not? I just think it makes it very black and white and easier to decide when there are other factors at play.

Carol was very confident in the DDDM process. As a general education teacher, she contributed analyzed data for special education students' assessments on several occasions. She commented:

> I'm pretty good at taking data, and I'm pretty good at interpreting data. I had to do VAAPs [Virginia Alternate Assessment Programs] for the state several times. I've had to contribute to portfolio assessments with my children several times, so yeah, I got that!

Theme: Confidently Identify Instructional Needs of Students. To better understand the teachers' experience with DDDM and self-efficacy, special education and general education teachers were asked how confident they felt in using data to support special education and general education instruction. Kalyn was feeling more confident in maneuvering through the DDDM process as she noted her progression from the beginning of learning about data to the present. She shared:

> I feel very confident in using it[data], and before, I didn't understand the importance of collecting it and setting goals. I now understand that the importance of it is to see if the students are reaching these goals. And once they reach the goal, changing the goals to be able to meet their educational needs. So, I'm learning more and more and more. I'm not as comfortable or confident as I would like to be, but I do think I'm getting there.

Shirley was also confident in her analyses of the data. She used data to determine the appropriateness of the content for the students' ability and delegated the time to teach specific concepts per the needs of the students. When analyzing the data, Shirley said:

> I can take that data well. This was an easy topic for them. We need to move on, or this is kind of above their head. Do I need to take maybe three weeks to cover it, or do we need to keep continuously teaching it throughout the entire year?

Barb serviced students in an inclusion setting, allowing her to work with both special education and general education students. She felt confident in working with data for both groups of students. When asked if she felt confident about the DDDM process, Barb shared:

> I would say yes, I do because I am in a collaborative setting. I work with all of the students whether or not they have special education needs or are identified with special education needs. And especially this year when we've had so many students who really didn't have a preschool experience coming in.

Jane, unlike Barb, was a general education teacher. She was noted here because she also discussed serving special education students in her inclusion classroom. Jane shared, "I feel like I can use the data with the special education students in my class and the group that I work with most. The data shows me where they really are and how I can extend their learning." Jane served all of her students through the DDDM process regardless of their classification.

Carlene expressed her confidence in engaging in DDDM to instruct her students. Like Barb and Jane, Carlene also discussed using data to service all students who cross her classroom threshold. In particular, she spoke about English language learners who are being served in her classroom this year. She shared:

> I think that the data is important for any instruction for any kids. I have some English language learners this year, so I'm definitely using some data to help drive their instruction and make it specific to their needs.

Carlene was also very sure of her degree of confidence in the DDDM process:

> Absolutely, I think it's [DDDM] fiber here, and we want the kids to learn. And just through my experiences, if you're giving them instruction based on what they already know and what they don't yet know through that data collection, then they're going to be more engaged, they're going to be more excited, and they're going to be willing to participate and do the work.

The factors *data-driven decision making anxiety* and the factor *efficacy for instructional strategies* were found to have no statistically significant difference between special education and general education teachers in the "self-judgment of their sense of trepidation, tension, and apprehension related to their ability to successfully engage in DDDM" (Dunn et al., 2013b, p. 239). The anchor scales of the means were presented for later discussion. The themes of *confidently engage in the DDDM process* and *confidently identify instructional needs of students* were discussed through the responses of the interview participants. The next chapter will include the conclusions, discussions, and implications for practice and research.

CHAPTER V

CONCLUSIONS, DISCUSSIONS, AND IMPLICATIONS FOR PRACTICE & RESEARCH

Conclusions

The purpose of this study was to investigate the self-efficacy of special education and general education elementary school teachers in the area of data-driven decision making (DDDM). To develop a rich description of special education and general education teachers' self-efficacy for DDDM, a survey and interviews with teachers were conducted. The study data from the quantitative survey and qualitative interview were collected to answer the following research questions:

1) To what extent do special education and general education teachers use DDDM to gauge student performance?
2) What is the difference between special and general education teachers' self-efficacy in using data to plan instruction?
3) How does self-efficacy in DDDM differ between special education and general education teachers?

The quantitative survey, *Teacher's Self-Efficacy for Data-Driven Decision Making Survey,* included Dunn et al.'s (2013b) *Data-Driven Decision-Making Efficacy and Anxiety Inventory* (3D-MEA). This instrument included 5 factors: *efficacy for data identification and access scale*, *efficacy for data technology use scale*, *efficacy for application of data to instruction scale*, and the *data-driven decision making (DDDM) anxiety* factor. Tschannen-Moran and Hoy's (2001) *Teachers' Sense of Efficacy Scale* (TSES), including the subscale *efficacy for instructional strategies*, was also included in the survey. Responses from 127 special education and general education teachers were collected through the survey. The interview results were used to gather the special education and general education teachers' voices about their self-efficacy for DDDM.

