THE RELATIONSHIP BETWEEN USING A COMPUTER-ASSISTED INSTRUCTION PROGRAM AND END-OF-COURSE PERFORMANCE OF ALGEBRA 1 STUDENTS

by
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Abstract

Background: Each year in a large urban district in southeast Texas, students enter middle and high school classrooms with achievement gaps in mathematics. Students have various levels of prerequisite knowledge, and individual differentiation is necessary for success. The district implemented an initiative where every student enrolled in a high school course was assigned a laptop to address these disparities. A computer-assisted instruction program was also purchased to provide differentiated instruction to under-achieving students within mathematics classrooms. Since Algebra 1 is the prerequisite for all high school mathematics courses, the program is currently used in algebra classes.

Purpose: The purpose of this study was to examine any relationship between the use of a computer-assisted program, *Imagine Math*, by Algebra 1 students, and their performance on the State of Texas Assessment of Academic Readiness (STAAR) end-of-course assessment. In this study, we investigated whether using a computer-assisted program helped with mastery of mathematical concepts and consequently enhanced performance on the State of Texas Assessment of Academic Readiness (STAAR). The proposed study addressed the following research question: What is the relationship between the number of successfully completed computer-assisted Algebra 1 mathematics instruction lessons and performance on the State of Texas Assessment of Academic Readiness?

Methods: This correlation study examined the relationship between the number of lessons passed in *Imagine Math* and students' performance on the STAAR end-of-course assessment. Participants for this study included approximately 4,800 students enrolled in Algebra 1 for the first time in the 2018-2019 school year. All participants were part of a large urban school district in southeast Texas. Correlation and linear regression were used to examine the relationship between the number of lessons completed in a computer-assisted program and students' performance on the STAAR exam. **Results**: A hierarchical and quantile regression was used to analyze the data. The statistical analysis showed there was a positive linear relationship between the number of lessons passed in *Imagine Math* and students' scale scores on the STAAR Algebra 1 end-of-course assessment. Results from the hierarchical regression showed the full model of gender, grade level, ethnicity, and total *Imagine Math* lessons passed to predict students' scale scores on the STAAR Algebra 1 end-of-course assessment was statistically significant, $R^2 = .295$, $F(4, 12782) = 1339.220$, $p < .001$, adjusted $R^2 = .295$. Results from the quantile regression showed a moderate positive relationship between the variables, with a Pearson's r-value of .39. Quantile-25 and Quantile-50 accounted for more than 16% of the explained variability in scale scores. **Conclusion**: Although there is no definitive proof that the relationship is strictly due to the passing of lessons in the program, *Imagine Math* could be one instructional tool to assist students in learning and mastering concepts in Algebra 1.

Keywords

computer-assisted instruction, differentiation, *Imagine Math*, Algebra 1, algebra instruction, secondary mathematics, distance learning

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Chapter I

Introduction

The use of computers in the classroom has evolved over the years. At one point, computers were only used for teachers to keep grades; now, they are used almost regularly throughout the day by teachers and students alike. With the beginning of computers in the classroom, came the development of computer-assisted instruction (CAI) projects in which teachers incorporate the use of a computer to present instructional material (Glanze et al., 2001). One of the earliest computer-assisted instruction projects began in 1963 with its original focus on developing a tutorial system in elementary mathematics and language arts (Burns & Bozeman, 1981). Today, computers are used for various purposes, from motivating and engaging students to differentiating instruction and providing instructional strategies and interventions, and improving standardized test scores (Kleiman, 2004). According to Blair (2012), a dramatic shift is sweeping through the country. It is apparent when you see kindergarteners using an iPad with finesse, elementary school students texting on cell phones, and middle and high school students with substantial social media followers. Many high schools are one-to-one with every student having a laptop, while elementary and middle schools tend to use laptop carts or the computer lab. Teachers of today must learn how to effectively integrate these new technologies into their curriculum if they want to grasp students' attention and keep them involved. Many schools have adopted computer-assisted programs, and teachers have the task of finding creative ways to supplement instruction with these programs.

