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The Influence of Venables' Data Action Model on the Academic Performance of Urban Grade 3, Grade 6, and Algebra I New Jersey Students on the Mathematics Section of the 2018 PARCC

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Abstract

This quantitative study examined the impact of utilizing Venables' Data Action Model as the focus of a professional learning community (PLC) in a small urban school district on mathematics achievement in Grade 3, Grade 6, and Algebra I courses, as measured by the 2018 mathematics PARCC assessment. More specifically, this study evaluated the impact of teacher-developed action plans that addressed the needs of selected students within all three tiers of the multi-tiered system of support (MTSS) model. The findings in this study contributed to the larger body of research on data-driven instruction and effective strategies for supporting teachers throughout the decision-making process as it relates to data-informed instruction. This quantitative study was conducted using a comparative, post-facto quasi-experimental design. Propensity Score Matching (PSM) was utilized to mimic a randomized experimental design without randomized delegation of subjects for both the treatment and control groups. Multiple regression analyses were conducted on variables to better isolate the impact that the teacher participating in the district-level data action PLC may have on students' academic performance in mathematics. The findings of this study show that there is value in ensuring there are effective PLCs in the school and teachers are using data to drive instruction on a consistent basis. Although the model did not produce a statistically significant finding, the mean differences in scale score on the mathematics PARCC inspire further inquiry. Final recommendations encourage schools to promote an effective PLC with practices that permeate the entire school building and district and to prioritize data-driven decision-making professional development along with increased focus on building mathematics content knowledge.

Keywords: Venables' Data Action Model, professional learning community, PARCC testing, data-driven instruction, multi-tiered system of support

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Dedication

This dissertation is dedicated to the ones who have been a reflection of God’s love to me in human form:

Grandma, who continues to watch over me.
Mommy, who loves me without limits.
Tawny, the pillar of strength who walks beside me.

My Trinity

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CHAPTER 1

INTRODUCTION

Across the nation, school districts and individual schools have developed a laser-like focus on learning strategies intended to increase academic achievement for all pupils. At the federal and local levels, there has been a mandated push for school reform, especially after the publication of *A Nation at Risk* (National Commission on Excellence in Education, 1983). Educational reform was exposed as a necessity many years prior to this report. In 1954, the Brown v. Board of Education decision was considered to repair educational damage caused by segregation; however, it is apparent that the achievement gap still exists to this day. Initially, President Lyndon B. Johnson signed the Elementary and Secondary Education Act (ESEA) into law as step toward education reform. ESEA offered school districts serving low-income students funding for instructional material and special education centers. Additional funding was provided at the elementary and secondary level to improve the quality of education offered to various populations (Elementary and Secondary Education Act, 1965). During this time, it became apparent that additional funding was not the only needed element to close the existing achievement gap.

This push for improving public school education and more specifically teacher accountability intensified with No Child Left Behind (NCLB, 2002). NCLB was the first mandate put in place to attack the growing achievement gaps among traditionally underserved students and others. This federal mandate addressed these gaps through sanctions and financial consequences. This was a long-awaited response to the achievement gaps that existed even prior to the ESEA.

NCLB intended to put pressure on the public education system to raise student achievement for all public school pupils. This mandate required 100% of students to meet or exceed proficiency as defined by their respective state (Fuller et al., 2006). The purpose of this act was to ensure that educators are held responsible for bringing about necessary changes to education in their schools across the nation. All instructional stakeholders were mandated to implement effective research-based instructional strategies for improvement and to evaluate students' progress. NCLB increased pressure on the public education system to increase success for all students. These mandates included the following three components: goal setting, use of mandated assessments, and financial consequences for not meeting expected goals (Anthes, 2002). It is evident that the understanding of data-driven instruction (DDI) would be needed to accomplish these mandates. Understanding the individual needs of students and using research-based strategies to meet those needs have become two of the most essentials tools to helping to close the achievement gap.

The NCLB's strong focus on closing the achievement gap continues with the Every Student Succeeds Act (ESSA). ESSA was signed by President Obama on December 10, 2015, and upholds the standard that there will be accountability and specified actions required to effect positive change in our lowest-performing school districts where graduation rates are low over extended periods of time and students are not achieving expected growth (Anthes, 2002). Within the expectations of the law, in the state of New Jersey, testing requirements are similar to those of NCLB. ESSA preserves the requirement that states govern annual assessments and there is a condition that students sit for state assessments in Grades 38 and once during high school. It mandates that test results remain an essential component of states' accountability plans and continues to require states to identify and intervene when schools are struggling with meeting

testing requirements. This plan has continuity with NCLB, maintaining a strong focus on closing the achievement gap.

As the emphasis on accountability increases with federal mandates, schools are adjusting to meet the required expectations set by local and federal leaders. States must determine schools' levels of success based on multiple factors: academic and at least one non-academic factor that speaks to school quality. Schools must also review test scores to ascertain data related to the number of students on grade level in reading and mathematics and the number of students showing growth if they are not presently on their intended grade level. In order to meet students where they are, schools are required to take a deeper dive into the data to understand needed next steps. As the need for data-driven decision-making increased, there was an increase in the utilization of Professional Learning Communities (PLCs). This is evident through the most basic understanding of PLCs: to guarantee that students are not only exposed to material but are indeed learning (DuFour, 2004). There are three questions that drive the work of a PLC, according to DuFour: "What do we want each student to learn? How will we know when each student has learned it? How will we respond when a student experiences difficulty with their learning?" (p. 33). These questions cannot be answered on any level without the analysis of micro- and macro-data (DuFour et al. 2006).

As Naylor (2005) has noted, guidance around PLCs is mainly focused on paying attention to specifying goals, defining a focus for the team, and examining DDI along with best practices. This pursuit of improvement is often referred to as school improvement, school reform, or a host of other terms that describe the efforts schools engage in to improve student learning. Hipp and Huffman (2010) defined the concept of PLCs as "professional educators working collectively and purposefully to create and sustain a culture of learning for all students and adults" (p. 12).

One goal of effective PLCs is to examine data collectively in order to recognize trends in students' learning. This approach has proven to lead to improvements for individual teachers as well as whole departments (Vescio et al., 2008). It is challenging for teachers to effect change in isolation and therefore there is an increased demand on the effective use of data teams at all levels, including both school and district.

Despite various attempts at reform through different approaches, significant systemic changes in classroom practice and student achievement have yet to be realized (Gallucci, 2008). Data from the U.S. Department of Education revealed that students in primary grades in the United States, overall, lack basic mathematics skills. This statistic is more prevalent in students from a low-SES background (Institute of Education Sciences, 2010). The achievement in mathematics data reveal that students from low-SES backgrounds consistently exhibit inferior performance compared to their affluent peers. These pupils usually show a deficit in basic math skills, which makes it challenging to move forward with new material learned (Poncy et al., 2010). This trend continues when interventions are not put in place to remediate the gaps. According to The National Assessment of Educational Progress (as cited in Bandeira de Mello et al., 2009), African American, Latino, and poor students of all backgrounds in fourth grade are at least two years behind their Asian and White counterparts. According to this same national assessment, by eighth grade, those same students have slipped three years behind. It is imperative that students from low-SES backgrounds master mathematics standards in a way that ensures retention of the content and that they continue to build upon concepts that enable them to compete with their peers (Davies & Qudisat, 2015). With the enactment of NCLB and ESSA, data analysis is no longer optional. The requirements force schools to take a more extensive look

at data and plan accordingly. The expectation is that a thorough understanding of student needs will yield more favorable results for struggling students.

Statement of the Problem

Although education reformists understand the importance and value of having a model for instructional decision-making based on data, research on the effectiveness of implementation is scarce. With the mandates and requirements under NCLB and ESSA, many school districts still are looking for additional ways to improve student achievement. As Orfield and Kornhaber (2001) have explained, American leaders have placed great trust in testing as a catalyst: “For almost two decades, all national leaders of both parties have embraced the theory that our schools have deteriorated and that they can be saved by high-stakes tests” (p. 4). There has also been a paradigm shift appearing in the way educators gauge teacher effectiveness. There is now more of a focus on student outcomes vs. teacher input (Corcoran, 2010).

As stated by DuFour et al. (2006), schools are “data rich and information poor” (p. 215). Educational institutions are ascertaining more and more data; however, this does not necessarily equate to instructional improvement, and even when it does, in many cases it helps the institution make just minimal strides. Due to the national push to use data to inform instruction, schools have more data available to them than ever before. For teachers, collecting data is insufficient without analysis; teachers need time to fully explore the data for instructional purposes (Slavit et al., 2011). They also need a strong model to follow that enables them to successfully analyze data to drive their instruction. Reeves (as cited in Hattie, 2008) explained the value of data when they are properly used to inform decisions:

> The essence of data-driven decision making is not about perfection and finding the decision that is popular. It is about finding the decision that is most likely to improve

> student achievement, produce the best results for most students, and promote the long-term goal of excellence and equity. (p. 24)

The problem is that there is not enough empirical evidence on the use of data-driven decision-making to adequately determine if this push is having an impact on closing the achievement gap and improving instruction in urban school districts. Consequently, this study will help to contribute to the empirical knowledge base concerning data-driven decision-making as it relates to classroom instruction and student achievement.

Purpose of Study

Leadership of the small urban district in northern New Jersey utilized for this study has mandated that teachers utilize data to inform instruction. The district of focus in this study will be referred to as XYZ. Schools in XYZ district developed data teams and analyzed data during their common planning time meetings; however, this has yielded limited growth on state assessments. Teachers were not receiving the expected results on student testing and were perplexed as to why this was occurring. There have also been limited opportunities for teachers to utilize a systematic way of looking and analyzing both macro- and micro-data. Teachers have been advised and mandated to use data to drive instruction; however, they have not been provided with formal training and guidance on the most effective way to do so. Based on the lack of growth specifically in the mathematics department, the director has opted to utilize Venables' Data Action Model (VDAM) coupled with Multi-Tiered System of Support (MTSS) methods to meet the individualized needs of all students.

VDAM is composed of three main phases: Gathering and Reviewing Data, Identifying Gaps, and Planning for and Evaluating Action (Venables, 2014). Integrated MTSS model provides all students with the best opportunities to prosper, both behaviorally and academically.

Law Insider (n.d.) defines MTSS as: “a comprehensive system of differentiated supports that includes evidence-based instruction, universal screening, progress monitoring, formative assessments, research-based interventions matched to student’s needs, and educational decision-making using student outcome data.” The blend of the two systems enables teachers to meet the various learning modalities of the students with appropriate next steps to improve achievement.

In this study, the math department took on the task of training teachers to effectively use data to drive instruction. This included providing various resources to acquire both macro- and micro-data, a system for analyzing the data, and instructional guidance on effective next steps. This approach was implemented based on the lack of improvement made in the past few years on the PARCC. According to the website of XYZ district, the mathematics performance has been low for the past three years with minimal growth, as evident in Table 1.

Table 1

Performance on the PARCC in XYZ School District (2015-2017)

Grade/ Subject	2015- Did not meet expectations	2016- Did not meet expectations	2017- Did not meet expectations	ST- 2017- Did not meet expectations	Difference 2017
3- Math	85%	72%	74%	47%	27%
4- Math	81%	80%	76%	52%	24%
5- Math	82%	79%	83%	54%	29%
6- Math	85%	85%	82%	54%	28%
7- Math	82%	84%	83%	60%	23%
8-Math	87%	83%	91%	62%	29%

Educators need to have a comprehensive understanding of how to effectively analyze student data and use that analysis to inform further instruction. This is what is meant when referring to formative assessments and their utilization to improve student achievement. With such diverse curricula and achievement expectations for each child, teachers tend to struggle with identifying the precise strengths and weaknesses of the students under their instruction (DuFour et al., 2006). The National Study of Education Data Systems and Decision Making found that the level of the educators' confidence in their knowledge of data analysis and data interpretation impacted the likelihood of them using data in decision-making (U.S. Department of Education 2008).

Consequently, the purpose of this study was to examine the impact of utilizing a VDAM design in XYZ school district on mathematics achievement in third-grade, sixth-grade, and Algebra I students. More specifically, this study evaluated the impact of teacher- and district leader-developed action plans that address the needs of selected students within all three tiers of the (MTSS) model. This study contributes to the larger body of research on DDI and effective strategies for supporting teachers throughout the decision-making process as it relates to effective data-informed instruction. According to Engage NY (n.d.) "Data Driven Instruction and Inquiry (DDI) is a systematic approach to improving student outcomes and results. The inquiry cycle of data-driven instruction includes assessment, analysis, and action and is a key framework for school-wide support of all student success." In this study, Venables' Data Action Model (VDAM) was adopted and implemented in three different grade levels at three different schools within XYZ school district.

Theoretical Framework

The push for accountability and improvement has created an academic environment filled with an abundance of data and evidence of student performance. These data represent what is working in our school system and needed areas of improvement. School systems have established the common goal of improving academic achievement for all students and then working collaboratively to accomplish that goal. This goal enables this study to be grounded in the theoretical foundation of social capital theory. This theoretical framework was selected based on the need for participants in this study to have collaborative leadership, PLCs, and positive group dynamics. A district-based PLC that has a focus on DDI to improve student achievement embodies the main factors of social capital theory.

The main concept of social capital theory is predicated upon the belief that, "networks of relationships constitute a valuable resource for the conduct of social affairs, providing their members with the collectivity-owned capital, a 'credential' which entitles them to credit, in the various senses of the word" (Bourdieu, 1986, p. 249). Within any system or organization, a shared vision contributes to this aspect of social capital theory, which produces group and individual mindsets and actions that lead to the benefit of the whole group. As it relates to this research of study, the definition of social capital theory shared by the World Bank is most appropriate: "The norms and social relations embedded in social structures that enable people to coordinate action to achieve desired goals" (Cohen & Prusak, 2001, p. 3). If implemented correctly, this model will produce significant academic achievement in a typical classroom. Data from this research will enhance instructional effectiveness and lead to a better understanding of school- and district-based data decision-making efforts.

Research Questions

The research questions for this study are as follows:

Research Question 1-Is there a difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the VDAM and students who were not assigned to participating teachers in Grade 3 when controls for both student and teacher demographic information are applied?