The study's special education and general education teacher data were gathered during the 2021-2022 school year. With the elephant in the room—COVID-19—divisions and teachers were not as willing to participate in studies that would put teachers at risk of increased stress. As personnel from one division that declined to participate in the study wrote, “We have discussed and considered your request, however, due to prior commitments, teacher time requirements, a continuation of online instruction for some students, and a shortage of teachers, we cannot support your proposal” (citation redacted to preserve confidentiality). Pressley (2021), in their study on the efficacy of elementary school teachers, stated that the teachers’ stress had been increased due to the pandemic, “The pandemic has impacted everyone differently, and administrators need to be aware of how teachers are feeling, specifically the amount of anxiety and stress teachers are feeling returning to teaching during a pandemic” (p. 1621). As a result, the number of participating divisions that agreed to engage in the study was not as high as I had expected.

The quantitative results showed no statistically significant difference between special education and general education elementary teachers in 5 out of 6 factors examined in the study. The factors *efficacy for data identification and access scale, efficacy for data technology use scale*, *efficacy for data analysis and interpretation scale*, *DDDM anxiety*, and the factor *efficacy for instructional strategies* did not elicit a statistically significant difference between special education and general education teachers per the *t*-tests that were calculated by the Statistical Package for the Social Sciences (SPSS; IBM, n. d.) software. However, the factor *efficacy for application of data to instruction scale* was found to be statistically significant for special education and general education elementary teachers showed a statistically significant difference in their "self-judgment of his or her ability to connect and apply what was learned from data interpretation to instruction in order to improve student learning" (Dunn et al., 2013b, p. 239).

Although only one factor was found to be statistically significant, the other 5 factors in the survey revealed some important findings of the study. There are several factors in the DDDM process that, when examined, initially may seem unimpressive. Then I had to look at what I was asking, how the participant responded, and what it meant regarding the Likert scale. When comparing the means, anchors, and Likert scales, it was evident that there was a positive outcome of the results despite the insignificant findings. The acceptance of the Null hypothesis meant that there was no difference between special education and general education teachers in their self-efficacy for DDDM. Bandura (2000) wrote that teachers' self-efficacy beliefs "affect their general orientation toward the education process as well as their specific instructional activities" (p. 241). To find more in-depth information about the teachers' use of DDDM to gauge student performance and their self-efficacy in using data to plan instruction, I interviewed 9 of the survey participants who volunteered to be interviewed. The teachers interviewed shared information about their introduction to student data and the process of DDDM, which included pre-service teacher training and on-the-job professional development. The interviewees expressed their thoughts on the benefits of the DDDM process for teachers and students. The participants revealed their use of data to plan their instruction and their confidence in using the data to determine student instruction. The interview revealed that special education and general education elementary teachers were confident in the DDDM process when they were gathering and analyzing student data in their instructional areas of certification. The interviewed participants gained knowledge about the DDDM process through their pre-service courses and on-the-job professional development. These were avenues by which special education and general education teachers were able to learn about student data and the DDDM process.

Discussion

This study contributes to the growing body of literature focused on the self-efficacy of special education and general education elementary teachers in the area of DDDM. Some studies have focused on the self-efficacy of teachers (Jennett et al., 2003; Kuronja et al., 2019; Pressley, 2021). Other studies focused on teachers' DDDM (Schildkamp et al., 2017; van Geel et al., 2016). And still other studies have examined the efficacy of elementary school teachers and DDDM (Park & Datnow, 2017; Walker et al., 2018), but the research was lacking in the area of comparing special education and general education elementary school teachers' self-efficacy for DDDM.