Computer-assisted instruction offers many benefits to students. One of the most significant benefits of using CAI in the classroom is its potential to motivate students and make learning more enjoyable. It helps to improve student involvement as well as their concentration and provides new ways of learning (Serin & Oz, 2017). Computer-assisted instruction facilitates both mastering skills taught and remediation of concepts not learned well; however, without student attention, engagement, and effort, those objectives might not come to fruition (Becker, 2000). The use of the computer can assist with motivation and participation by taking into account the needs of the individual student.

Another benefit of computer-assisted instruction is the ability to differentiate instruction for individual learners. Differentiated instruction occurs when the teacher recognizes that students have different ways of learning and making sense of ideas (Tomlinson & McTighe, 2006). Many of the programs that provide computer-assisted instruction use some form of adaptive learning to customize pathways for the specific student based on how they respond. The computer has different tools available to deliver information appropriate to students in multiple ways and help them learn. Weary & Lewis (2010) assert, “the computer acts as an assistant teacher to provide differentiation in every classroom, freeing up teachers to involve students in rich, open-ended investigations and projects in class” (p. 151). Acting as an assistant, CAI can supplement what the teacher gives during instruction and can test for mastery of content.

Although technologies can rapidly differentiate for students, teachers still play an essential role in the use of and implementation of the technology. Researchers recommend using a blended environment with support provided for teachers to have a successful execution of computer-assisted instruction. A blended environment calls for students to use a combination of online and face-to-face instruction. Bebell et al. (2004) reported that The National Center for Educational Statistics (NCES) "conducted surveys on public school teachers access to and use of computers and the internet and concluded that although teachers used technology for some aspects of their professional activities, non-instructive technology was pervasive" (p. 47). This could be due to a lack of support. Support may come through professional development programs, online and face-to-face, onsite workshops, exposure to using digital resources, and experience using technology before using it with students (Kleiman, 2004). Computer-assisted instruction may be beneficial to student achievement but should be used to supplement instruction and not supplant it, working in conjunction with the teacher.

Purpose of the Study

The purpose of this study is to examine the effects of implementing the computer-assisted instruction program, *Imagine Math*, in Algebra 1 classes. This study also seeks to determine whether CAI can help impact student mastery of mathematical concepts and consequently enhance performance on the State of Texas Assessment of Academic Readiness (STAAR). The STAAR assessment for Algebra 1 is the only high school mathematics assessment required for students to pass to graduate, making it a high-stakes assessment for all Texas students.

Research Question

This study seeks to understand how students' participation in a computer-assisted program can support mastery and retention of mathematical content. When students master concepts and content, they can be successful on formative and summative assessments. The study addresses the question: What is the relationship between the number of successfully completed computer-assisted Algebra 1 mathematics instruction lessons and performance on the State of Texas Assessment of Academic Readiness?