Research Question 2-Is there a difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the VDAM and students who were not assigned to participating teachers in Grade 6 when controls for both student and teacher demographic information are applied?

Research Question 3-Is there a difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the VDAM and students who were not assigned to participating teachers in the Algebra I course when controls for both student and teacher demographic information are applied?

Study and Design

This quantitative study was conducted using a comparative, post-facto quasi-experimental design. This researcher was unable to implement a randomized experimental design because this researcher was analyzing a program already in place prior to the start of the study. Propensity Score Matching (PSM) was utilized to mimic a randomized experimental design without randomized delegation of subjects for both the treatment and control groups. PSM

provides a sampling technique that is balanced and reduces bias in selection in an effort to replicate a randomized design. In combination with PSM for selecting an impartial, overall sample, multiple regression analysis, independent sample *t* test, and one-way ANOVA were used to answer the research questions raised in this study.

PSM is a progressive way to develop a matched-pair design, according to Rudner and Peyton (2006). They have explained:

> The covariates are combined to yield a propensity score, and individuals in the treatment group are matched to individuals in the control group based on their propensity score. Using this method, one is weighing the variables by their relative importance and matching based on an optimal composite, rather than by equally weighted individual variables. (p. 2)

This statistical technique allows a treatment case and control case to be matched based on each case's propensity score. According to Randolph et al. (2014), PSM has the ability to strengthen casual arguments in observational studies and quasi-experimental by reducing selection bias. This method is preferred when random assignment of a treatment to a group and comparison to another group is not an option. This study is grounded in understanding the difference in impact on student mathematics PARCC results for students with teachers who are a part of the VDAM Professional Learning Community (PLC) and students with teachers who are not. The fundamental concern when comparing treatments is normally whether an individual would do better with one approach or treatment vs. another approach or treatment. It is challenging to provide the same treatment to an individual and ascertain the impact of each treatment. PSM provides a means for adjusting for selection bias in observational studies of causal effects, and the score summarizes all of the background information about treatment selection into a scalar.

Ultimately, this enables the researcher to compare the impact of the treatment with little bias from the covariates.

Population

The participants in this study were determined and selected from a small urban pre-K12 school district located in northern New Jersey. The town selected in this study is approximately 2.2 square miles with a population of approximately 30,134 people. The District Factor Group (DFG) for the district is A. The DFG is labeled from A (lowest) to J (highest) and is an indicator of the socioeconomic status of the residents living within the school district. According to the NJDOE (2004), the DFGs represent an approximate measure of a community's relative socioeconomic status (SES). According to the NJDOE Report card for XYZ school district, 61% of students are considered economically disadvantaged. The classification system enables us to examine student achievement and compare similarly situated school districts in various analyses.

The racial makeup of the township in 2018 was 12.80% (3,857) White, 71.83% (21,645) Black or African American, 0.57% (173) Native American, 1.51% (455) Asian, 0.02% (6) Pacific Islander, 9.95% (2,999) from other races, and 3.32% (999) from two or more races. Hispanic or Latino of any race were 21.67% (6,531) of the population. The data consisted of student assessment scores from the 2018 PARCC Exam for mathematics for Grades 3, 6, and 9. There were 239 students who received instruction from a teacher who participated in the VDAM PLC. The student population consisted of General Education, Special Education, and English Language Learners (ELLs). In efforts to track progress throughout the school year, teachers utilized an assessment that enabled them to test three times throughout the school year. This enabled them to monitor students' progress but also was an instrumental factor in developing responsive instructional techniques.

Teacher participation in this Data Action Model means that they engaged in the following activities:

1. Met with the Mathematics Supervisor/Director on at least five occasions over the course of the school year.
2. Attended at least three district-level PLCs with a focus on VDAM.
3. Received training from district supervisors on MTSS prior to engaging in VDAM.
4. Read *How Teachers Can Turn Data into Action* by Daniel R. Venables.
5. Developed individualized student action plans based on data following the recommendations in *How Teachers Can Turn Data into Action*.
6. Met weekly with school-based PLC members to revisit and evaluate student action plans.
7. Consulted District Mathematics Supervisor/Director for support throughout the process as needed.

Significance of Study

The significance of this study lies in the understanding that there are limited quantitative studies on the effectiveness of VDAM for DDI. Earl and Katz (2006) recommended that teachers become literate in data analysis by reviewing relevant data, searching for ways to connect data sources, thinking about what the results mean, and implementing changes based on the analysis. There is much research surrounding the need for teachers to be data-driven instructors; however, there are a limited number of studies assessing the efficacy of a Data Action Model implemented at the district level in an urban school district. Brookhart (2016) suggested the need for additional research to determine how teachers' skills of examining data match their actual practice with data. In addition to evaluating the effectiveness of VDAM, it is imperative to continue to

discover ways to close the current existing achievement gap and ensure all students are acquiring the appropriate knowledge to be college and career ready. The intention of this study was to investigate whether VDAM has a positive impact on student achievement in mathematics, thereby helping school districts with similar backgrounds and makeups to develop a method that supports utilizing PLCs in a way that has a direct impact on student academic improvement.

Limitations of the Study

There were several limitations to this quantitative study as related to the relationship between student performance and teacher participation in the VDAM with the mathematics department. As a result, it is difficult to generalize the results of this study.

1. This study had limitations in the number of schools and types of schools participating in the study. The schools were all from XYZ school district in northern New Jersey, which lacks socioeconomic and cultural diversity. The majority of the students who participated in this study received free or reduced lunch, were classified as of lower socioeconomic background, and were African American. The district was chosen based on its pilot program in which selected teachers participated in a district-level PLC to use data to drive instruction more effectively.
2. Leadership within the math department altered throughout the duration of the study. Two supervisors left, and there was a gap in leadership for two months. This is a limitation because the supervisors led the major data action meetings and provided the level of expertise to ensure teachers were developing appropriate action plans.
3. Due to the fact that the treatment was applied prior to the start of the study, a non-experimental research design was utilized in this study. While non-experimental designs are used frequently in education research, they are not as reliable as

experimental research, and cause and effect conclusions cannot be drawn from non-experimental designs. The use of PSM attempted to mitigate this limitation.

4. Multiple regression analysis was conducted on multiple variables to isolate the relationship that teachers participating in a district-level data action PLC class may have had on student performance. However, not all variables could be accounted for.
5. The fidelity of the implementation of VDAM based on teacher understanding of the model could have varied from teacher to teacher.
6. This researcher could not control for what the teachers who were not part of VDAM PLC did relating to DDI.

Delimitations

There were several delimitations in this quantitative study. Only one small school district's data were analyzed for this study. The study did not include students from various SESs. The public-school district had students who were from a lower-class urban area in northern New Jersey. While this study may be used to draw conclusions for similar populations in similar school districts, the outcomes are not generalizable to all students and school districts. The data collected and analyzed were limited to one school year (the 20172018 academic year), and only three grade levels participated in this study: third-grade students, sixth-grade students, and students taking Algebra I.

Definition of Terms

Academic Achievement – PARCC stands for Partnership for Assessment of Readiness for College and Careers. For the purposes of this study, academic achievement is measured by individual student mathematics outcomes on the 2018 PARCC for students in Grades 3, 6 and Algebra I.

Analysis – The examination of facts and data to provide a basis for effective decisions (Bernhardt, 2004).

Data Action Model – A systematic process for reviewing and responding to data. The Data Action Model is composed of three main phases: Gathering and reviewing data, identifying gaps, and planning for evaluating action (Venables, 2014, p. 3).

Formative Data – Formative data provides information about how students are doing during instruction so that actions or, more specifically, reactions can modify based on that information. Formative data are used to inform instruction (Venables 14).

No Child Left Behind Act of 2001 – The No Child Left Behind Act of 2001 (NCLB) provided an overhaul of the education system and requires states to establish challenging academic standards for all schools, to test students regularly to ensure they are meeting those standards, and to employ teachers who are highly qualified (NCLB, 2002).

Macro-Data – For the purposes of this study, macro-data will be referred to when mentioning data such as the end of the course or Common Core State Standards assessments data. Macro-data are particularly well suited for providing teacher teams with the information necessary to ask big questions about their students' learning (Boudett & Steele, 2007).

Micro-Data – For the purposes of this study, micro-data will refer to data such as but not limited exit tickets, quizzes, classwork, completed homework, and data received from any formative assessments (Boudett & Steele, 2007).

Integrated Multi-Tiered Systems of Support – An integrated Multi-Tiered Systems of Support (MTSS) model provides all students with the best opportunities to succeed both academically and behaviorally in school. MTSS focuses on providing high-quality instruction and interventions matched to student need across domains and monitoring progress frequently to

make decisions about changes instruction or goals. It is not simply the implementation of both academic Response to Intervention and Positive Behavioral Interventions and Supports systems. There is a systemic and careful integration of these systems to enhance the efficiency and effectiveness of all school systems (McIntosh & Goodman, 2016).

PARCC – The Partnership for Assessment of Readiness for College and Careers (PARCC) is a group of states working together to develop a set of assessments that measure whether students are on track to be successful in college and careers.

Professional Learning Community – A professional staff of teachers and administrators who continually seek and share learning, and act on their learning; conceptualized as five related dimensions that reflect the essences of a PLC: Shared and Supported Leadership, Shared Vision and Values, Collective Learning and Application, Supportive Conditions, and Shared Personal Practice (Hord, 1996).

Race to the Top – A federal initiative under the Obama administration designed to improve assessments and develop more rigorous standards, adopt better progress-monitoring tools for school districts, assist in teacher school leader development, and place a greater emphasis on intervening in and improving low-performing schools (Boser, 2012.

Summative Data – Summative data are used to evaluate instruction. Summative data exist to classify, categorize, and label students' level of mastery and, as such, to classify, categorize, and label the teacher's instruction (Venables, 2014, p. 15).

Organization of Dissertation

Chapter 1 provided a succinct overview of the journey of reform within education in the United States and the need for purposeful DDI to improve academic achievement for all students. Terms such as Data Action Model, macro-data, and micro-data were defined to better

understand how they are used in this study. In addition, the statement of the problem on a national and local level was shared, the purpose of the study was introduced, and social capital theory as a theoretical framework was provided. Lastly, the significance of the study was explained.

Chapter 2 reveals the literature search procedures and criteria for research. This chapter also includes the literature behind all the variables connected to the students that can impact students' achievement. The goal is to understand how the variables impact student achievement and ultimately to isolate them and determine the impact of the main variable being evaluated. Chapter 3 reveals the research design of this study. This methodology section provides demographic information about the population that was included in the study. More importantly, this chapter provides the assessment instrument that will be utilized and the data collection and analysis of data. Chapter 4 provides the results in order to answer the research questions. This chapter also includes a summary of the results. Chapter 5 reiterates the findings for the three research questions addressed and shares recommendations for future research. This chapter also reveals policy recommendations for DDI for educators servicing students in Grades K-12 in small urban school districts.

CHAPTER 2

REVIEW OF THE LITERATURE

As the emphasis on accountability rises in public education, school districts are looking for practical and efficient approaches to improve instruction. NCLB (2002) and ESSA (2015) are two examples of legislation that have been designed to increase teacher accountability and ultimately improve student achievement for all. There has been an increase in studies examining effective PLCs, the use of DDI and the influence of both on student achievement. The school district utilized in this study adopted methods involving DDI and the use of a PLC for the purpose of trying to meet the required expectations under education legislation. DuFour (2004) proposed that schools should create an environment where “Every teacher team participates in an ongoing process of identifying the current level of student achievement, establishing a goal to improve the current level, working together to achieve that goal, and providing periodic evidence of progress” (p. 10).

This study looked at a district-level PLC that used a Data Action Model developed by Daniel R. Venables to improve instruction in mathematics for students in Grades 3, 6 and Algebra I. The goal of this literature review is to provide a historical framework around the use and impact of PLCs and data-driven decision-making approaches. The literature review for this quantitative study is divided into these sections: literature search procedures, criteria for research, literature surrounding the social capital theory as the theoretical framework, extensive literature review on PLCs, historical research on data-driven practices with a focus on VDAM, and research involving student variables and their impact on student achievement. This chapter also explores information on PSM, as it is at the heart of the quantitative analyses. PSM was used as a sampling methodology to provide valid data to answer the overarching research

question and limit overall selection bias.

Literature Search Procedures

A widespread and inclusive literature search was conducted with the goal of determining literature that offers the historical background for the elements of this study and places this background within its current and related context. This literature review was also intended to determine relevant theories and concepts directly connected to DDI and PLCs. Electronic sources were attained through educational databases such as JSTOR, ERIC, ProQuest, EBSCO, and an array of dissertation abstracts. Also, an examination of peer-reviewed journals, government reports, periodicals, and web-based searches was conducted to ensure all possible literature surrounding these topics was reviewed and taken into consideration when providing background.

The following keywords were employed to obtain pertinent research and literature: data-driven instruction, PLCs, data action models, Multi-Tiered System of Support, academic achievement, common planning time, socio-economic status and academic achievement, propensity score matching, mathematics achievement, race, gender, attendance and its relationship to academic achievement, school leadership, classroom instruction, teacher efficacy and evaluations. The above topics were searched in efforts to ensure sufficient research was incorporated into the literature review.

Criteria for Research

Standards for studies used in this literature review encompassed the following:

1. Qualitative, quantitative, and mixed-methods studies were reviewed and included in this literature review to yield information from all perspectives on the topics mentioned in this study.

2. To ensure validity and quality, only peer-reviewed research was examined in this this study.
3. The empirical studies that were examined for this study utilized school districts in a K-12 setting in the United States.