Research Question 1

The first research question guiding this study was, To what extent do special education and general education teachers use DDDM to gauge student performance? The findings suggested that the factor *efficacy for data identification and access scale* did not reveal a statistically significant difference between special education and general education elementary school teachers' beliefs about their ability to gauge their students' performance based on gathering and accessing appropriate student records (Dunn et al., 2013b). I further examined the data more closely by scrutinizing the means of the special education and general education teachers and compared them with the factor's anchors and Likert scales. The means for the *efficacy for data identification and access scale* were $M = 4.15$ for special education teachers and $M = 4.06$ for general education teachers (see Table 4). The difference of the mean scores was .09. According to the 5-point Likert scale, both means were a little over the *agree* anchor, which meant that the statistical data of the survey revealed that special education and general education teachers agreed that they were able to “identify, access, and gather appropriate reports needed for DDDM” (Dunn et al., 2013b, p. 239) similarly when using DDDM to gauge student performance. The theme of identifying student data for DDDM revealed the teachers' beginning awareness of the importance of the DDDM process from their university courses to their divisions' professional development. Cox and colleagues (2017) suggested: "that institutions are starting to embrace recent calls to increase the use of assessment and DDDM" (p. 849). As noted in this study, not all the teacher participants interviewed experienced viable information and training on DDDM in their pre-service classes. Mandinach and Gummer (2016b) stressed the need for more DDDM teacher training research. Most of the teachers interviewed were made aware of the DDDM process through years of on-the-job training and professional development offered by their division. The teachers spoke about the pre-service and on-the-job professional development experiences of DDDM that guided them through the process of gathering, analyzing, and using data to determine current student performance. The teacher participants' comments on their pre-service experience and on-the-job training were mixed. Depending on the number of years since they were in a pre-service program, some participants could not remember or did not have any courses pertaining to student data. The novice special education teacher, Kalyn, learned about the DDDM process when she began teaching. Audrey took and gave professional development classes in DDDM. Barb took a statistical class years ago and, in years past, worked with students who were severely disabled. Lynn earned her master's, and on-the-job training was inundated with DDDM. Shirley learned about student data at her university. Jane, a general education teacher, was made aware of collecting and using student data because she worked as a teaching assistant before she began her teaching career but did not mention any course work on DDDM. Carlene used student data since the beginning of her teaching career but didn't get the full impact of the DDDM process until 7 years ago. For Carol, on-the-job training really helped her understand the DDDM process. Finally, Amani learned about the DDDM process after she was hired. The on-the-job training seemed to impact the participants' ability to maneuver through the DDDM process. Dunn et al. (2013b) wrote, "professional learning or job-embedded training may provide an optimal arena in which to address teachers' DDDM efficacy and DDDM concerns" (p. 236).

Research Question 2

The second research question that drove this study was, What is the difference between special and general education teachers' self-efficacy in using data to plan instruction? The *efficacy for data technology use scale* revealed that the statistical significance difference between special education teachers and general education was not significant when using technology to access DDDM. Although, when I examined the mean scores for special education teachers (M = 3.36) and general education teachers (M = 3.58), I found a difference in the mean of .22 points as general education teachers scored higher. The 5-point Likert scale put the mean scores between *neither agree nor disagree* and *agree* anchors. The *efficacy for data technology use scale* centered around the teachers' confidence in using technology for DDDM. I examined the means of the special education and general education teachers, and it did appear that general education teachers rated their self-efficacy higher than special education teachers in their ability to "utilize and navigate district and state level technology tools to access information for DDDM" (Dunn et al., 2013b, p. 239). Bandura (2000) wrote, "Teachers' beliefs in their efficacy affect their receptivity to and adoption of educational technologies" (p. 241).

The themes of tools for student assessment and data use for student instruction were examined in the *efficacy for data technology use scale* for special education and general education teachers. Dogan and Demirbolat (2021) argued that "it is understood that the data-driven decision-making process is influenced by technological infrastructure and hardware, data usage culture in school, data usage purpose, and the level of data literacy of educators" (p. 519). Special education teachers used data to plan for their instruction. They used pre-assessments to gauge their students' current performance and differentiation for grouping students. Data were used to determine mastery of benchmarks on their Individual Educational Program (IEP) goals and the students' ongoing learning needs. Additionally, they used data to identify gaps in their students' learning and identified instructional strategies to close the gaps. General education teachers also used technology for pre-assessments to group students at particular levels. They further stressed the need for pre-assessments to determine the next steps of instruction and closing gaps in the students' learning caused by the issues involved with COVID-19.

No statistically significant difference was found in the factor *efficacy for data analysis and interpretation scale* between special education and general education teachers' assessment of their "ability to analyze and interpret basic components of student performance data" (Dunn et al., 2013b, p. 239). I examined the means, anchors, and the 5-point Likert scale of the special education and general education teachers. I found that the mean for the special education teachers in factor *efficacy for data analysis and interpretation scale* was $M = 4.15$ and $M = 3.98$ for the general education teachers. The difference between the scores was .17, with the special education teachers scoring higher on the efficacy for data analysis and interpretation scale. Both teacher groups ranged in the *agree* anchor based on the 5-point Likert scale, which confirmed that there was no difference in their ability "a teacher's self- judgment of his or her ability to analyze and interpret basic components of student performance data" (Dunn et al., 2013b, p. 239). At the same time, the findings show that special education and general education teachers were confident in their abilities to traverse the DDDM process.