Significance of the Study

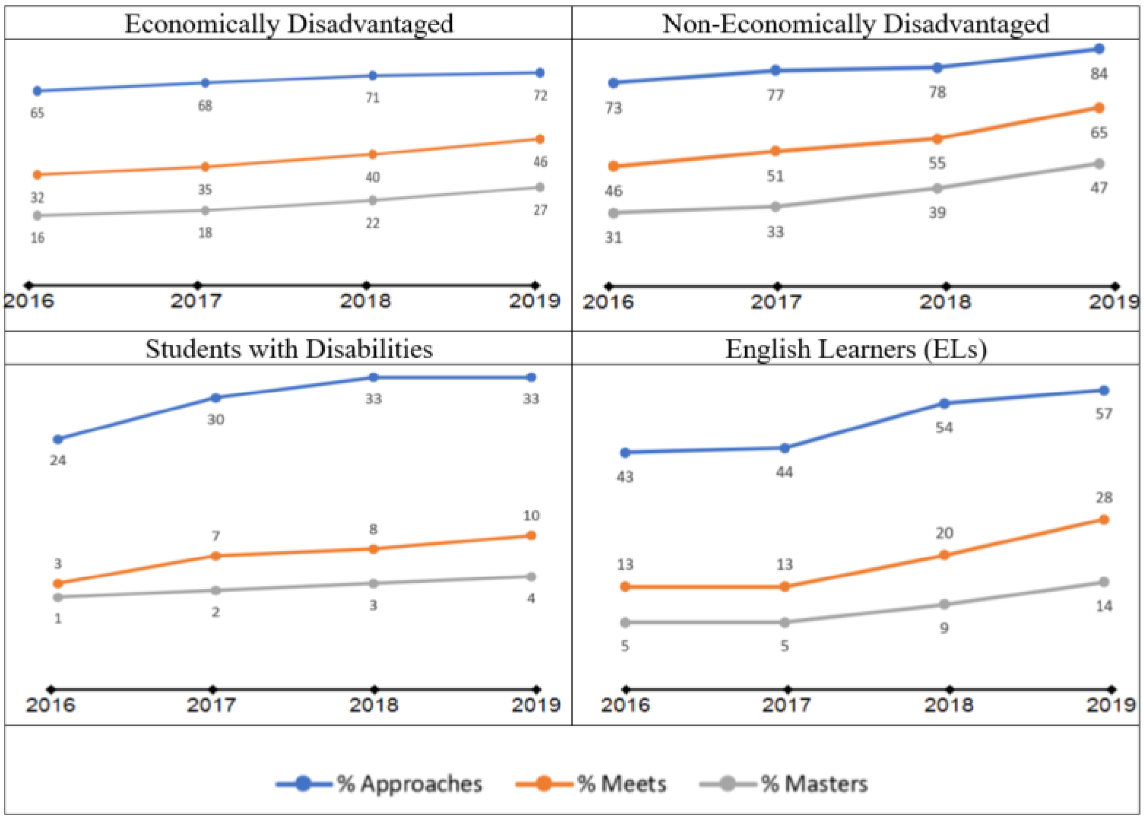
Comprised of 284 schools, the district in this study is one of the largest urban school districts in Texas and the eighth largest district in the United States. Approximately 20% of the schools have been rated Improvement Required (IR) by the Texas Education Agency (TEA), meaning the state has mandated the district must enact supports that address student deficits in the area of mathematics. Traditional instruction, where students work at the same pace on the same lesson, is no longer feasible (Walkington et al., 2014).

In the researcher's role as Curriculum Specialist, they coach mathematics teachers and assist with planning and implementing lessons and classroom management. Within their job, they work with a diverse group of teachers, comprised of both new and experienced teachers. Both groups often express concerns that their students arrive to class with limited to no prior knowledge of concepts. The pressure of getting students to pass the STAAR exam becomes overwhelming. The researcher's job entails helping teachers address the needs of all students, which seems like an insurmountable task. Computer-assisted instruction sounds like a viable option to explore.

In this large urban school district, where the achievement gap seems to widen yearly, and traditional instruction does not reach all learners, an alternative is crucial. This is evident in the fact that at least 20% of the schools in the district are classified as Improvement Required (IR), which implies that campuses received an overall rating of *D* or *F* (TEA, 2019). Figure 1 shows the STAAR end-of-course performance for specific subgroups in the district.

Figure 1

District STAAR EOC Performance by Subgroups: 2016-2019



In Texas, Algebra 1 is the foundation for all high school courses, and students who are not successful cannot advance to the next level of instruction (Texas Education Agency [TEA], 2015).

While there have been various studies conducted that conclude the use of computer-assisted instruction is beneficial and useful for students, there are other studies that show no statistical significance in using computer-assisted versus traditional instruction. Computer-assisted instruction, when used to supplement instruction, can provide tools and resources to help engage students and foster collaboration to deepen understanding.

Imagine Learning®, creator of *Imagine Math*, claims that students who pass a certain number of lessons will perform better on the STAAR end-of-course assessments. This is significant because the district spends a substantial amount of money each year to fund the program. Currently, there 26 middle, 62 high, and 15 K-12 schools that utilize the *Imagine Math* program. The program averages about $13,000 per school per year, which amounts to $1,339,000 per year. This is funding that could be allocated to other resources should the claims of *Imagine Learning*® prove to be false.