Theoretical Framework

The factors of social capital theory provide the theoretical framework for this quantitative study. The shift from teachers learning in isolation to the concept of the PLCs has been embraced in schools across the nation. The definition of a PLC and accomplishing a unified goal of improving student achievement directly connects to the root of social capital theory. Pierre Bourdieu, Robert Putnam, and James Coleman have been referred to as three critical leaders in the field of social capital theory; however, there are different definitions of and approaches to their theories. All three theories are different yet connect as it relates to unifying to accomplish a goal. Coleman (1988) defined social capital theory as a set of socio-structural resources:

> It is not a single entity but a variety of different entities, with two elements in common: they all consist of some aspects of social structures, and they facilitate certain actions of actors–whether persons or corporate actors-within the structure. (p. 98)

Putnam lengthened the definition by adding elements such as a sense of belonging, civic engagement, community cooperation, and norms of trust and reciprocity. Overall, Putnam expressed a strong belief that social capital is essentially the degree of trust available in a particular culture or society (Putnam, 1993, 2000). Lastly, Bourdieu (1986) explained social capital in terms of social networks and connections. Social capital, he said:

> is the aggregate of the actual or potential resources which are linked to possession of a durable network of more or less institutionalized relationships of mutual acquaintance

> and recognition- or in other words, to membership in a group which provides each of its members with the backing of the collectively owned capital. (p. 21)

In all three theories, there is one common theme of a shared vision and collaboration to meet the expectations of that vision. Having a shared vision is at the root of all effective PLCs. Social capital can be used to support many different pursuits in economics, politics, education, sociology, and anthropology. For the purposes of this research, the definition provided by OECD (2001) will be used: “networks together with shared norms, values, and understandings that facilitate cooperation within or among groups” (p. 41).

Social capital theory associates the productivity of an individual with the extent of social relationships and benefits received from them (Adler & Kwon, 2002). The concept of a PLC with the objective of improving academic achievement has a direct connection to all theories related to social capital theory. Peter Senge’s book *The Fifth Discipline* (1990) offered a new approach that embraced ideologies around social capital theory for both business and educational philosophy. He stated:

> The most successful corporation in the future will be a learning organization. Where people continually expand their capacity to create the results they truly desire, where new and expansive patterns of thinking are nurtured, where collective aspiration is set free, and where people are continually learning how to learn together. (p.3)

This notion was embraced and expanded on by researchers such as Hord (1996) and DuFour (2004), and much of their research support the effectiveness of PLCs.

Professional Learning Communities/Venables’ Data Action Model

An abundance of literature on PLCs has noted that school districts with efficient PLCs support and inspire teachers’ professional development and produce increased student

achievement (Newmann et al., 2000; Vescio et al., 2008; Wiley, 2001). The PLC that is utilized in this study used VDAM as the primary approach to improve academic performance in mathematics. This Data Action Model is a systematic process for reviewing and making instructional adjustments based on data in cycles of at least two weeks and up to a maximum of nine weeks. This method is considered to be teacher-friendly and can be repeated as many times as needed. The model enabled the PLC to identify serious learning deficiencies and related gaps in instruction, collaborate on resolutions and develop a goal-driven plan of action, and assess the effectiveness of the plan after execution and determine the next steps to take (Venables, 2014). Venables provided templates and protocols to focus and deepen data conversations. This guide delineates exactly what should be accomplished in each team meeting to translate data into practice. This model helped drive all meetings in which the PLC members engaged. VDAM required the members to follow the following list of meeting agenda items.

1. Review existing data (macro-data & micro-data)
2. Ask exploratory questions (decide on additional data needed)
3. Pursue additional data (triangulate)
4. Identify learning gaps (learner-centered problem—specifically, what is happening?)
5. Link to instructional gaps (problem of practice—what are we doing/not doing?)
6. Set goals & plan corrective action—what will we do/change?)
7. Plan evaluation measure (how will we know if our corrective plan is working?)
8. Implement corrective plan
9. Implement evaluation plan (adjust or move on). (Venables, 2014)

Venables (2014) asserted that often, teachers make decisions based on hunches, and although these hunches can sometimes be right, they can sometimes be wrong. VDAM helps teacher

teams slow down their decision-making to more accurately diagnose where students are and what should be done as a result. Looking at student and teacher work is a key part of what PLCs do (Venables, 2011). Venables asserted that the Data Action Model impels teacher teams to collaborate to find best solutions and strategies to improve student understating of material and ultimate achievement. He added that it is imperative for PLCs to focus on collaborating on identifying students' learning gaps and deciding on a plan of action to correct them (Venables, 2011). This concept extends the work of DuFour et al. (2006) in which they contend that the question we should be asking is not "are teachers collaborating?" but instead "what are they collaborating about?"

According to the research, the PLCs that use formative data, data used to inform instruction, and a schedule that is developed to allow teachers to work in a collaborative environment will foster an environment for best practices (DuFour et al., 2006; Fink & Resnick, 2001; Fullan & Hargreaves, 1991). At the root of the PLC is the opportunity for PLC members to have common planning meetings on a regular basis. This same philosophy is applied to meet the expectations of the VDAM. A seminal report, *This We Believe: Keys to Educating Young Adolescents* (National Middle School Association, 2010), examined the significance of planning collaboratively during a common planning session and how this is essential for planning curriculum, assessing student work samples, engaging in discourse surrounding current research-based approaches, and finally reflecting on best instructional practices., A study conducted by Cook and Faulkner (2010) looked at educators using common planning sessions in two different interdisciplinary groups in Kentucky. In both schools, common planning time was regarded as critical to the school's achievement. The study showcased the importance of scheduling interdisciplinary team planning meetings, grade level planning sessions, and PLCs for the entire

school. Vescio et al. (2008) examined 11 studies that featured the impact of PLCs and in their findings; they included collective results of various studies related to PLCs. Their study addressed the following research questions: in what ways does teaching practice change as a result of participation in a PLC? And, what components of the PLCs support these changes? Their second main question was: does the literature support the belief that student learning improves when teachers participate in a PLC? And, what aspects of the PLCs support improved student learning? The authors found that PLCs have an impact on student learning. The findings provided preliminary evidence of the benefit of the learning communities for teachers and their students. This is a result of teachers becoming more student centered and because PLCs increase collaboration and continuous learning on the part of the teachers (Vescio et al., 2008).

A few years before the study by Vescio et al., the Annenberg Institute for School Reform (2004) analyzed their work with PLCs for the purpose of improving professionalism in school cultures. They noted that in order to address inequities and improve student achievement for all, implementation of a district-wide approach would yield the best results. The authors provided evidence to support improving professional culture and more specifically identified aspects of the PLC that encouraged improvement. They cited the importance of ensuring that the PLC has a focus on issues of trust and equity, capacity, collaborative leadership, and ensuring focus on instruction. Furthermore, they highlighted that in school-based teams that included grade- and content-level meetings that focused on instructional adjustments, there was dramatic improvement in student performance by the end of the year. This research was similar to that of Vescio et al. (2008) in which six studies showed that PLC had an impact on student achievement. The role of PLCs has become more important as educators adjust to the new national system of the Common Core State Standards (CCSS, 2011), according to which the most prevalent

requirement of educators is obtaining individual teacher capacity in content knowledge and pedagogy to effectively implement learning for all of their students (Fullan & Hargreaves, 1991). Bolam et al. (2005) and Louis and Marks (1998) uncovered that higher student performance was associated with their teachers being part of strong learning communities.

Data-Driven Instruction

The concept of diagnosing the problem and then fixing it is becoming the most dominant approach when working towards closing the achievement gap. Data-driven approaches are being used to turn around schools and drive a teacher's lesson plans from day to day. Today, data is seen as a primary component for closing the achievement gap (Noell & Gansle, 2006). Mandinach (2012) stated, "data-driven decision-making (DDDM) pertains to the systematic collection, analysis, examination, and interpretation of data to inform practice and policy in educational settings" (p. 71). Fulton (2003) stated:

> The current factory-model school, while seemingly efficient, is, in fact, grossly inefficient, inappropriate and ultimately inequitable, as it requires that all children adapt to the mean. Those who do not learn at the speed of the assembly line lose out and/or drop out; those who could learn more do not. Individualizing instruction for each learner is no longer a dream–it is an educational birthright for all children. (p. 32)

School districts have established different systems to meet the mandates for improving academic achievement, DDI being one of the main approaches. No longer is letting students fall behind the expected standard an option; in fact, NCLB required that 100% percent of students acquire a proficient or above result on required state math and reading tests by the 2013–2014 academic year. Although this mandate was not realized by many school districts, it did not stop school districts from working toward trying to uncover methods to meet this mandate. It is

understood that students learn through the learning opportunities that are provided by their instructors. Educators know that learners differ in many ways; therefore, educators understand the need for differentiated instruction. Cowan (2009) reviewed the practice of implementing interventions in different school settings and emphasized the relationship between data collection and appropriate intervention for at-risk students. He concluded that the most successful intervention programs are those based on proper data analysis.

According to Carlson et al. (2011), there are three large-scale empirical analyses that focus on DDI. One of the studies, which was conducted by May and Robinson (2007), evaluated Ohio's Personalized Assessment Reporting System (PARS) for the Ohio graduation test. This study found statistical significance in achievement improvement connected to data-driven decision-making. Students who initially failed the Ohio graduation test produced statistically significant results on the PARS when retested after receiving personalized instruction from their teachers. By utilizing data to drive their instruction, teachers were better suited to meet the individual needs of the students as they prepared to retest. Students in districts that used PARS were 4 times more likely to retake the test and scored higher than theirs peers in districts that did not operate under the PARS System. DDI is considered a form of differentiated instruction because it involves the teaching of "the same standard to a range of learners by employing a variety of teaching and learning modes" (Tomlinson, 2000, p. 9) that are needed by the learner. Differentiated instruction has become key to ensuring students' individual needs are met, whether it is learning style, prior knowledge, multiple intelligence, personal preference, or social/emotional development. Students are different, and it and it is up to the educator to determine the appropriate methods to educate that student. A study conducted by Carlson et al. included seven states and up to 60 school districts. The researchers determined that data-driven

reform efforts result in substantial and statically significant improvement in academic achievement. They contended that their study provided the best evidence to date as it relates to this outcome. Based on this research, there has been an increase in various strategies for improving public schools, such as development of student assessments and the use of data systems for higher levels of accountability (Carlson et al., 2011).

Schools that support organizational learning tend produce teachers who incorporate data into their decision-making (Carlson & Turner, 2011). Black and William (1998) contended that students' performance can be improved 20% to 40% if teachers utilize formative assessments on a regular basis and modify their instruction accordingly.

Propensity Score Matching

PSM is an approach to statistical analysis developed by Rosenbaum and Rubin (1983), and it is intended to balance the distribution of the observed covariates between the controlled and treatment groups in efforts to increase the weight of a causal inference in an observational study (Bai, 2011). According to Bai (2011), a propensity score is determined, and is used to reduce the selection bias by balancing groups and developing matched pairs, and this allows for direct comparisons. This study used matched sampling to increase the validity of causal inferences. Matched sampling is a method for selecting units of the sample from a large pool of potential samples to produce a sample group that is similar to a treated group with respect to the distribution of observed covariates. PSM has been commonly used in various fields of study; however, it has recently become a method utilized in education (Lane & Henson, 2010). Randomly assigning instructional methods to different students would be unethical because all students should receive the best instructional practices available at the time. Therefore, utilizing matched sampling was the best option for this study.

School Variables: Factors Influencing Mathematics Achievement

Several factors in addition to making data-driven decisions regarding instruction may influence student achievement. These variables, identified in the literature, may include but are not limited to gender, SES, ethnicity, teacher evaluation rating and attendance, and student attendance. The combination of these variables in addition to the teachers' involvement in a district-wide data-driven PLC may influence student achievement. This literature review provides a deeper understanding of the variables that can impact students' achievement. Examining other student variables was a necessity, as research in this literature review shows they may have an impact on student achievement.

Teacher Efficacy

Greater attention has been given to the role that the quality of teacher pedagogy plays in student students' academic achievement. This is attention is due to the evolution of standards for learning in various states (National Commission on Teaching and America's Future, 1996). Previous research has supported that "schools bring little influence to bear upon a child's achievement that is independent of his background and general social context" (Coleman et al., 1966, p. 325). Research suggests that, among school-related factors, teachers have one of the greatest impacts. When it comes to student performance on mathematics and reading tests, a teacher is estimated to have the dominant impact over any other school factor, such as class size, facilities, and a principal's leadership (Chetty et al., 2014).

Sanders and Rivers (1996) completed a study in which they evaluated teacher impact on student performance on statewide exams in Tennessee. The outcome of the study revealed that teachers had a strong effect on student achievement. In fact, the study revealed that students instructed by high-performing teachers who were rated highly effective over three years in a row

scored about the 95th percentile on state mathematics assessments. In addition, students who were instructed by teachers rated ineffective for three years in a row were not as successful and scored below the 50th percentile on the same assessment.

Evaluations/Student Growth Percentile

New Jersey enacted the TEACHNJ Act in August 2012, and this was a major change to tenure laws within the education system. Determining whether a teacher receives tenure or not would depend on his or her evaluation score, and guaranteed tenure for the reminder of a teacher's career no longer existed. According to Title 18A Chapter 6, the legislature finds and declares:

> The goal of this legislation is to raise student achievement by improving instruction through the adoption of evaluations that provides specific feedback to educators, informs the provision of aligned professional development, and informs personnel decisions; The New Jersey Supreme Court has found that a multitude of factors play a vital role in the quality of a child's education, including effectiveness in teaching methods and evaluations. Changing the current evaluation system to focus on improved student outcomes, including objective measures of student growth, is critical to improving teacher effectiveness, raising student achievement, and meeting the objectives of the federal No Child Left Behind Act of 2001. (Teacher Effectiveness and Accountability for the Children of New Jersey [TEACHNJ] Act, Chapter 26, 2, 2012)

In efforts to support the new tenure laws, New Jersey changed the teacher and administrator evaluation system to include both teacher practices and student achievement. Student achievement measures consisted of student growth objectives (SGOs), and depending on the grade and subject one taught they could receive a Student Growth Percentile (SGP) as well.

The combination of the two determines the teacher and administrator summative rating. This change was one of the many changes of AchieveNJ. The 2013 academic year was the first year New Jersey implemented SGPs. An SGP shows a student's growth over the course of an academic year compared to students who earned similar test scores the prior year. It formally compares their growth to the growth of their academic peers. This process is perceived as complex; however, the information learned provides valuable information for evaluators (TEACHNJ, 2012).