Datnow and Hubbard (2015) posited that "As students are asked to monitor their own progress and to design learning strategies to boost their individual achievement, they too will need to learn how to become reflective learners and gain the capacity to examine data" (p. 21). The theme of the benefits of interpreting student assessment revealed the participants' beliefs on the benefits of assessment data for teachers and students. The special education teachers were able to analyze student data to guide the direction of their students' instruction in a timely fashion and pinpoint specific areas of deficits that needed to be addressed. They were able to gather information on students' ability to apply the knowledge they learned in other applications, and they were able to determine growth in their students' IEP goals. The special education teacher participants expressed that interpreting assessments were beneficial for special education students because they could visualize their uptick of chart lines and graph bars showing their incremental improvements. The students were able to see their areas of goal mastery and experience growth as new goals were being set so that they could actually see where they were going in their instructional journey.

According to the general education teacher participants, the benefit of interpreting student assessments was the status of the students' knowledge: who grasped the concept being taught, who did not grasp it, and what was needed to change the presentation of the lesson? The teachers were able to discern the students' strengths and weaknesses and assist them in assigning groups, planning, time management, and motivating their students. The benefit of interpreting assessments for general education students, according to their teachers, was the ability of the students to experience instructional successes by self-monitoring their progress which emphasizes the students' understanding of the concepts and their need for more assistance. It is important for the students to experience success and growth.

The *efficacy for application of data to instruction scale* was the factor that was found to be statistically significant in this study. Therefore, special education teachers and general education teachers experienced differences in their "self-judgment of his or her ability to connect and apply what was learned from data interpretation to instruction in order to improve student learning" (Dunn et al., 2013b, p. 239). The special education teacher participants reported that they analyzed the student data to address the direction of their instruction that were applicable to the students' IEP goals. Barb noted the importance of using more qualitative student data that focused on specific instructional areas. General education teachers shared that they used district math assessments, running records for reading assessments, the Phonological Awareness Literacy Screening (PALS; University of Virginia, 2022), and the software PowerUp (Lexia Learning, 2022) to group students for instruction. General education teachers' application of data to instruction was based on the curriculum for all students, but for special education students, it included their progress on the IEP as well (Petersen, 2016). According to their interview responses, it was typical for special education and general education teachers to look at the assessments and view the data to determine the instructional direction. I noted a general education teacher who said she "separates the goats from the sheep" by doing a quick lesson to determine those who qualified to be put in the enrichment group and those who required another round of instruction at a slower pace.

Research Question 3

The third research question was, How does self-efficacy in data-driven decision making differ between special education and general education teachers? The teachers' self-efficacy to engage in the DDDM process from gathering the data, analyzing it, and using it for student purposes was the focus of the factor *data-driven decision making (DDDM) anxiety scale*. Through my analysis of the data in SPSS, I found that the *DDDM anxiety scale* had no statistical significance. Therefore, there was no difference between special education and general education teachers' beliefs about DDDM anxiety. When I examined the mean value for special education M = 2.03 and the mean value for general education teachers M = 2.28, The means were just over the *disagree* anchor. The findings in the survey suggested that the special education and general education teachers disagreed with the belief that they were intimidated by the DDDM process. This was a positive outcome to note as, in the past, teachers have been intimidated by using student data which lowered their self-efficacy in DDDM. Datnow and Hubbard (2016) wrote, "Many teachers believe they do not have the knowledge to understand the data and/or to translate it into practice" (p. 19). Questions were asked of special education and general education teachers about their confidence in engaging in the DDDM process. Bandura (1997) defined perceived self-efficacy as "beliefs in one's capabilities to organize and execute the courses of action required to produce given attainments" (p. 3). The survey participants who engaged in the survey and interview expressed their confidence in analyzing and interpreting special education and general education student data. According to Dunn and colleagues (2013b), "increasing teacher DDDM efficacy will likely serve to decrease their DDDM anxiety" (p. 236). The special education and general education teachers did not experience anxiety when engaging in the DDDM process. This contrasts with Datnow and Hubbard's (2016) study that revealed that teachers were not prepared to collect, analyze, and interpret student assessment data in the DDDM process.

A novice special education teacher, Kalyn, was confident in her ability to manage the DDDM process and expressed that she would improve her skills in analyzing and interpreting data as she continued to get help from her coach and administrator. Datnow and Hubbard (2016) stressed that teachers' development of assessment data depends on trusting their collaborators like the "principal, instructional coaches, university researchers, or consultants who serve as facilitators" (p. 23) in their data information journey. The special education teachers believed their confidence in the DDDM process was necessary. It was based on their required daily and yearly assessment data when addressing goals on their IEPs. Barb stated, "It just makes sense to use data-driven instruction." The general education teachers also felt it was part of the requirement for their job to be confident in the DDDM process. Amani saw DDDM as a "clear-cut procedure." Carol went through the DDDM process of collecting, analyzing, and determining instructional directions by being involved with Virginia Alternate Assessment Programs (VAAP) and other portfolio assessments.