Definition of Terms

Blended Learning

Blended learning is a combination of online and face-to-face instruction (Grant & Basye, 2014). In the blended learning environment, teachers determine the right combination that works for them and their students (Tucker, 2013). Students learn some content through online delivery and have some control over time, location, and pace of lessons. Face-to-face discussions are sometimes used for students to brainstorm and share ideas, while online activities provide students with multimedia-rich content anywhere students have access to the internet (Grant & Basye, 2014).

Computer-assisted Instruction (CAI)

In traditional classrooms, teachers continue to struggle to meet the needs of the diverse population of students. It is possible to have multiple students at various levels of understanding in one classroom. In this dominant age of technology, the National Council of Teachers of Mathematics (NCTM) believes that technology is essential to teaching and learning mathematics (NCTM, 2004). With the advent of computers, the use of computer-assisted instruction has become widely popular. Computer-assisted instruction is defined as a teaching process that incorporates the use of a computer to present instructional material in such a way that requires students to interact with it (Glanze et al., 2001). CAI helps students learn and apply mathematics concepts and skills (Foster et al., 2016).

Differentiation

Differentiation is the process of making lessons developmentally appropriate for all students (Zuckerbrod, 2011). Differentiation allows students to work at their own pace. Differentiation is what happens once teachers understand what students know, what motivates them to learn, and how the student learns best (Tomlinson, 2008). When students are motivated and can work at their own pace, they begin to enjoy mathematics (O'Roark, 2013).

Imagine Math

Imagine Math is an adaptive computer program that provides instruction through tutorials and problem-solving activities (Imagine, n.d.). The program is one component of the Imagine Learning system, and more information is available through the website https://www.imaginelearning.com.

Personalized Learning

Personalized learning is student experiences customized to their individual needs, interests, and skills that empower them to take ownership of their learning (Childress & Benson, 2014). Personalized learning helps improve cognitive processes and helps students to overcome obstacles that hinder their progression (Albano et al., 2015). Teachers create materials for students and help them set their individual learning goals. As students progress at their own pace, the teacher can devote time and instruction where it's most needed (Childress & Benson, 2014).

State Testing

State testing is an accountability measurement of student achievement based on standards provided by the TEA. The State of Texas Assessment of Academic Readiness is currently used for accountability (Texas Education Agency [TEA], 2019).

STAAR

STAAR is an acronym for the State of Texas Assessment of Academic Readiness, a state assessment program for students in grades three through eight and high school. Aligned to the Texas Essential Knowledge and Skills (TEKS), STAAR includes assessments in mathematics and science, administered in grade 9, social studies is given in grade 11, and English language arts administered in grades 9 and 10. Algebra I STAAR is the end-of-course for mathematics, and students must successfully pass to graduate. Administration occurs in the spring of each school year (TEA, 2019).

Methodology

This study will employ quantitative research incorporating a correlational design. Data to be analyzed will include the number of lessons passed in the *Imagine Math* program and data from the State of Texas Assessment of Academic Readiness End-of-Course assessment for Algebra 1. The number of lessons passed will be used to understand student engagement and understanding in the program, and the STAAR end-of-course data will be used to determine if students have shown growth since beginning the *Imagine Math* program. All data will be used to analyze student growth.

Summary

The purpose of this study is to examine the effects of implementing computer-assisted instruction in Algebra 1 classes and determine whether there is a relationship between the number of lessons passed and performance on the State of Texas Assessment of Academic Readiness (STAAR). This study seeks to understand how students' participation in a computer-assisted program can support mastery and retention of mathematical content.

In conventional classrooms, teachers continue to struggle to meet the needs of the diverse population of students. It is possible to have multiple students at various levels of understanding in one classroom. Traditional instruction, where students work at the same pace on the same lesson, is no longer feasible.

In this large urban school district, where the achievement gap seems to widen yearly, and traditional instruction does not reach all learners, an alternative is crucial. Computer-assisted instruction, when used to supplement instruction, can provide tools and resources to help engage students and foster collaboration to deepen understanding.

The study includes the following: (1) a review of relevant literature, (2) methods of study, (3) results, and (4) conclusions.