New Jersey was not the first state to implement teacher evaluations inclusive of teacher practice and student performance. Tennessee implemented a similar practice and found that it had a positive impact on student achievement. The state mandated that 50% of teacher evaluations would be based on student performance in mathematics, science, and language arts assessments (Piro et al., 2011). During the initial year of implementation, it was reported that state assessment scores improved drastically. It was reported by administrators that this new evaluation system had a positive impact on instructional practices and student achievement (Tennessee Department of Education, 2012).

Race/Ethnicity

Race/ethnicity is a variable that has played a significant role when understanding elements that influence student achievement. Differences in academic achievement across racial groups has been a topic of interest since the Coleman report. According to the Coleman report, there was a significant gap between minorities and their White peers, but more importantly, the gap widened as students continued their studies. Evidence showed an increase in the achievement gap as students moved from Grade 6 to Grade 12 (Coleman et al., 1966). Coleman and his team were the first to document the disparities between various ethnic groups of students;

African American children were multiple grade levels behind their White counterparts in school. This disparity was later to be known as and called the achievement gap. In this report, SES was deemed the strongest predictor concerning student achievement. It also became known that the performance of poor children, both Black and White, straggled behind that of more affluent white students. Often, race and ethnicity are aligned with socioeconomic background; however, there is a large body of research that speaks to race and ethnicity specifically and its connection to student achievement. Researchers such as Hampden-Thompson (2009) and Howard (2010) among others have affirmed race as being a critical factor in the achievement gaps that exist among various races. The National Assessment of Educational Progress (as cited in Bandeira de Mello et al., 2009) stated that by the end of fourth grade, African American, Latino, and poor students of all races are at least two years behind their White and Asian non-poor counterparts. Furthermore, by eighth grade, those same students have slipped three years behind, and this pattern continues as students progress in grade level.

Notwithstanding years of restructurings targeted at closing racial gaps in achievement, there continues to be a correlation between students' mathematics performance and race. This is evidenced by a meta regression analysis by Mickelson et al. (2013) in which

> the data indicate that some of the gaps among the racial groups increase as students' progress from elementary through secondary school. Interracial gaps change as students advance in school. The Black-White gap grows by 11 points between Grades 4 and 12, the White–Asian gap grows by 8 points, and the Latino/a–White gap grows by 10 points. (p. 123)

Socioeconomic Status

As Bloom et al. (2008) have explained, “Significant gaps in achievement between student population groups: The Black/White, Hispanic/White, and high-poverty/low-poverty gaps are often close to one standard deviation in size” (p. 172). According to the American Psychological Association (n.d.), “Socioeconomic status (SES) encompasses not just income but also educational attainment, financial security, and subjective perceptions of social status and social class. Socioeconomic status can encompass quality of life attributes as well as the opportunities and privileges afforded to people within society.”

According to the U.S. Department of Agriculture (n.d.), qualifying for free or reduced lunch is based upon family income level. There is a long history of SES being reported to correlate with educational achievement. Students who are products of parents with lower reported income are more likely to underachieve as compared to their more affluent peers (Dishman-Horst & Martin, 2007; Taylor, 2005). According to the National Commission on Children (1991), several factors contribute to the lower academic achievement of minority students: Minority students are more likely to live in low-income households or single-parent families, their parents are more likely to have less education, and they attend underfunded schools. All of these factors are components of SES and connected to academic achievement (National Commission on Children, 1991).

Current research supports the Coleman report and adds to the literature surrounding SES having a significant impact on student achievement (Mickelson et al., 2013; Schwartz, 2011. Schwartz (2011) conducted a longitudinal study that lasted from 20012007. The study examined the impact of the inclusionary zoning program of Montgomery County, Maryland, on the achievement gap. The researcher noted that academic achievement decreased as the percentage

of students qualifying for free and reduced lunch increased. Ultimately, this study is consistent with research supporting that there is a direct correlation between SES and students' academic performance levels. More significantly, the study concludes that "economic integration could be a more effective tool to improve the achievement of low-income students over the long run than even well-designed and sustained interventions such as the one Montgomery County has made in its most impacted schools" (p. 33).

Attendance

There is a general understanding that there is a direct connection between school attendance and students' academic performance. This topic has been well researched over an extended period. Research shows that students who have high absentee rates score lower on high-stakes state assessments than their peers with regular attendance rates. Gottfried (2009) conducted a study using multilevel, longitudinal data from 19942000, consisting of all students in Grades 24 in the Philadelphia School District. He separated excused and unexcused absences to see if there was a difference in impact. The researcher uncovered that the absence had a negative impact on student achievement despite whether it was excused or unexcused. If a student is not present to learn material, it will have a lasting impact on their performance. As the number of absent days increase, student performance decreases.

There is also research that supports that attendance may be a predictor of future academic performance. In addition, students who consistently show a pattern of truant behavior will not only fall behind academically but will also begin to show challenging behavior within their various communities (Aden et al., 2013). According to Archambault et al. (2013), adults who have proven to be chronically absent from school are more likely than others to experience teen pregnancy, be incarcerated, live in poverty, and work in low-paying positions (Archambault et

al., 2013).

Recent studies continue to show a significant pattern between student attendance and academic performance. Parke and Kanyongo (2012) reviewed the effect of attendance and mobility on mathematics achievement in students in Grades 112. There were 32,000 participants in this study, which revealed that mobility and low attendance have an adverse impact on achievement, and, more specifically, mathematics achievement. The researchers also indicated that various ethnic subgroups presented comparable trends related to attendance and mathematics achievement (Parke & Kanyongo, 2012).

Gender

Gender is a variable that has been researched when investigating the various impacts and influences on student achievement. Although there is a wealth of research in this area, Pope et al. (2006) asserted that gender accounts for only a minute amount of variance in assessments outcomes between males and females. Test scores and grades are frequently measures for mathematics achievement at the K-12 level. Gender differences vary in an interesting way when comparing test scores vs. grades. Male and female students perform similarly when it comes to overall academic performance; however, girls have higher grade point averages in science, technology, engineering, and mathematics, while boys have higher test scores (Britner, 2008 Saunders et al., 2004).

Matthews et al. (2009) asserted that when looking at gender there was no significant difference uncovered on five academic outcomes as measured by the Woodcock–Johnson III Tests of Achievement. The academic ability and acumen of females and males in subjects related to mathematics shows little to no difference (Jacobs, 2005; Mickelson, 1989). Later research has supported the trend that there is little difference in gender performance on state assessments.

Despite the fact that females are underrepresented in math and science fields, females perform as well as boys on standardized mathematics assessments, (Hyde et al., 1990).

Summary

The literature reviewed advocates the need for PLCs to help with educational reform efforts and the importance of using data to drive instruction. However, there is limited research on the efficacy of VDAM, and this study can add to and enhance the existing body of research surrounding data-driven decision-making through VDAM. Chapter 3 details the methodology that was utilized in this study.

CHAPTER 3

METHODOLOGY

The purpose of this quantitative study was to examine the influence of a district-wide implementation of VDAM on the performance of students on the mathematics section of the 2018 PARCC assessment in XYZ school district. More specifically, it sought to answer the question: Is there a difference in influence on student mathematics achievement between students who were instructed by teachers participating in the VDAM PLC versus students whose teachers were not participating in the PLC when other covariates are controlled? Subsequently, this study will review the influence of other student-related variables such as gender, SES, attendance, race/ethnicity, and status as Special Education and/or ELL. In addition to the student variables, this study will also control for teacher-related variables such as teacher performance ratings, attendance, educational level and years of experience.

The district in this study used a combination of research surrounding PLCs and DDI to develop the plan for this PLC. Daniel R. Venables is the author of *How Teachers Can Turn Data into Action and The Practice of Authentic PLC, A Guide to Effective Teacher Teams*. Much of his work focuses on data-driven decision-making and PLCs. This study explored how the use of these two educational approaches influences student learning in mathematics. This study will help district leaders make instructional decisions that will help them meet expectations around various federal mandates.

VDAM is a teacher-friendly way of looking at data as a team and addressing the needs of students. Earlier studies that have examined the influence of data-driven teaching on various grade levels in K-12 school districts, such as Davis Bianco (2010), have not incorporated the use of a district-wide PLC supporting teachers through the process. This study sought to add to the

body of research surrounding teachers' use of data to drive instruction while collaborating within a structured PLC. This chapter reveals the procedures and methods used to examine the influence of VDAM on the mathematics PARCC scores in a small urban district. The methods and procedures are discussed in the following sections: Research Questions, Null Hypotheses, Research Design, Sample and Population Data Sources, Data Collection Instrumentation, and Data Analysis.

Research Questions

This study was guided by the following research questions:

Research Question 1: Is there a difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the VDAM and students who were not assigned to participating teachers in Grade 3 when controls for both student and teacher demographic information are applied?

Research Question 2: Is there a difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the VDAM and students who were not assigned to participating teachers in Grade 6 when controls for both student and teacher demographic information are applied?

Research Question 3: Is there a difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the VDAM and students who were not assigned to participating teachers in the Algebra I course when controls for both student and teacher demographic information are applied?

Null Hypotheses

Null Hypothesis 1: There is no difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the VDAM and students who were not assigned to participating teachers in Grade 3 when controls for both student and teacher demographic information are applied.

Null Hypothesis 2: There is no difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the VDAM and students who were not assigned to participating teachers in Grade 6 when controls for both student and teacher demographic information are applied.

Null Hypothesis 3: There is no difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the VDAM and students who were not assigned to participating teachers in the Algebra I course when controls for both student and teacher demographic information are applied.

Research Design

This study used a comparative, non-experimental, cross-sectional explanatory quantitative methodology, which is one approach of inquiry used to answer questions about relationships among variables. Quantitative studies are intended to create controlled environments to predict and explain phenomena (Gay et al., 2009). Prior to the start of the study, students were enrolled in Grades 3, 6, and 9 mathematics classrooms where they were instructed by VDAM teachers or non-VDAM teachers. This prevented the researcher from ensuring that

students were randomly placed. There are many factors that could have contributed to the placement of the students, such as parent preferences or prior classroom placement, and this have could potentially biased the sample.

PSM was used to establish the sample in order to reduce selection bias and replicate a randomized design. The sample came from multiple schools in an urban district in northern New Jersey. The subjects were instructed by teachers who participated in the district-wide PLC that had a focus on VDAM. According to Dehejia and Wahba (2002), "pairing student units provides a natural weighting scheme that yields unbiased estimates of the treatment impact" (p. 151). PSM allows comparison groups that are similar on multiple significant variables except for the treatment variable (Gay et al., 2012). This study reviewed the 2018 mathematics PARCC results and the way these results might have been influenced by VDAM. Descriptive statistical methods were used to compare the independent and dependent variables. In combination with PSM for selecting the sample, multiple regression analysis, factorial ANCOVA, and logistic regression were used to answer the three research questions.

Sample and Population/Data Source

The participants of this study were selected from multiple schools in an urban district in northern New Jersey. To ensure anonymity, the specific city are not identified, and the schools are labeled with a non-identifier. According to the United States Census Bureau, The City of XYY has a population of approximately 30,813 residents, 11,471 households, and an average of 2.64 persons per household. The racial makeup of the township is approximately 72.7% black, 10.9 white, 0.3% American Indian, 22.6% Hispanic or Latino, 1.4 % Asian, 0.1% Pacific Islander, and 1.5% identifying two or more races. The median household income is $35,895, and 25.1% of the residents are considered impoverished. The per capita income for the township is

$20,140. The district is comprised of 11 schools and serves about 6,131 students in pre-K through Grade 12. The district has one pre-kindergarten school, seven elementary schools that consist of grades p-reK-7, one middle school, and two high schools. The district is classified by the New Jersey Department of Education as being in DFG A. According to the New Jersey Department of Education, DFGs were developed in 1975 with the intent of comparing demographically similar school districts' performance on statewide assessments. The categories are developed based on the Census Bureau and updated every ten years. From lowest SES to highest, the categories are A, B, CD, DE, FG, GH, I, and J (New Jersey Department of Education, 2004).

For the purposes of this study, the sample population came from eight schools within the district. Three grade levels were selected to participate: third grade, sixth grade, and Algebra I students.

Propensity Score Matching (Sampling Protocol)

The final sample utilized in the study was determined using PSM. As Randolph et al. (2014) have explained: "Propensity Score Matching is a statistical technique in which a treatment case is matched with one or more control cases based on each case's propensity score" (p. 1). By using PSM, an argument can be strengthened in a quasi-experimental design because selection bias is reduced, and the sampling process better replicates a randomized design. According to Rosenbaum and Rubin (1983), non-randomized samples may have major differences from one another depending upon the covariates. When the differences are not factored in, selection bias may rise and the researchers may analyze treatment effects which may or may not be influenced by group differences that exist because of lack non-randomization. By utilizing PSM, researchers can control for group differences when estimating treatment effects

(Lane & Henson, 2010). A propensity score is a single summary score that represents the relationship between multiple observed characteristics for group members and treatment group assignments (Rudner & Peyton, 2006).

Data Analysis

In this quantitative study, multiple regression models were utilized to understand the influence participation in the VDAM PLC had on the 2018 mathematics PARCC scores. According to Balkin (2008), the power of a study is dependent upon sample size, effect size, and alpha level. Power is influenced by error: the less error measured in a study, the more power. For multiple regression, the typical formula for sample size is 104 + k where k represents the number of independent variables the study controlled for (Field, 2013). Consequently, the minimum sample size for this study was 118 (104 + 14 = 118) in order to account for enough statistical power to utilize the 95% confidence level and at least .50-effect size. For the purposes of this study, the unit of analysis will be the student. Table 2 and Table 3 speak to the coding used for the Statistical Package for the Social Sciences (SPSS) analysis and the independent and dependent variables.

The primary analyses, multiple regression, sample *t* test and one-way ANOVA, were employed to determine the effect of the independent variables (treatment, gender, SES, race/ethnicity, attendance, and teacher variables (performance evaluation, attendance, years of experience) on the dependent variable, performance on the mathematics portion of the 2018 Grades 3, 6, and Algebra I PARCC Assessments.