The *t*-test calculated on the factor *efficacy for instructional strategies* revealed that the difference between special education and general education teachers was not statistically significant. Therefore, there was no statistically significant difference between the special education and general education teachers in their instructional strategies, which included using assessments, giving examples, crafting questions, responding to questions, adjusting lessons, gauging student comprehension, and providing challenges to students (Tschannen-Moran & Hoy, 2001). Based on the 9-point Likert scale, the range of the means was between the anchors *quite a bit* and *a great deal*. The self-efficacy for special education teachers and general education teachers was in the high range. Datnow and Hubbard (2016) noted, “Examining teachers’ beliefs allows for greater understanding of their capacity for data use efforts” (p. 18). In my study, I examined the self-efficacy of the special education and general education teachers’ perceptions of their self-efficacy for DDDM. The finding revealed that there was mostly no statistically significant difference between the teachers’ self-efficacy for DDDM.

Dunn and colleagues (2013b) postulated in their study the need to address teachers' self-efficacy for DDDM as many teachers found DDDM challenging. My study presented evidence of Dunn and colleagues’ (2013a) suggestions being put into practice, "The expectation is that teachers will use data to inform instructional decisions to improve student achievement" (p. 95). The interview participants shared DDDM protocols and instructions in their pre-service university training and DDDM professional development training. As mentioned earlier, one participant shared her experiences of getting assistance from coaches and administrators to guide her through the DDDM process, which increased her self-efficacy in this area. Datnow and Hubbard (2016) reported that divisions that focus on data "typically seek to engage all teachers, but they often do not account for—nor address—the wide range of beliefs that teachers hold about data, data use, assessment, and instructional change” (p. 24). Differences were reported in the interviews on methods and procedures used by special education and general education teachers to address the instructional needs of their students. The special education teachers focused on IEP goals to direct their instruction and gauge their performance with scores based on their individual objectives. Special education teachers also present the instruction based on the student's classification (Learning Disabled, Emotionally Handicapped, Autistic, etc.). General education teachers focused on the grade level curriculum and objectives. They presented the instruction based on the whole group and small group instruction. These differences in procedures did not negate the quantitative survey findings that revealed that 5 of the 6 factors examined showed no statistically significant difference between special education and general education teachers' self-efficacy for DDDM.

The novice teacher who I interviewed said that she was still learning. The other special education teachers said they were made aware of using data through their pre-service training at a university. Still others were made aware of using data through their districts' professional development courses. Similarly, the general education teachers were also aware of using data to inform their instruction through their university courses and professional development experiences. In addition, the general education teachers were made aware of using data through hands-on experiences when working with students and administering district assessments that required analysis for further review.

The special education teacher participants used assessment data tools to plan their instruction of students. The IEPs were used to determine the objective and amount of time spent on goals. Benchmark data were used to assess mastery of skills and for screening. Baseline data were used to determine where the students are and where they need to be. The general education teachers reported using pre-assessment data to plan instruction when beginning a unit to differentiate the lesson. Data were used to differentiate students into instructional groups and determine the gaps caused by the time out of school due to the COVID-19 pandemic.

Special education and general education teachers interviewed found benefits in using student assessment data for teachers and students. Special education participants expressed that they benefitted from the student assessment data because it allowed them to focus on attaining specific IEP goals. The assessment data revealed a mastery of IEP goals and areas that were challenging to the students. Also, the assessment data results helped change the students' instructional directions. The special education teachers reported that the special education students benefitted from the assessment data when they could see where they were going. The students could check their progress by charting and graphing their progress throughout the educational process. Students were also given the opportunity to identify the type of errors they made to see their growth. An increase of one point was an opportunity to celebrate a student. The general education teachers interviewed mentioned that they benefitted from assessment data because the information allowed them to plan and guide the instruction for students. It allowed the teachers to make sure that students were engaged and excited about learning. It helped to save time by not reteaching concepts already mastered and revealed areas of student frustration in the curriculum. General education students benefitted when they have instruction tailored to their needs. It is important for students when they can see that they have accomplished something and can meet the instructional goals that were set for them. The general education teachers expressed the importance of students self-monitoring their instructional progress.

When special education teachers plan for instruction, they are required to take into account the IEP goals of their students. They analyze the assessment data to differentiate the students’ lessons and determine if they can master their goals. Shirley shared, "I take and analyze the data and say okay, this is where their needs are, and that's what I'll do for their IEP goals or meeting goals in the classroom. The teaching approach may be changed during the planning to accommodate the students’ needs. Kalyn said, “we use the data that's collected to see if the goals are met or if the goals are not being met and then to see if we need to take a different approach.” When remarking about the next steps for instruction, special education teachers focused on their analysis process to determine where the students were and what goals they had mastered. Student ability groupings were revealed, and the most appropriate instructional procedures were elicited to meet the needs of the students. According to one special education teacher, it was important to examine students' qualitative data with the qualitative aspects of their assessment data.