Chapter II

Literature Review

The purpose of this study is to determine the effects of implementing computer-assisted instruction in Algebra 1 classes. Specifically, this study will examine whether computer-assisted instruction can help impact student mastery of mathematical concepts and consequently enhance performance on the State of Texas Assessment of Academic Readiness. The purpose of this chapter is to review the body of research regarding computer-assisted teaching practices related to mathematics instruction. The chapter will include the following sections: (1) applications of computer-assisted instruction; (2) computer-assisted instruction: embedded learning and instructional theory; (3) the effects of computer-assisted instruction on various learners; importance of algebra; and (4) a summary.

Applications of Computer-assisted Instruction

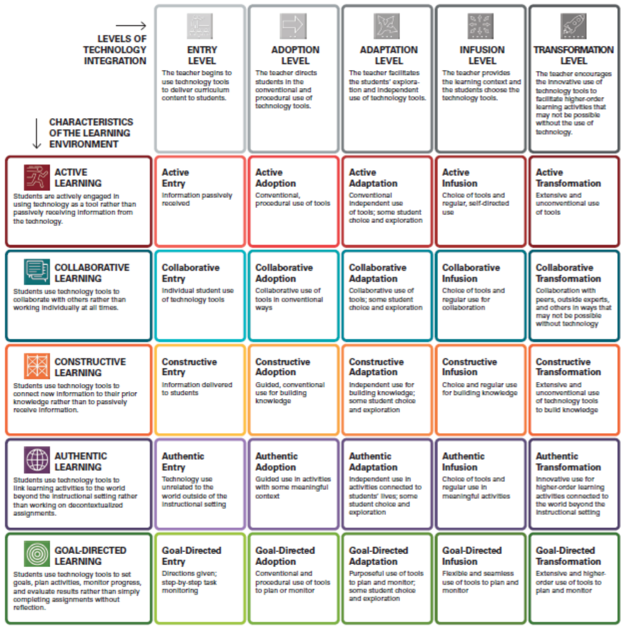
In 2000, NCTM released a revolutionary document, *The Principles and Standards for School Mathematics*, to provide guidance to teachers and administrators responsible for educational decisions regarding students in mathematics classrooms. The Standards addressed the mathematical knowledge and skills students should obtain from pre-kindergarten through grade 12. The Principles also provide the foundation for best practices and essential elements in successful programs. There are six Principles, which include equity, curriculum, teaching, learning, assessment, and technology. One of the dominant themes was technology. Technology is essential to teaching and learning mathematics, enhances students’ learning, and is necessary for teaching mathematics

(NCTM, 2004). Mathematics educators view it as critical to building active learning in mathematics. “It is impossible for me to imagine how school leaders who are focused on more authentic ways of doing math and science, who are developing rich environments for learning, can achieve that without technology,” says Linda Roberts, advisor on technology to the Secretary of Education (Trotter, 1997, p. 1).

Supporting NCTM’s call for integrating technology into mathematics classrooms, the Technology Integration Matrix (TIM), a framework for describing and targeting the use of technology to enhance learning, was developed by the Florida Center for Instructional Technology (Welsh et al., 2011). The TIM includes five characteristics of meaningful learning environments: active, collaborative, constructive, authentic, and goal-directed. The characteristics are then associated with five levels of technology integration: entry, adoption, adaptation, infusion, and transformation. Many teachers have started using computer-assisted instruction to support the implementation of the Technology Integration Matrix (Welsh et al., 2011).

Figure 2

The Technology Integration Matrix



Note. A project of the Florida Center for Instructional Technology, College of Education, University of South Florida © 2005-2019 (Welsh et al., 2011).

Computer-assisted instruction is defined as a teaching process that incorporates the use of a computer to present instructional material in such a way that requires students to interact with it (Glanze et al., 2001). It is sometimes referred to as computer-based instruction. It may be used to address instructional interventions as well as differentiation for students in the classroom. Some computer-assisted instruction differentiates by analyzing students' comprehension level and adapting instruction to meet the needs of the individual. Differentiation is the process of making lessons developmentally appropriate for all students (Zuckerbrod, 2011). Moreover, the technology provides immediate feedback on the student's progress and delivers instruction to address the area of identified need.