Table 2

Student Variables–Coding for SPSS Analysis

Student Variable	Measure	Coding
SES/Free and Reduced Lunch Eligible	Nominal/Dichotomous	0 = No, 1 = Yes
Gender	Nominal/Dichotomous	0 = Male, 1 = Female
Taught by Teacher in the VDAM PLC	Nominal/Dichotomous	0 = No, 1 = Yes
Attendance	Scale	Number Indicated
Ethnicity	Nominal/Categorical	0 = Black 1 = Asian 2 = Hispanic 3 = White 4 = Multiracial
Days Absent	Scale	Number Indicated
PARCC Scores	Scale	Scores Indicated
Classified Special Education	Nominal/Dichotomous	0 = does not receive SPED services, 1 = does receive SPED
ELL	Nominal/Dichotomous	0 = does not receive ELL services, 1 = does receive ELL services
Final Math Grade	Scale	Scores Indicated

Table 3

Teacher Variables–Coding for SPSS Analysis

Staff Variable	Measure	Coding
Attendance	Scale	Number Indicated
Participated in the VDAM PLC	Nominal/Dichotomous	0 = No, 1 = Yes
Teacher Rating	Scale	Scores Indicated
Years of Experience	Scale	Scores Indicated
Education Level	Scale	Scores Indicated

Instrumentation/Reliability/Validity

The instrument used for this study is a statewide assessment administered yearly. The 2018 PARCC assessment is aligned to the New Jersey Student Learning Standards for Mathematics and was first administered during the 2014-2015 school year. During its first school year of implementation, 98% of the students took the PARCC examination online (Heyboer, 2015). According to the New Jersey Department of Education (2016),

> The (PARCC) assessments are aligned to high-level thinking skills and were created to measure students' ability to apply their knowledge of concepts rather than repeat memorized facts. The PARCC assessments for mathematics require students to solve problems using mathematical reasoning and to be able to model mathematical principles. In English Language Arts (ELA), students are required to closely read multiple passages and to write essay responses in literary analysis, research tasks, and narrative tasks.

The total score is used to classify students in terms of college and career readiness as it relates to their progress throughout their K-12 experience. The levels are called performance levels, and are broken down as follows: Level 5: Exceed Expectations, Level 4: Met Expectations, Level 3: Approached Expectations, Level 2: Partially Met Expectations, and Level

1: Did Not Meet Expectations. In order to show that they are on level, students must receive a 4 or better on the PARCC in the state of New Jersey. Yearly, following the spring administration of the PARCC examination, Pearson releases the technical report on the reliability and validity of the previous year's examination.

The PARCC assessments are intended to evaluate students' levels and provide yearly evidence as to whether students are on track to be successful in college. This success will be predicated upon their mastery of the NJSLA standards, which were developed with college readiness at the forefront. These assessments are structured to access the full range of NJSLS and access the total ability of student performance. This state test provides macro-data that will help teachers evaluate student abilities and develop a plan that will place them on a trajectory for academic success.

Data Collection

After presenting the study to the curriculum committee of XYZ school district and completing the IRB process, the Board of Education and the Assistant Superintendent of Schools granted permission to the researcher to use all requested resources. Once permission was granted by the Assistant Superintendent, data were collected by the Director of Curriculum and the Director of the Mathematics and shared via an Excel sheet. Each participant, both students and teachers, was assigned a number for anonymity and confidentiality. The data shared contained information from the 2016-2017 school year and the 2017-2018 school year. Student records with missing data were omitted from the study.

Conclusion

The best possible sample was selected by using PSM to reduce selection bias. By using multiple levels of analysis, the three research questions were answered to determine the influence

of VDAM on the 2018 mathematics PARCC Assessment scores. Chapter 4 includes the SPSS tables and the interpretation of these results. Significance was based on the .05 significance level to determine if the variable of interest had a significant impact on the 2018 PARCC assessment in mathematics. Finally, Chapter 5 includes recommendations for best practices as related to DDI and the use of PLC at the district level. Chapter 5 will also discuss recommendations for further research related to these two topics.

CHAPTER 4

ANALYSIS OF THE DATA

Chapter 4 offers the findings and results of this study, which address the problem and research questions proposed in Chapter 1. The purpose of this comparative, non-experimental, cross-sectional explanatory quantitative study was to examine the impact of utilizing VDAM design in XYZ school district on the mathematics section of 2018 PARCC in Grade 3, Grade 6, and Algebra I. Subsequently, the study assessed the influence of additional student-related variables such as SES, gender, ethnicity, attendance, and status as Special Education and/or ELL. Additionally, this study controlled for teacher-related variables such as teacher performance using an end-of-year evaluation rating, educational level, and years of experience.

Ultimately, this study was designed to add to the body of research-based evidence related to the academic performance in mathematics of students who are taught by teachers who engage in PLCs focused on data-driven instruction (DDI). This chapter includes a review of the research questions and null hypotheses that guided the study. When applicable, the degree and validation of results and statistical significance are presented. The qualifying experimental treatment sample (N = 222) and alternative sample (N = 222) consisted of third grade, sixth grade, and Algebra I classes from eight schools in XYZ school district.

Research Questions and Null Hypotheses

Specific individual SPSS analyses were used to answer the following research questions:

Research Question 1: Is there a significant difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the Venables' Data Action Model and students

who were not assigned to participating teachers in Grade 3 when controls for both student and teacher demographic information are applied?

Null Hypothesis 1: There is no difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the Venables' Data Action Model and students who were not assigned to participating teachers in Grade 3 when controls for both student and teacher demographic information are applied.

Research Question 2: Is there a difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the Venables' Data Action Model and students who were not assigned to participating teachers in Grade 6 when controls for both student and teacher demographic information are applied?

Null Hypothesis 2: There is no difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the Venables' Data Action Model and students who were not assigned to participating teachers in Grade 6 when controls for both student and teacher demographic information are applied.

Research Question 3*:* Is there a difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the Venables' Data Action Model and students who were not assigned to participating teachers in Algebra I when controls for both student and teacher demographic information are applied?

Null Hypothesis 3: There is no difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the Venables' Data Action Model and students who were not assigned to participating teachers in Algebra I when controls for both student and teacher demographic information are applied.

Analysis and Results

Based on the original sample, a total of 1,091 students from third grade, sixth grade, and Algebra I classes were included. This sample was drawn from eight schools in a small urban school district. The sample was limited to students with 2018 PARCC mathematics assessment scores for their respective grades and having complete demographic data, thereby resulting in a total of 1,049 students. Independent variables included SES, gender, ethnicity, attendance (days absent), 2018 final mathematics grades, and treatment status (students who did or did not receive instruction from teachers participating in VDAM PLC. The original sample was composed of 536 males and 513 females. Of the students, 416 were third graders, 364 were sixth graders, and 269 were enrolled in an Algebra I course. Of the total sample, 827 students were taught by teachers who did not participate in VDAM and 222 students were taught by teachers who participated in the district-level PLC that used VDAM for DDI.

In addition to VDAM participation, the teacher's years of experience, performance rating, and degree level were included within various models for analyses. As discussed in Chapter 2, research has shown these variables can influence achievement for students in mathematics. Teachers with a BA taught 468 students and teachers with an MA taught 581 students. The average years of experience for all teachers involved in the study was m = 12.8 and the average evaluation rating for all teachers involved in the study was m = 3.25 with a maximum of 4. Of

the students, 766 received free and reduced lunch while 283 did not. The number of general education students was 928, and 121 students were classified as students with disabilities. Sixty students were classified as ELLs, and 989 students were not. Table 4 displays student-level variables and how they were coded in SPSS. Table 5 shows teacher-level variables and how they were coded in SPSS.

Table 4

Student Variables–Coding for SPSS Analysis

Student Variable	Measure	Coding
SES/Free and Reduced Lunch Eligible	Nominal/Dichotomous	0 = No, 1 = Yes
Gender	Nominal/Dichotomous	0 = Male, 1 = Female
Taught by Teacher in the VDAM PLC	Nominal/Dichotomous	0 = No, 1 = Yes
Attendance	Scale	Total number of days student was not present in school out of a possible 180 school days.
Ethnicity	Nominal/Categorical	0 = Black 1 = Asian 2 = Hispanic 3 = White 4 = Multiracial
PARCC Scores	Scale	Scores Indicated, Range 650-850
Classified Special Education	Nominal/Dichotomous	0 = does not receive SPED services, 1=does receive SPED
ELL	Nominal/Dichotomous	0 = does did not receive ELL services, 1 = does receive ELL services
Final Math Grade for 2018	Scale	Scores Indicated, Range 50-100

Table 5

Teacher Variables–Coding for SPSS Analysis

Staff Variable	Measure	Coding
Participated in the VDAM PLC	Nominal/Dichotomous	0 = No, 1 = Yes
Teacher Rating	Scale	Scores Indicated Range 1.0 (Ineffective) to 4.0 (Highly Effective)
Years of Experience	Scale	Scores Indicated
Education Level	Ordinal	Scores Indicated 1 = BA, 2 = BA15, 3 = MA, 4 = MA32

Propensity Score Matching

The final sample used for statistical analysis in this study was identified using PSM. This approach was used to mimic a randomized design methodology and to reduce sampling bias. PSM, developed by Rosenbaum and Rubin (1983), endeavors to increase the legitimacy of causal inference from observational studies by leveling the distribution of the observed independent variables between the treatment and control groups (Bai, 2011). Along with the ability to compare student academic achievement in this manner, PSM offers the artificial structure of a randomized design methodology, which has been well-established as being one of the soundest methodologies of all research designs (Goodman & Blum, 1996).

PSM further creates statistically equivalent clusters created through match sampling as opposed to randomly assigning students to various classes or teachers, which could be impractical, and, in some cases, unethical. PSM enables educational researchers to employ a statistical analysis strategy that has been widely used in many other fields, and it helps to minimize the impact of selection bias (Lane & Henson, 2010). For this study, all student and teacher data were collected by XYZ district’s data administrator and entered into an Excel file where the data were scrubbed and anonymized.

This non-experimental, cross-sectional explanatory research design matched students from the control group (students with teachers who did not participate in VDAM) with students from the treatment group (students who were instructed by teachers who participated in VDAM). The final file was uploaded into SPSS, dummy-coded, and used for the purpose of obtaining descriptive information and analytical results.

After applying PSM against seven independent student-level variables: gender, SES, ethnicity, Special Education classification, ELL status, attendance, and final grades and four independent teacher-level variables: years of teaching experience, education level, annual performance rating, and their status in the VDAM professional learning community, 444 students were paired within the final sample (222 students in the final treatment sample and 222 in the final control sample). Application of PSM resulted in a sample of 96 Algebra I students (48 treatment/48 control), 210 sixth-grade students (105 treatment/105 control), and 138 third-grade students (69 treatment/69 control) to make a total of 444 participants in the sample. Descriptive statics are found in Tables 6, 7, and 8.

Table 6

Descriptive Statistics of Propensity Score Matching Sample (Grade 3 Students)

Demographics	N	Percent
Gender		
Male	74	53.6
Female	64	46.4
English Language Learner		
No	132	95.7
Yes	6	4.3
Student w/Disability		
No	120	87
Yes	18	13
VDAM Teacher		
No	69	50
Yes	69	50
Economic Disadvantage Status		
No	40	29
Yes	98	71

Table 7

Descriptive Statistics of Propensity Score Matching Sample (Grade 6 Students)

Demographics	N	Percent
Gender		
Male	114	54.3
Female	96	45.7
English Language Learner		
No	205	97.6
Yes	5	2.4
Student w/Disability		
No	120	87
Yes	18	13
VDAM Teacher		
No	105	50
Yes	105	50
Economic Disadvantage Status		
No	52	24.8
Yes	158	75.2

Table 8

Descriptive Statistic of Propensity Score Matching Sample (Algebra I Students)

Demographics	N	Percent
Gender		
Male	114	54.3
Female	96	45.7
English Language Learner		
No	205	97.6
Yes	5	2.4
Student w/Disability		
No	120	87
Yes	18	13
VDAM Teacher		
No	105	50
Yes	105	50
Economic Disadvantage Status		
No	52	24.8
Yes	158	75.2

Research Question 1: Analysis and Results

Research Question 1: Is there a significant difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the VDAM and students who were not assigned to participating teachers in Grade 3 when controls for both student and teacher demographic information are applied?

Null Hypothesis 1: There is no difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the VDAM and students who were not assigned to participating teachers in Grade 3 when controls for both student and teacher demographic information are applied.

An independent samples *t* test was conducted on the third-grade sample determined by PSM as seen in Tables 9 and 10 to answer the first research question as it relates solely to the

treatment variable. The 2018 PARCC mean scale score for the VDAM Treatment group (N = 69) was 734.10 (SD = 34.379). The 2018 PARCC mean score for the students who were not connected to the non-treatment group (N = 69) was 732.71 (SD = 33.006). The Levene's test, used to check the assumption of homogeneity of variance, was not statistically significant (F = 0.358, p = 0.551). This indicates that the error variance of the dependent variable, performance on the 2018 mathematics PARCC assessment, is equal across groups (Leech et al., 2013. (See Table 8). The independent samples *t* test, (t(136) = -0.242, p = 0.809), showed that there is no significant difference in the level of academic achievement in mathematics as measured by the 2018 PARCC assessment between students who were instructed by teachers who were part of the PLC that utilized the VDAM and students who were not instructed by participating teachers in Grade 3 when controls for both student and teacher demographic information are applied.

Table 9

Independent Sample t Test for Grade 3 2018 Mathematics PARCC Scores by Treatment Group

						95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
PARCC Math Test Scale Score	-0.242	136	0.809	-1.391	5.737	-12.737	9.955

A simultaneous multiple regression was run as a follow up to the independent samples *t* test to determine further analysis of the first research question. The purpose was to determine the amount of influence the independent variables of gender, ethnicity, SES, status as an ELL student, attendance (days absent), teacher rating, teacher education level, teacher years of experience, and placement in a classroom taught by a teacher who was part of the VDAM PLC

or not (henceforth referenced as VDAM status) had on third-grade students' performance on the 2018 PARCC mathematics assessment. This model (Model 1) includes 138 third-grade students. The dependent variable is the 2018 PARCC scaled scores in mathematics for third grade. In this model, the value *R* squared is .759, which indicates that 76% of the variance in performance on the mathematics section of the 2018 mathematics PARCC assessment can be attributed to the independent variables. The adjusted *R* square is 0.735, which signifies that the independent variables contribute to 74% of the variability in this regression model with respect to the population from which the sample was drawn. The Durbin-Watson score was 1.883, and this indicates that the residuals of the variable are not related and the assumption for regression is met. (See Table 10.) The regression Model 1is statistically significant (F = 32.457, df = 124, p = 0.000). (See Table 11.)