General education teachers reported using assessment data to plan for differentiating instruction. They accommodate students who need extra instructional time, small groups, or enrichment activities. After teachers administer a pre-assessment to the students, Jane said that:

> You're going to have a lesson that you pitch to the whole group. And then you have a small group lesson where you are differentiating between students who either have gotten the objective or need enrichment. Or you need to give them something else to dig into, or you're going to have students who are about ready to get this concept. They can work independently, but they're still working and practicing it. And then you have those students who seem to be struggling and maybe are not quite ready for that subject or not quite ready for that objective. And, so, you may need to back up and determine where the gap is or what exactly they're not getting.

This year's focus has also been to close the educational gap caused by COVID-19. According to the general education teachers who were interviewed, the use of assessment instruments like running records, PALS (University of Virginia, 2022), and the software PowerUp (Lexia Learning, 2022) was used to enhance the teachers' knowledge of current student performance. The teachers analyzed the data for the next instructional steps based on the assessments.

According to van der Sheer (2016), "teachers with a higher sense of efficacy have more confidence in their ability to influence student performance" (p. 42). From the novice to the more experienced teachers, special education and general education teachers who were interviewed felt confident in the DDDM process. They collected, analyzed, and interpreted the data to determine the next steps in the process based on their training. The special education teachers’ confidence in the DDDM process was based on their interpretation of assessment data and daily experience with students' IEP goals for mastery throughout the year. One special education participant said, "It just makes sense to use data-driven instruction." General education teachers said the DDDM process becomes clearer, they need to feel confident in the process, and teachers need to know if the students understand what they have been taught.

In the same vein, the participants interviewed were confident in using data to support their instruction. Special education teachers understood the importance of the data and the appropriateness of the student content being taught. General education teachers expressed their use of data was used to support the instruction of their inclusion students, making the instruction specific to the students' needs, and determining what they currently know and what they need to know.

Implications for Practice

The current study offers another perspective on teachers' self-efficacy for DDDM. These findings provide insight into special education and general education teachers' current beliefs about DDDM self-efficacy. Barnes and colleagues (2019) suggested in their study that "teachers' beliefs about data use functioned to filter, frame, and guide their perception, interpretation, and use of data" (p. 521). Student assessment data are important to determine the next steps in classroom instruction (Dunlap & Piro, 2016). Datnow and Hubbard (2016) reported the importance of addressing teachers' beliefs in accordance with their capacity to use student data. The special education and general education teachers' self-efficacy in DDDM are presented through the instructional directions that teachers find most effective for their students. Mandinach and Gummer (2016a) wrote:

> As they develop instructional plans, teachers will keep in mind the data, their knowledge of pedagogy specific to their content area, and their understanding of how students can best learn that content. Then teachers must use the data to develop instructional plans. (p. 45)

van der Scheer and Visscher (2016) wrote, “A teacher’s sense of efficacy regarding instructional strategies and student engagement can be improved significantly by means of an intensive intervention” (p. 42). I did not, however, provide intensive intervention to my study participants. I met the special education and general education teachers in the state of mind where they were—after most schools went virtual overnight and gradually returned to face-to-face instruction due to COVID-19. I had to keep in mind the teaching challenges and stresses of the participants as I navigated my study (Pressley, 2021). Dunn and colleagues (2013b) postulated that stress and anxiety could overwhelm teachers' ability to confidently analyze student data to make instructional decisions. It was not a major hindrance for the participants in their ability to maneuver the DDDM process. Determining the status of special education and general education teachers' self-efficacy in the DDDM process will help focus on issues of DDDM for change. It will spotlight university offerings on DDDM and future professional development that occurs at the school division level, as noted below.