Table 10

Model Summary for Grade 3

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.871a	0.759	0.735	17.346	1.833

a. Predictors: (Constant), Education Level, English Learner EL, Gender, Days Absent, Black/African American, Student With Disabilities, Economic Disadvantage Status, Final Grades for 2018, Years in XYZ

Table 11

ANOVA Table for Grade 3 Mathematics, 2018 PARCC

Model		Sum of Squares	df	Mean Square	F	Sig.
1						
	Regression	117186.749	12	9765.562	32.457	0.000b
	Residual	37309.266	124	300.881		
	Total	154.015	136			

a. Dependent Variable: TestScaleScore
b. Predictors: (Constant), Educational Level, English Learner EL, Gender, Days Absent, Black/African American, StudentWithDisabilities, EconomicDisadvantageStatus, Final Grades for 2018, Years in XYZ (start through 17-18), 2018 Summative Rating, Hispanic/Latino, VDAM Teacher

A review of the standardized beta coefficients table (see Table 12) denotes that there are four statistically significant predictors of performance on the mathematics section of 2018 PARCC assessment for third grade. The statistically significant variables are students' 2018 final grades, classification as Special Education, status as ELL, and student SES status, which account for 68.4% of the variance in this regression model. Multicollinearity was not a concern because all predictor variables included in the regression met the tolerance level threshold for this model, .27 (> 1 - R^2) (Leech et al., 2013).

Students' 2018 final grades were a significant predictor of performance on the 2018 mathematics section of the PARCC (B = 2.975, β = .751 t = 15.293, p = 0.000). 2018 final grades contribute to 56% of the variance in this regression model. The beta indicates that as the average final grade increased, third-grade performance on the 2018 mathematics section of the PARCC increased at the rate of 2.97 points.

Status as student with a disability was a statistically significant predictor of performance on the 2018 PARCC mathematics section (B = -28.164, β = -0.283 t = -5.640, p = .000); and contributes 8% of the variance of the third-grade student performance on the 2018 PARCC mathematics section. The negative beta indicates that students classified as students with disability are predicted to perform lower on the PARCC assessment, with average difference of 28.164 points as compared to students who are not classified.

Status as ELL was a statistically significant predictor of performance on the 2018 PARCC mathematics section (B = -30.43, β = -1.85, t = -3.844, p = .000). Status as an ELL student contributed to 3.4% of the variance for the third-grade student performance on the 2018 PARCC mathematics section. The negative beta indicates that students classified as ELLs are

predicted to perform lower than students who are not classified, with an average difference of 30.438 points.

SES was a statistically significant predictor of performance on the 2018 mathematics section of the PARCC (B = -7.447, β = -0.101, t = -2.022, p = 0.045). SES contributed to 1% of the variance in this regression model. The negative beta shows that students who receive free and reduced lunch are predicted to perform lower on the 2018 PARCC assessment in mathematics on average by approximately 7 points. (See Table 12.)

Table 12

Coefficient Table for Grade 3 Mathematics, 2018 PARCC

	Unstandardized Coefficients		Standard-ized Coeffi-cients	*t*	Sig.	95.0% Confidence Interval for B	
Model	B	Std. Error	Beta			Lower Bound	Upper Bound
1 (Constant)	503.43	1413.05		0.35	0.72	-2293.40	3300.2
VDAM Teacher	7.784	99.957	0.116	0.078	0.938	-190.059	205.62
Gender	-1.496	3.065	-0.022	-0.488	0.626	-7.562	4.56
Final Grades for 2018	2.975	0.195	0.751	15.293	0	2.59	3.36
Days Absent	-0.327	0.283	-0.054	-1.154	0.251	-0.887	0.23
Hispanic/Latino	-16.762	18.338	-0.232	-0.914	0.362	-53.059	19.53
Black/African American	-16.67	18.048	-0.232	-0.924	0.357	-52.392	19.05
English Learner EL	-30.438	7.918	-0.185	-3.844	0	-46.109	-14.76
Economic Disadvantage Status	-7.447	3.684	-0.101	-2.022	0.045	-14.738	-0.15
Student With Disabilities	-28.164	4.994	-0.283	-5.64	0	-38.04	-18.28
Years in XYZ (start through 17-18)	0.384	0.542	0.057	0.708	0.48	-0.68	1.456
2018 Summative Rating	3.882	387.284	0.012	0.01	0.992	-762.6	770.42
Educational Level	-1.024	52.233	-0.028	-0.02	0.984	-104.40	102.36

a. Dependent Variable: Test Scale Score

This simultaneous regression model suggest that students' final grade had the largest association with performance on the mathematics section of the 2018 PARCC. Students connected to teachers in the VDAM PLC or not was not statistically significant.

Based on the analysis of these results, the null hypothesis for this research question was not rejected. Placement in a class of a teacher who was a part of VDAM PLC did not have a statistically significant impact on third-grade student performance on the 2018 mathematics section of the PARCC when controlling for gender, final grades 2018, ethnicity, status as an ELL, SES, status as a Special Education student, teacher's rating, teacher, and teacher's years of experience. The conditional model confirmed the results of the independent samples *t* test originally run.

Research Question 2: Analysis and Results

Research Questions 2: Is there a difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the VDAM and students who were not assigned to participating teachers in Grade 6 when controls for both student and teacher demographic information are applied?

Null Hypothesis 2: There is no difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the VDAM and students who were not assigned to participating teachers in Grade 6 when controls for both student and teacher demographic information are applied.

An independent samples *t* test was conducted on the sixth-grade sample determined by PSM as seen in Tables 13 and 14 to answer the second research question as it relates solely to the

treatment variable. Levene's test, used to check the assumption of homogeneity of variance, showed $F = .037$ and was not statistically significant ($p > .05$). This indicates that the error variance of the dependent variable, performance on the 2018 mathematics PARCC assessment, is equal across groups (Leech et al., 2013). (See Table 13.) At the treatment level, the independent samples *t* test, ($t(208) = -2.669$, $p = .008$), showed that the null hypothesis was rejected and there was a significant difference in the level of academic achievement in mathematics as measured by the 2018 PARCC assessment between students who were assigned to teachers who were a part of the PLC that utilized VDAM and students who were not assigned to participating teachers in Grade 6 when controls for both student and teacher demographic information are applied. The 2018 PARCC mean scale score for the VDAM Treatment group ($N = 105$) was 731.69 ($SD = 28.255$).

The 2018 PARCC mean score for the students who were not connected to the VDAM group ($N = 105$) was 721.14 ($SD = 28.988$). There was a 10.543 mean difference between the control group and treatment group's performance on the 2018 PARCC assessment. Cohen's d was used to calculate the effect sizes of statistically significant outcomes, whereby 0.2 equates to a small effect, 0.5 equates to a medium effect, and effects larger than 0.8 equate to large effects (Cohen, 1988). In this case, Cohen's $d = (731.69 - 721.14) / 28.623846 = 0.368574$, which shows the effect size was small.

Table 13

Independent Sample t Test for Grade 6 2018 Mathematics PARCC Scores by Treatment Group

	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
						Lower	Upper
PARCC Math Test Scale Score	-2.669	208	0.008	-10.543	3.95	-18.331	-2.755

A simultaneous multiple regression was run as a follow up to the independent samples *t* test to determine the answer to the second research question and to see if the same results would be yielded within a conditional model. The purpose was to determine the amount of influence the independent variables gender, ethnicity, SES, status as an ELL, attendance, teacher rating, teacher education level, teacher years of experience, and placement in a classroom with a teacher who participated in the VDAM PLC or not on sixth-grade students' performance on the 2018 mathematics section of the PARCC assessment. This model (Table 15) involves 210 sixth-grade students. In multiple regression model 1, the dependent variable is the 2018 mathematics PARCC scaled scores for sixth grade. In this model, the value *R* squared is .673, which indicates that 67% of the variance in performance on the mathematics section of the 2018 mathematics PARCC assessment can be attributed to the independent variables. The adjusted R square is 0.653, which indicates that the independent variables would contribute to 65.35 of the variability in this regression model with respect to the population from which the sample was drawn. The Durbin-Watson score was 2.215. This indicates that the residuals of the variable are not related and the assumption for regression is met (see Table 14). Regression Model 1 is statistically significant (F = 33.266, *df* = 12, 194, *p* = .000). (See Table 15.)

Table 14

Model Summaryb for Grade 6

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	0.820a	0.673	0.653	16.67	1.936

a. Predictors: (Constant), Educational Level, Black/African American, Gender, EconomicDisadvantageStatus, Days Absent, StudentWithDisabilities, Final Grades for 2018

b. Dependent Variable: TestScaleScore

Table 15

ANOVA Table for Grade 6 Mathematics, 2018 PARCC

Model		Sum of Squares	df	Mean Square	F	Sig.
1						
	Regression	110926.778	12	9243.9	33.266	0.000
	Residual	53909.145	194	27.882		
	Total	164835.923	206			

a. Dependent Variable: TestScaleScore
b. Predictors: (Constant), Educational Level, Black/African American, Gender, EconomicDisadvantageStatus, Days Absent, StudentWithDisabilities, Final Grades for 2018

A review of the standardized beta coefficients table (see Table 16) indicates that there are four statistically significant predictors of performance on the mathematics section of 2018 PARCC assessment for sixth grade. The statistically significant variables are students' 2018 final grades, classification as Special Education, status as ELL, and student SES status, which account for 56.8% of the variance in this regression model. Multicollinearity was not a concern because all predictor variables included in the regression met the tolerance level threshold for this model, .327 (>1-R^2) (Leech et al., 2013).

Table 16

Coefficient Table for Grade 6 Mathematics, 2018 PARCC

	Model	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standard-ized Coeffi-cients Beta	*t*	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound
1	(Constant)	618.39	26.28		23.526	0	566.55	670.23
	VDAM Teacher	-6.73	3.59	-0.119	-1.874	0.062	-13.83	0.35
	Gender	-1.64	2.41	-0.029	-0.684	0.495	-6.40	3.10
	Final Grades for 2018	2.43	0.17	0.666	14.207	0	2.10	2.77
	Days Absent	-0.30	0.24	-0.055	-1.262	0.209	-0.77	0.17
	Hispanic/Latino	-10.17	7.62	-0.163	-1.333	0.184	-25.21	4.87
	Black/African American	-7.62	7.80	-0.12	-0.977	0.33	-23.02	7.77
	English Learner EL	-6.07	7.87	-0.033	-0.771	0.442	-21.61	9.46
	Economic Disadvantage Status	1.10	2.83	0.017	0.39	0.697	-4.47	6.68
	Student With Disabilities	-16.03	4.26	-0.168	-3.761	0	-24.43	-7.62
	Years in Orange (start through 17-18)	0.247	0.36	0.059	0.681	0.497	-0.46	0.96
	2018 Summative Rating	-18.14	7.44	-0.135	-2.438	0.016	-32.81	-3.46
	Educational Level	-7.892	1.88	-0.287	-4.187	0	-11.61	-4.17

Students' 2018 final grades were a significant predictor of performance on the 2018 mathematics section of the PARCC (B = 2.439, β = .666 t = 14.207, p < .050). Final grades contributed to 44% of the variance in this regression model. The beta indicates that as average final grade increased, performance on the 2018 mathematics section of the PARCC increased on average 2.43 points.

Student disability classification was a statistically significant predictor of performance on the 2018 PARCC mathematics section (B = -16.030, β = -0.168, t = -3.761, P < .05). Status as a student with a disability contributes to 2.8% of the variance of the sixth-grade performance on the PARCC. The negative beta indicates that students classified with a disability were likely to perform lower than students who were not classified by an average of 16.03 points.

Teacher summative rating and education level both were statistically significant predictors of performance on the 2018 mathematics section of the PARCC. Summative rating (B = -18.14, β = -0.135, *t* - 2.438, p = 0.016) contributed to 1.8% of the variance in the model. Education level (B = -0.287, β = -0.287, *t* = -4.187, p = 0.000) contributed to 8.2% variance of the model. The negative beta indicates that as education level increased the PARCC scores seemed to decrease by 7.89 points for this sample.

Based on this analysis, the null hypothesis for this research question was rejected. This conditional model did not produce the same results as the unconditional independent sample *t* test. Placement in a class of a teacher who was a part of VDAM PLC did not have a statistically significant on Grade 6 student performance on the 2018 mathematics section of the PARCC when controlling for gender, final grades 2018, ethnicity, status as an ELL, SES, status as a Special Education student, teacher's rating, teacher's education level, and teacher's years of experience.

Research Question 3: Analysis and Results

Research Question 3: Is there a difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the VDAM and students who were not assigned to participating teachers in Grade 9 when controls for both student and teacher demographic information are applied?

Null Hypothesis 3: There is no difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the VDAM and students who were not assigned to

participating teachers in Grade 9 when controls for both student and teacher demographic information are applied.

An independent samples *t* test was conducted on the Algebra I sample determined by PSM as seen in Tables 17 and 18 to answer the third research question as it relates solely to the treatment variable. The Levene's test used to check the assumption of homogeneity of variance and the resultant was not statistically significant ($p > .05$). This indicates that the error variance of the dependent variable, performance on the 2018 mathematics PARCC assessment, is equal across groups (Leech et al., 2013). (See Table 18.) At the treatment level, an independent samples *t* test, ($t(94) = -15.491$, $p = .000$), showed that the null hypothesis was rejected and there was a significant difference in the level of academic achievement in mathematics as measured by the 2018 mathematics section of the PARCC assessment between students assigned to teachers who took part in the PLC that utilized the VDAM and students who were not assigned to participating teachers in Algebra I when controls for both student and teacher demographic information are applied. The 2018 PARCC mean scale score for the VDAM Treatment group ($N = 48$) was 778.31 ($SD = 23.379$). The 2018 PARCC mean score for the students who were not connected to the VDAM group ($N = 48$) was 721.14 ($SD = 22.213$). There was a 72.104-point difference between the control group's and treatment group's performance on the 2018 PARCC assessment. Cohen's d was used to calculate the effect sizes of statistically significant outcomes, whereby 0.2 equates to a small effect, 0.5 equates to a medium effect, and effects larger than 0.8 equate to large effects (Cohen, 1988). This model showed large effect size as the results were Cohen's $d = (778.31 - 706.21) / 22.803454 = 3.161802$.

Table 17

Independent Sample t Test for Algebra I 2018 Mathematics PARCC Scores by Treatment Group

	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
						Lower	Upper
PARCC Math Test Scale Score	-15.491	94	0.975	-72.104	4.655	-81.346	-62.862

A simultaneous multiple regression was used as a follow up to the independent samples *t* test to further analyze research question 3. The purpose was to determine the amount of influence the independent variables gender, ethnicity, SES, status as an ELL, attendance, teacher rating, teacher education level, teacher years of experience, and placement in a classroom taught by a teacher who was part of the VDAM PLC had on Algebra I students' performance on the 2018 mathematics section of PARCC assessment. This model involves 96 Algebra I students. In this multiple regression model, the dependent variable is the 2018 mathematics PARCC scaled scores for Algebra I students. In this model, the value *R* squared is .796, which indicates that approximately 80% of the variance in performance on the mathematics section of the 2018 mathematics PARCC assessment can be attributed to the independent variables. The adjusted R square is 0.773, which indicates that the independent variables would contribute to 77.3% of the variability in this regression model with respect to the population from which the sample was drawn. The Durbin-Watson score was 1.327. This indicates that the residuals of the variable are not related and the assumption for regression is met. (See Table 18.) Regression Model 1 is statically significant (F = 34.56, df = 7, 62, P = .000). (See Table 19.)

Table 18

Model Summary for Algebra I

Model	R	R Square	Adjusted R Square	St. Error of the Estimate	Durbin-Watson
1	0.892a	0.796	0.773	16.611	1.327

a. Predictors: (Constant), Educational Level, Black/African American, Gender, EconomicDisadvantageStatus, Days Absent, StudentWithDisabilities, Final Grades for 2018
b. Dependent Variable: TestScaleScore

Table 19

ANOVA Table for Algebra I Mathematics, 2018 PARCC

	Model	Sum of Squares	df	Mean Square	F	Sig.
1						
	Regression	66756.2	7	9536.6	34.563	0.000b
	Residual	17106.9	62	275.917		
	Total	83863.1	69			

a. Dependent Variable: TestScaleScore
b. Predictors: (Constant), Educational Level, Black/African American, Gender, EconomicDisadvantageStatus, Days Absent, StudentWithDisabilities, Final Grades for 2018

A review of the standardized beta coefficients table (Table 20) indicates that there are four statistically significant predictors of performance on the mathematics section of 2018 PARCC assessment. The statistically significant variables are student 2018 final grades, classification as Special Education, teacher education level, and days absent for students. These four variables account for 59.2% of the variance in this regression model. There were 4 independent variables that SPSS excluded in this regression since there was a significant collinearity. They were VDAM Teacher, Hispanic/Latino, years in Orange, and 2018 teacher summative rating. Multicollinearity was not a concern for the independent variables that remained in the Model.

Students' 2018 final grades is a significant predictor of performance on the 2018 mathematics section of the PARCC (B = 1.761, β = .561, *t* = 6.944, p = 0.000). 2018 final grades contributed to 31% of the variance in this regression model. The beta indicates that as the average final grade increased, performance on the 2018 mathematics section of the PARCC increased on average 1.761 points.

Student disability classification was a statistically significant predictor of performance on the 2018 PARCC mathematics section (B = -25.467, β = -0.149 *t* = -2.276, p = .026). Status as a student with disability contributed to 1.9% of the variance of the Algebra I student performance on the PARCC 2018 mathematics section. The negative beta indicated that students who were classified as students with disability were predicted to perform on average 25.46 points lower than students who were not classified.

Educational level of the teacher was a significant predictor of the performance on the 2018 mathematics section of the PARCC. Educational level (B = 37.050, β = 0.497, *t* = 6.361, p = 0.000) contributed to 24% variance of the model. The positive beta show that as the teacher's education level increased, the performance on 2018 mathematics section of the PARCC for Algebra I students increased 37.05 points.

Student attendance (days absent) was a significant predictor of the performance on the 2018 mathematics section of the PARCC. Attendance (B = .575, β = .146, *t* = 2.129, p = 0.037) contributed to 1.9% variance of the model. The positive beta shows that as the students' absences increased, the performance on 2018 mathematics section of the PARCC for Algebra I students increased .57 points in this model.

Table 20

Coefficient Table for Algebra I Mathematics, 2018 PARCC

	Model	Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	*t*	Sig.	95.0% Confidence Interval for B Lower Bound	95.0% Confidence Interval for B Upper Bound
1	(Constant)	475.23	22.21		21.39	0	430.83	519.6
	Gender	-6.65	4.14	-0.096	-1.60	0.114	-14.94	1.63
	Final Grades for 2018	1.76	0.25	0.561	6.94	0	1.25	2.26
	Days Absent	0.57	0.27	0.146	2.129	0.037	0.03	1.11
	Black/African American	2.45	4.85	0.034	0.50	0.615	-7.25	12.167
	Economic Disadvantage Status	4.10	6.36	0.042	0.64	0.521	-8.608	16.82
	StudentWithDisabilities	-25.46	11.18	-0.149	-2.27	0.026	-47.83	-3.1
	Educational Level	37.05	5.82	0.497	6.36	0	25.40	48.69

Based on this analysis, the null hypothesis for this research question was not rejected. Placement in a class of a teacher who was a part of VDAM PLC did not have a statistically significant impact on Algebra I student performance on the 2018 mathematics section of the PARCC when controlling for gender, final grades 2018, ethnicity, status as an ELL, SES, status as a Special Education student, teacher’s rating, teacher’s education level, and teacher’s years of experience. Table 21 represents the findings for all three questions as they relate to significance levels for all three variables.

Table 21

Summary of Findings, Simultaneous Multiple Regression

Independent Variables	3rd Grade *P<0.05*	6th Grade *P<0.05*	Algebra I *P<0.05*
Gender	No	No	No
Final Grades	Yes B = 2.9 (56%)	Yes B = 2.43 (44%)	Yes B = 1.761 (31%)
Days Absent	No	No	Yes B = .575 (1.9%)
Hispanic/Latino	No	No	No
Black/African American	No	No	No
English Language Learner	Yes B = -30.43 (3.4%)	No	No
SES Status	Yes B = -7.44 (1%)	No	No
Students with Disabilities	Yes B = -28.6 (8%)	Yes B = -16.03 (2.8%)	Yes B = -25.467 (1.9%)
Teacher - Years in XYZ	No	No	No
Teacher - Summative Rating	No	Yes B= -18.14 (1.8%)	No
Teacher- Education Level	No	Yes B= -0.28 (8.2%)	Yes B = 37.5 (24%)
Teacher - VDAM Status	No	No	No

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

As accountability becomes increasingly important in public education, school districts are looking for practical and efficient ways to improve instruction and ensure students are making significant academic gains. NCLB (2002) and ESSA (2015) are two examples of legislation that have been designed to increase teacher accountability and ultimately improve student achievement for all. There has been an increase in studies examining effective PLCs, the use of DDI and the influence of both on student achievement. This study looked at a district-level PLC that used a Data Action Model developed by Daniel R. Venables to improve instruction in mathematics for students in Grade 3, Grade 6, and Algebra I.

Purpose

The purpose of this comparative, non-experimental, cross-sectional explanatory quantitative study was to examine the impact of utilizing VDAM design in XYZ school district on the mathematics section of 2018 PARCC in Grade 3, Grade 6, and Algebra I courses. Furthermore, the study examined the influence of student variables such as gender, attendance (days absent), SES, ethnicity, Special Education status, final grades, and student status as an ELL. This study also controlled for variables such as the teacher's education level, performance rating, and years of experience in the field of education.

Chapter Organization

This chapter consists of restating and discussing the three main research questions. The findings of this research will be compared to the body of research that exists surrounding this topic. After analyzing the findings, recommendations for educational policy and best practices are made, along with recommendations for future research that can enhance the theories and

findings as they relate to PLCs and DDI. More specifically, this study will give recommendations related to VDAM and its implementation in a small urban school district.

Sample

Sample participants in this study were identified from eight K-12 schools located in a small urban school district in north New Jersey. The study initially included 1,091 students who were enrolled in Grace 3, Grade 6, and Algebra I classes in XYZ school district. The final sample selected in this study included 444 students from all eight schools, and the sample was obtained using PSM. As stated in Chapter 3, PSM is a process that attempts to reduce the selection bias by creating an environment that allows direct comparisons. This is what a researcher would see in a randomized study. This approach was used in order to reduce the possibility of a Type I error. It also allowed for the combination of all school samples into one overall population and to identify the effects of condition on an individual student's performance. It was determined that statistically significant differences existed between student groups in the various schools on the following identified independent variables: SES, ethnicity, placement in a classroom taught by a teacher trained in VDAM, and attendance, and there were statically significant findings as related to several of the teacher-level covariates.

Research Questions and Discussion

Research Question 1: Is there a difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the VDAM and students who were not assigned to participating teachers in Grade 3 when controls for both student and teacher demographic information are applied?

Null Hypothesis 1: There is no difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the VDAM and students who were not assigned to participating teachers in Grade 3 when controls for both student and teacher demographic information are applied.

Answer and discussion: Based on the results, the null hypothesis for this research question was not rejected. A significant difference was not found in the level of academic achievement in mathematics as measured by the 2018 PARCC assessment between students who were assigned to teachers who were a part of the PLC that utilized the VDAM and students who were not assigned to participating teachers in Grade 3 when controls for both student and teacher demographic information were applied. These results were found in both the independent sample *t* test and the simultaneous multiple regression. Out of the 439 students in the district, 138 were used for this study based on their connection to a teacher who was a part of the VDAM PLC and the results of the PSM.

Although the null hypothesis was not rejected, there was still valuable information discovered that can lend itself to an understating of best practices. This study also looked at multiple independent variables and their impact on student achievement on the 2018 mathematics PARCC assessment. As expected, based on the literature, SES, status as an ELL, and status as Special Education student significantly impacted performance on this assessment (Bloom et al., 2008, Mickelson et al., 2013; Schwartz, 2011). Also, the higher the grade students received on the math final grade, the better they performed on the state assessments. This illustrated a direct connection between students' performance in the classroom and the 2018 PARCC assessment. These four independent variables accounted for 68% of the variance in the

simultaneous multiple regression model. The correlation between final grades and performance on the 2018 PARCC can showcase that teachers have a clear understanding of the expectations of the PARCC and are aligning their instruction and grading policy to the standards and expectations on the PARCC.

Despite the anticipated results of the null hypothesis being rejected, there are multiple theories as to why this researcher did not see the VDAM model impacting the dependent variable as expected. As mentioned in Chapter 2, the population that was not a part of the VDAM PLC could still have implemented best practices aligned with DDI. Based on the findings, this study enabled educators to use data in their courses to develop and execute effective lessons and administer appropriate assessments. This approach is the heart of the VDAM; however, there is no evidence to support that other teachers did not take a similar approach of DDI, and therefore both bodies of students could have been equally impacted by DDI. In addition, this study does not evaluate the effectiveness of implementation of the model. The study assumes all aspects of the model were implemented correctly; however, if a teacher struggled with content knowledge and didn't conclude the best next steps for students based on the data, this could negatively impact the results of the study. Analysis from this study revealed that teachers who participated in the VDAM PLC did have a higher average scale score on the assessment; however, it was not found to be significant. The small sample size could contribute to the fact that there is a large difference in the mean scale score but no significance.

Research Question 2: Is there a difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the VDAM and students who were not assigned

to participating teachers in Grade 6 when controls for both student and teacher demographic information are applied?

Null Hypothesis 2: There is no difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the VDAM and students who were not assigned to participating teachers in Grade 6 when controls for both student and teacher demographic information are applied.

Answer and discussion: There is no significant difference in the level of academic achievement in mathematics as measured by the 2018 PARCC assessment between students who were assigned to teachers who were part of the PLC that utilized the VDAM and students who were not assigned to participating teachers in Grade 6 when controls for both student and teacher demographic information were applied. Unlike in Grade 3, the initial independent sample *t* test showed a statistical significance; however, when placed in a controlled model, the simultaneous multiple regression showed that there were factors that influenced the students' performance on the PARCC test other than the VDAM PLC. There was a 10.5 mean difference in which students connected to teachers that were a part of VDAM outperformed students who were connected to the teachers who were not. It is important for the lack of statistical significance in this study to be assessed with caution. Although there was a difference in the performance, the difference was not statistically significant, and this could be due to the small sample size. This researcher was not able to determine the sample size prior to running the PSM and therefore the sample size could have skewed the results. In addition, similar to the analysis of Grade 3, this researcher was not able to control for data-driven approaches not being implemented with the students who did not receive the treatment. The fact that the teachers of the students in the control group did not

participate in the VDAM PLC does not necessarily indicate that they did not receive instruction in similar practices. This dilemma lends itself to a future mixed method studies in which we can have qualitative feedback to better understand accuracy of the implementation of VDAM and practices implemented by teachers who were not part of VDAM. Such a study would allow for the development of a narrative that would show the experiences of students in both the control and treatment group, painting a more complete picture.

This research question also looked at multiple independent variables and their impact on student achievement on the 2018 mathematics PARCC assessment in Grade 6. As expected, based on the literature, status as a Special Education student significantly impacted performance on this assessment (Bloom et al., 2008; Michelson et al., 2013; Schwartz, 2011). Teacher's summative evaluation rating and education level also impacted performance on the assessment in this model (Sanders & Rivers, 1996). Similar to the results found for students in Grade 3, students' final grades were aligned with student performance on the state test. These four variables accounted for 57% of the variance in the multiple regression model.

Research Question 3: Is there a difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the VDAM and students who were not assigned to participating teachers in Algebra I when controls for both student and teacher demographic information are applied?