When the participants were asked, “What suggestions do you have to increase teachers' confidence in DDDM?” the special education and general education teachers responded by saying to give teachers time to reflect and analyze the data. Cox and colleagues (2017) noted, “To effectively make informed decisions, institutional decision makers need easy access to timely and relevant data presented in a clear and simple format” (p. 854). In addition, all teachers who are involved with the student need to be involved collaboratively in the process of determining instructional directions for the student. Dunn and colleagues (2013b) posited that teachers "who were more confident in their ability to successfully engage in DDDM were more likely to be working with colleagues to improve and increase the use of DDDM in their classrooms" (p. 235). One participant expressed the importance of accessing the student data and using it. Another participant mentioned that it would increase her confidence in DDDM "if the assessments reflected the needs of the students and measured what it was supposed to measure." Mandinach and Gummer (2016a) stressed that “Using data includes sets of knowledge and skills such as knowing what data are appropriate and actionable to the problem” (p. 45). I noticed from the participant responses the need to have pre-service classes specific to DDDM. The results from Ogan-Bekiroglu and Suzuk’s (2014) study suggested, “Teacher education programmes should have an assessment course that highlights theories of assessment and types of evaluation, stresses validity and reliability of an assessment…and provides students with opportunities to reflect, practice, and revise these methods” (p. 362). To stress this point further on pre-service teaching programs, Mandinach and Gummer (2016a) expressed a broader focus on data in the curriculum. They envisioned “integrating data use throughout their curricula, through stand-alone courses, and in practical experiences. Integration must include data use as part of content, pedagogy, and methods courses” (p. 46). Hiring new teachers who are familiar with the DDDM process will benefit divisions. Novice teachers may need training regarding the particular specifications followed by the division. Still, they will acquire some knowledge and experience in data collection, analysis, and interpretation for instructional purposes. The DDDM courses should be required by special education and general education teachers seeking certification in K-12 programs.

A couple of study participants did not trust the validity of certain assessment instruments and found other ways to assess their students. To increase the teachers' trust when using the assessment data instruments, Barnes and colleagues (2019) suggested:

> It seems reasonable that if teachers had the conditional knowledge to know which assessments were appropriate to use and when, and they had the skills and expertise to design assessments that produced valid inferences, then they would be more likely to trust the data and interpretations gleaned from these assessments. (p. 529)

This can also be a part of the course selections in pre-service courses that would add to the marketability of the teachers being hired.

Implications for Future Research

Since implementing federal mandates that included the No Child Left Behind Act of 2002 (NCLB) and the Every Student Succeeds Act of 2015 (ESSA), emphasis has been placed on teachers' knowledge and ability to collect, interpret, and analyze student data for instructional purposes. Dunn and colleagues (2020) wrote:

> ESSA specifies requirements for the use of evidence-based practices. Under ESSA, state and local education agencies that plan to use their federal education dollars to support activities or interventions for struggling students must justify their selection of interventions based on a tiered, strength-of-evidence model. (p. 16)

Future research would be warranted in the area of evidence-based teacher practices to increase student learning in elementary, middle, and high school settings. Takahashi (2011) reported that evidence-based decision making is used as an instructional tool that examines the improvement of student learning.

The current study focused on special education and general education elementary school teachers' self-efficacy for DDDM. Gable and colleagues (2012) argued, "It would appear that there continues to be a substantial gap in research-to-practice with regard to both special education teachers and general education teachers" (p. 514). During the interview, a couple of the participants mentioned that they felt confident in DDDM but not as confident when assessing students who were outside of their certified teaching areas. Future research should continue to focus on the methods of gathering student data and the implications for instructional directions that involve the collaboration of special education and general education teachers and how it affects their self-efficacy (Sehgal et al., 2017). Datnow and Hubbard (2016) referenced the issues of teachers' abilities to adjust their instruction as it may have no relevance to their ability to understand data. They wrote, "While the teachers may develop the skills to access and make sense of data, they may lack knowledge of how to adjust their instruction" (p. 23). They further noted:

> It is often presumed that this knowledge is shared when teachers work with their colleagues in collaborative groups, however, whether this happens depends a great deal on the instructional expertise within the group and whether there is sufficient time for delving into instruction. (p. 23)

Teachers need to be comfortable with the environment when sharing successes and issues with various aspects of the DDDM process (Mandinach & Gummer, 2016a).

In her interview, the novice teacher who participated in the study revealed that she was assisted by two people who guided her through the DDDM journey. Her coach and one of her administrators gave her valuable information that raised her self-efficacy for the DDDM process.

A two-year study on the impact of mentors and coaches who guided novice teachers through the DDDM process during the first year in the division may benefit the school division. The focus of the second year of the study includes the impact on the second year teachers' self-efficacy for DDDM (Tschannen-Moran & Hoy, 2001). The research questions may consist of Tschannen-Moran and Hay's (2001) suggestions:

> How do the efficacy beliefs of mentors [or coaches] impact the sense of efficacy of the novice? What features of mentoring [or coaching] have the greatest impact on efficacy beliefs? What are the effects of the teaching environment and context? (p. 802)

Another avenue of research would be determining the benefits of teacher peer coaching. Peer coaching involves the interaction of two or more teachers observing each other. It can include observing assessment data procedures, teaching styles, and interactions with the students. The teachers later discuss and give feedback on ways to improve their teaching (Dunn et al., 2013b).