Null Hypothesis 3: There is no difference in the level of academic achievement in mathematics as measured by the 2018 PARCC Assessment between students who are assigned to teachers who are a part of the PLC that utilized the VDAM and students who were not assigned to

participating teachers in Algebra I when controls for both student and teacher demographic information are applied.

Answer and discussion: There is no significant difference in the level of academic achievement in mathematics as measured by the 2018 PARCC assessment between students who are assigned to teachers who are a part of the PLC that utilized the VDAM and students who were not assigned to participating teachers in Algebra I when controls for both student and teacher demographic information were applied. Unlike in Grade 3, the initial independent sample *t* test showed a statistical significance; however, when placed in a controlled model, the simultaneous multiple regression showed that there were other factors that had a significant impact on student performance on the PARCC assessment scale score.

This study also looked at multiple independent variables and their impact on student achievement on the 2018 mathematics PARCC assessment in Algebra I. As expected, based on the literature, attendance and status as Special Education students significantly impacted performance on this assessment (Bloom et al., 2008; Mickelson et al., 2013; Schwartz, 2011). Teacher's education level also impacted performance on the assessment in this model (Darling Hammond & Youngs, 2002).. These four variables accounted for 59% of the variance in the multiple regression model. In all three grade levels, the research around gender is consistent with that of Matthews et al. (2009), in which they found that there were no significant gender differences relating to performance on the achievement test.

According to the research, the PLCs that use formative data, data used to inform instruction, and a schedule that is developed to allow teachers to work in a collaborative environment will foster an environment for best practices (DuFour et al., 2006; Fink & Resnick, 2001; Fullan & Hargreaves, 1991). VDAM PLC uses the same approach as mentioned in this

research and therefore this researcher assumed the variance in performance would be significant as it relates to the VDAM treatment; however, similar to the results for Grades 3 and 6, there was no evidence to support that the group that did not receive the treatment did not use DDI collaboratively.

Conclusion

According to the findings, this study shows that there is value in ensuring there are effective PLCs in the school and teachers are using data to drive instruction on a consistent basis. In all three grade levels examined in this study, the mean score on the 2018 mathematics PARCC assessment was higher with students who were instructed by teachers who participated in VDAM PLC. The VDAM approach encompassed research surrounding the effectiveness of PLCs and using data to drive instruction. At the third-grade level the mean score of the PARCC was 734.10 for students whose teachers were part of the VDAM PLC, and the mean scale score for students connected to teachers who were not was 732.71. At the sixth-grade level students connected to teachers in the VDAM PLC produced a mean scale score of 731.69, and the students who were not produced a mean score of 721.14. In the Algebra I courses, the average scale score was 778.31 for students connected to the VDAM teachers, and students who were not connected to these teachers had an average 706.21. Although the model did not produce a statistically significant finding, the mean differences in scale score on the mathematics PARCC inspire further inquiry. As mentioned in the discussion, VDAM consists of research-based best practices involving PLCs and DDI. If the non-treatment group implemented some of these practices separate from the VDAM, this could limit the statistical significance in the findings. Small sample sizes often do not yield statistical significance, and in the case of this study there were only six teachers who were part of the VDAM pilot (Krejcie & Morgan, 1970). It is

imperative to note that the small sample size of teachers who were part of the VDAM could have impacted the results of the simultaneous multiple regression. In review, it has become apparent that additional factors that were not included in this analysis could have impacted the outcomes along with the limitations that were identified at the onset of this study. The study was limited to participants from eight schools in an urban school district in New Jersey, which lacks cultural and socioeconomic diversity. The majority of students were from a lower socioeconomic background and were African American. The district was chosen based on its pilot program in which selected teachers participated in a district-level PLC to use data to drive instruction more effectively. Important aspects of the study were predetermined based on the pilot program requirements.

A non-experimental research design was used in this study because this researcher evaluated a preexisting pilot program in XYZ school district. Although non-experimental designs are very popular in education research, they are not as reliable as experimental designs, and cause and effect conclusions should not be drawn from them. The use of PSM attempted to mitigate this limitation. Leadership within the math department altered throughout the duration of the study. Two supervisors left and there was a gap in leadership for 2 months. This is a limitation because the supervisors led the majority of data action meetings and monitored implementation of the model. The absence of content experts could have negatively impacted the teachers' ability to determine concrete next steps based on the data.

Multiple regression analyses were conducted on variables to better isolate the impact that the teacher participating in the district-level data action PLC may have on students' academic performance. Despite the use of PSM, not all variables could be accounted for. The last limitation was because this researcher could not control for what the teachers who were not a

part of VDAM did relating to DDI. For example, the teachers who were not part of the VDAM PLCs could have used similar practices during their grade-level meeting. Another factor could be ineffective implementation of VDAM on the part of the teachers in the VDAM group. This study did not identify the school factors that might have contributed to the results. Two out of three of the research questions were statically significant based on the independent sample *t* test; however, when including independent variables that research has shown to traditionally impact students' achievement, this researcher was able to see more of a correlation outcome as opposed to a causal.

Recommendations for Administrative Policy and Practice

The results and findings of this study may be shared with district-level and school-based administration in order to address extensive issues surrounding PLCs and teachers' ability to use data to drive their instructional practices. The findings from this study can add to dialogue about best ways to address the achievements gaps that exist currently in our schools.

Implementation/Professional Learning Communities

This particular study looked at a maximum of three classes in each school implementing VDAM; however, Love (2004) indicated that in order to tackle and begin to close the achievement gap, educators need to "influence school culture to be one in which educators use data continuously, collaboratively, and effectively to improve teaching and learning" (p. 1). It is imperative that changes be implemented at a school level to impact the culture of the entire school. PLCs have been documented by educational theorists and researchers as the newest necessity to school reform. The literature supports decreasing the isolation of teachers and moving toward a more collaborative approach for improvement in instructional approaches (DuFour & Eaker, 1998). Administrators should consider implementing this PLC model for all

teachers in a building and ensuring there is a common mindset among the staff members in the building. This implementation approach has been noted as the most promising strategy for improving student achievement. Within the pilot in XYZ school district, there were teachers who still worked in insolation from their peers in the building. This pilot focused on various classes within a district-wide implementation; however, research shows that a PLC focused on a whole school will yield the best results (DuFour, 2004).

Data Driven Instruction

It is imperative for districts to continue to build the content knowledge of staff members and their ability to determine next steps after reviewing the data. The VDAM makes assumptions that the teachers have the content knowledge to determine the correct next steps. Research has shown that the use of data is an important tool in school improvement, but studies indicate that educational data is used sparingly in the classroom (Love, 2004). It is important that school district not only require schools to use DDI approaches but that they provide the training and the time for this to happen. One important aspect to improving student achievement is the teacher's understanding of how to triangulate data to better understand the needs of the students. This is an aspect DDI that teachers often struggle with and can be a cause of limited student growth. Weekly content meetings addressing learning gaps, and developing best practices should be a staple of the school culture. The development of school structures to make use of the data in educational best practices is important: "Schools must have not only the desire to use data, but they must also have the capacity to use data" (Bettesworth, 2006, p.1). The use of using data to improve instruction has garnered much attention in the education system. Presently, most school districts have an abundance of data available but struggle with effective analysis and implementation that data for instructional purposes. District leaders should adopt a model to use

along with continuous professional development plan for DDI. This study revealed that district-level and school-level leaders should prioritize ensuring that teachers are comfortable with content knowledge and uncovering the individual needs of each student.

Teacher Fit

This study showed a significant influence of teacher education level, years of experience, and performance rating on the 2018 mathematics PARCC. This speaks to the importance of having effective teachers to meet the needs of the students. According to Martin (2007), academic performance is directly connected to the classroom instructor. Therefore, having the strongest educator and creating the ideal classroom environment should be the priority of most urban districts. Although this was not the original intent of the study, the data collected on this topic supported the current research about teacher impact on students' achievement in all subjects. Previous research has supported that "schools bring little influence to bear upon a child's achievement that is independent of his background and general social context" (Coleman et al., 1966, p. 325). Newer research related to the effectiveness and impact of the classroom teacher lends itself to policy makers prioritizing teacher efficacy.

Before implementing programs or protocols, administrators must be certain they have good fits for the various classroom roles. Although having access to data is a key component for effective DDI, obtaining tools and skills to use the data are paramount. Teachers must be content experts and trained on effective approaches to meet the needs of various students. Research has contended that knowing what data to use and how to use it are keys to successfully integrating data-driven decision-making into practice (Protheroe, 2001).

Recommendations for Future Research

The recommendations for future research are grounded in the understanding that multiple studies, set in various environments, will result in revealing patterns that allow us to determine which educational approach is most effective (Slavin et al., 2008). Although this study focused specifically on the impact of VDAM, the research lends itself to PLCs and DDI. This study sought to evaluate a pilot program that was already in motion prior to the implementation of the study. This created many limitations as far as sample size and selection at both the teacher and student levels. After a thorough analysis of this study, it is noted that further studies should include but not be limited to the following:

1. Recreate this study using two schools in the same school district; however, one school implements the model and the other school does not implement the model. In efforts to align with the research surrounding effective use of PLCs, it should be a whole school implementing the model.
2. Conduct a longitudinal study in which the researcher examines the academic achievement of a cohort of students over a three-year period. It is imperative that these students be taught by teachers participating in the VDAM. Simultaneously, examine a cohort of students with a similar makeup but who have no interaction with teachers who were exposed to this model.
3. Design a mixed-methods study involving both quantitative and qualitative elements in which teacher perceptions and attitudes toward DDI are analyzed, and then compare the academic achievement on state assessments.
4. Design a qualitative study with a focus on investigating the teachers' understanding of content knowledge and their ability to use data to drive their instruction.

Final Thoughts

In the final analysis, grander questions arise. Do various data action models matter, and can schools use district-level professional development to mitigate the current impact of disadvantage? Do student-related variables such as SES, ethnicity, and attendance overpower the possible positive impacts of effective DDI and PLCs? As reflected in current research, data-based instruction is a necessary component of effective classrooms (Volante & Fazio, 2007). Improving data-driven decision-making should be at the heart of any school reform. The common core standards movement, along with high levels of teacher accountability, present new requirements and opportunities for educators to use data to drive decision-making (Massell, 2001). Conversely, echoed throughout the literature is the lack of readiness of educators in data-driven decision-making. In addition, research denotes that developing data-driven decision-making strategies and skills related is absent in most teacher readiness courses (Frey & Schmitt, 2007; Volante & Fazio, 2007). The model used in this research gives a protocol to use data to drive instruction but does not ensure that teachers have correct next steps after diagnosing the problem based on data.

Improvements can be made to data-driven instructional approaches in the classroom and ultimately the learning environment based on information ascertained in the quantitative study. These improvements can be made at both the district and school levels. Therefore, it is this researcher’s final recommendation that schools (a) promote an effective PLC with practices that permeate the entire school building and district and (b) Schools prioritize data-driven decision-making professional development along with increased focus on building mathematics content knowledge. This and future program evaluation studies should serve to support school districts in meeting this significant and increasingly necessary goal.

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Appendix A

Request for Permission from XYZ District

SETON HALL UNIVERSITY
1856

November 1, 2018

Dear Dr. [redacted]

I am writing to request permission to conduct a research study in the [redacted] Public Schools. I am currently enrolled in the Seton Hall Traditional Doctoral program in K-12 Administration in South Orange, NJ and am in the process of writing my dissertation. The study is entitled, The Influence of Venables' Data Action Model on the Academic Performance of Urban 3rd, 6th and 9th grade (Algebra 1) New Jersey Students on the Mathematics Section of the 2018 PARCC.

Last year, your district decided to implement a district lead Professional Learning Community with a focus on Venables' Data Action Model to help improve performance in mathematics. My research will determine the influence the model had on 2018 PARCC Mathematics scores of 3rd, 6th and Algebra 1 students. I will be utilizing 2018 PARCC data of 3rd, 6th, and Algebra 1 students along with demographic data.

In order to conduct this research, I will need to be granted access to anonymous standardized test data coded only with student identification numbers. I will not have any direct contact with students during the study and the project will not interrupt or displace the regular instructional program. If approval is granted, the data utilized in the study will remain confidential and anonymous. No cost will be incurred by the school district to conduct this research. The completed dissertation will be reviewed and evaluated by Seton Hall mentor, Dr. Gerard Babo.

Your approval to conduct this study will be greatly appreciated. I would be happy to meet with you to answer any questions or concerns that you may have regarding this study. If you agree, kindly submit a signed letter of permission on your institution's letterhead acknowledging consent for me to conduct this study in your district.

Sincerely,

Devonii L. Reid

Devonii Reid
Doctoral Candidate
Seton Hall University

College of Education and Human Services
Executive Ed.D. Program
Tel: 973.275.2306 • Fax: 973.275.2484
400 South Orange Avenue • South Orange, New Jersey 07079-2685

Appendix B

Approval from XYZ District

[redacted]
ADMINISTRATION BUILDING
[redacted]
Tel. [redacted] Fax. [redacted]
[redacted]

[redacted]
Interim Superintendent of Schools

[redacted]
Deputy Superintendent

November 12, 2018

Dear Ms. Reid:

Your request to conduct educational research with data supplied by the [redacted] district has been approved, with the understanding that the names of students, staff and the district will be kept anonymous. Please contact Dr. [redacted] to receive the information requested.

Sincerely,

[redacted]
[redacted]
Deputy Superintendent of Schools

Appendix C

IRB Exemption

SETON HALL UNIVERSITY
1856

March 27, 2019

Devonii Reid
[redacted]

Dear Ms. Reid,

The Research Ethics Committee of the Seton Hall University Institutional Review Board office has reviewed your research proposal entitled "The Influence of Venables' Data Action Model on the Academic Performance of Urban 3rd, 6th, and Algebra 1 New Jersey Students on the Mathematics Section of the 2018 PARCC" and categorized it as exempt (reflecting the intent of the new federal regulations).

Enclosed for your records is the signed Request for Approval form.

If used, Informed Consent documents and recruitment flyers are no longer stamped.

Thank you for you cooperation.

Sincerely,

Mary F. Ruzicka, Ph.D

Mary F. Ružicka, Ph.D.
Professor
Director, Institutional Review Board

cc: Dr. Daniel Gutmore

Office of Institutional Review Board
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