One of the issues that special education and general education teachers brought up in the study was the amount of time it took to do all that was required to complete the DDDM tasks was daunting. The amount of time required for teachers to collect, analyze, and use data to make instructional decisions requires observations, thinking, writing, reporting, and execution of the findings. Future research could examine the times for specific procedures based on the number of students and the classification of their students. Additionally, the teachers noted the environment of where and with whom they completed the data procedure—for example, individually at home or collaboratively in school. In addition, this could add to the research about how to best provide time and support for teachers to engage in the DDDM process.

A couple of interview participants had an issue with the validity of the assessment in making sure the assessments are evaluating what they are supposed to be assessing. A future study may involve teachers who directly communicate with the assessment designers to critique their materials based on their alignment with the concepts being taught. Popham (2011) postulated that:

> The more that teachers understand about assessment, especially the requisite features of tests that can trigger sensible instructional choices, the more likely it is those teachers will know what to look for when identifying tests able to bolster the caliber of their instructional efforts. (p. 271)

Finally, special education and general education elementary teachers have revealed in the survey that they were not intimidated by the DDDM process (Dunn et al., 1213b; Tschannen-Moran & Hoy, 2001). The teachers who participated in the structured interview expressed their confidence in their ability to maneuver through the DDDM process. For the most part, there was no statistical difference between the special education and general education teachers' self-efficacy of DDDM.

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APPENDIX A

The Data-Driven Decision Making and Anxiety (ED-MEA) Inventory

1. I am confident in my ability to access state assessment results for my students
2. I am confident that I know what types of data or reports I need to assess group performance
3. I am confident that I know what types of data or reports I need to assess student performance
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
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
6. I am confident that I can use my district's data analysis technology to access standard reports
7. I am confident in my ability to understand assessment reports
8. I am confident in my ability to interpret student performance from a scaled score
9. I am confident in my ability to interpret subtest or strand scores to determine student strengths and weaknesses in a content area
10. I am confident that I can use data to identify students with special learning needs
11. I am confident that I can use data to identify gaps in student understanding of curricular concepts
12. I am confident that I can use assessment data to provide targeted feedback to students about their performance or progress
13. I am confident I can use assessment data to identify gaps in my instructional curriculum
14. I am confident that I can use data to group students with similar learning needs for instruction
15. I am confident in my ability to use data to guide my selection of targeted interventions for gaps in student understanding
16. I am intimidated by statistics
17. I am intimidated by the task of interpreting students' state level standardized assessments
18. I am concerned that I will feel or look ''dumb'' when it comes to data driven decision-making
19. I am intimidated by my district's data retrieval technology
20. I am intimidated by the process of connecting data analysis to my instructional practice
21. How do you define the process of data-driven decision making?
22. How do you as a special or general education teacher view your role in the data-driven decision making?
23. How do you think special and general education teachers use student data differently?

APPENDIX B

Factor 1: Efficacy for instructional strategies

1. To what extent can you use a variety of assessment strategies?
2. To what extent can you provide an alternative explanation or example when students are confused?
3. To what extent can you craft good questions for your students?
4. How well can you implement alternative strategies in your classroom?
5. How well can you respond to difficult questions from your students?
6. How much can you do to adjust your lessons to the proper level for individual students?
7. To what extent can you gauge student comprehension of what you have taught?
8. How well can you provide appropriate challenges for very capable students?

APPENDIX C

Interview Questions

Data-Driven Decision Making: A Teacher's Perspective

Interview:

1) What helped you or would help you feel more confident in data-driven decision making (collecting, analyzing, and interpreting data for classroom instruction and to improve student learning)?
2) How and when were you made aware of using student data to inform your instruction?
3) How did your teacher preparation program prepare you to work with student data and the process of DDDM?
4) Do you feel confident in using data to help with the instruction of special education students?
5) Do you feel confident in using data to help with the instruction of general education students?
6) How do you use data to plan the instruction of your students?
7) Do you find the use of student assessment data as beneficial for teachers and students? How is it beneficial for teachers? How is it beneficial for students?
8) What suggestions do you have to increase teachers' confidence of DDDM? (Refer to teacher candidate preparations and on the job training.)

Demographics:

1) How many years have you been teaching?
2) What is your teaching area?
2) What grade level(s) do you teach?
3) Are you a teacher who is teaching in the area of your state's certification?
4) Do you teach in an urban or rural environment?
5) What is your age range? 20-20, 30-39, 40-49, 50+
6) What is your race?

Bank of Interview Follow-Up Questions:

1) Is there anything else that has or would help you feel more confident in data-driven decision making?
2) Do you wish you were exposed to a more extensive hands-on experience with analyzing data?
3) What did you think of the process of collecting and interpreting student data in your first teaching experience?
4) Do you think that collecting and interpreting data is easier to perform for general or special education students? Or is it the same for both group of students?
5) What do you wish you were told about gathering and interpreting data for the purposes of determining instructional directions for students?

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PRESENTATIONS:

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