Categories and Types

Instruction using computers provides content through six different categories: (1) drill-and-practice, (2) tutorials, (3) games, (4) simulations, (5) discovery, and (6) problem-solving. The most widely used categories are drill-and-practice, tutorials, and simulations (Anderson, 1986). Drill-and-practice emphasizes rote memorization based on students consistently working on identical problems until they learn the content. Often it is used when learning basic mathematics skills. In some programs, continuous practice is accomplished using computer games. Tutorials use information that may include drill-and-practice, simulations, and games (Anderson, 1986). They typically ask questions, offer hints, and give explanations so that learners obtain a better understanding of the content. Based on how the student responds to questions posed, the computer may or may not advance the student to the next level, which allows for more flexibility for those who master information faster (Anderson, 1986). Finally, simulations provide a model that represents a real situation and assign a role for the student to play while interacting with the computer.

There are also different types of computer-assisted programs, which include artificial intelligence learning systems, adaptive learning, and intelligent adaptive learning. These categories and types of instruction are representative of many of the computer-assisted programs available for use, such as ALEKS®, IXL, SuccessMaker®, ST Math, *Imagine Math*, and DreamBox® Learning, just to name a few.

Table 1

Types of Computer-Assisted Instruction Programs

	CAI Program	Drill and Practice	Tutorial	Games	Simulations	Discovery	Problem solving
Artificial Intelligence Learning	ALEKS		x			x	x
Adaptive Learning	IXL	x					
	Success Maker			x			x
	ST Math			x		x	
	Imagine Math	x	x	x		x	x
Intelligent Adaptive Learning	DreamBox Learning				x	x	x

Note. CAI = computer-assisted instruction.

Artificial Intelligence Learning

Artificial intelligence learning systems assess students independently and continuously. “Assessment and LEarning in Knowledge Spaces (ALEKS) is a web-based learning system that uses adaptive questioning to quickly and accurately determine what a student knows and doesn’t know in a course” (“What is ALEKS,” n.d.). It also uses artificial intelligence to determine an individual’s knowledge of a subject and then provides a list of topics the individual is ready to learn. Students work through topics in a course, and the program continually reassesses the student to determine whether the topics covered are retained. The program tends to avoid multiple-choice questions and provides content mostly from the discovery and problem-solving categories while also offering one-on-one instruction from any web-based computer. Students begin by watching a brief tutorial on how to use the system and input answers. Then they take the

ALEKS® Assessment, and the program uses the responses from the assessment to develop a personalized pathway for the individual student, known as the Learning Mode ("What is ALEKS," n.d.). Students have a choice of what topics they want to learn based on the results from the assessment and can only advance to the next topic when the program determines the student has shown mastery by consistently answering problems correctly.

Adaptive Learning

Adaptive learning systems use algorithms to deliver differentiated resources and activities that address the unique needs of the individual learner. For example, if a student is working on a track covering solving equations and exhibit difficulty when solving equations that include fractions, the program will adapt and provide mini-lessons on fractions for the student. Several well-known programs use adaptive learning as their mode of instruction, including IXL Math, ST Math, SuccessMaker®, and *Imagine Math*. IXL Math offers content from the drill-and-practice category. Students engage in regular skill practice and are provided with personalized recommendations to help them understand how they can improve. Teachers can monitor student progress by viewing practice sessions to offer whole-group instruction or target small groups when students have common areas of need (IXL, n.d.). Spatial-Temporal Math, known as ST Math, is an adaptive learning program that uses games to engage students.

The program begins by presenting math concepts as visual puzzles and uses animated manipulatives to provide feedback on student solutions (Wendt et al., 2018). ST Math puzzles are engaging, visual, personalized, and creative. Each puzzle offers animated feedback that adjusts based on student response. In the beginning, concepts are shown without language and symbols so that the students may develop a conceptual understanding of the problems. Symbols are gradually introduced as the puzzles progress, and students must demonstrate mastery to move forward. The puzzles are customized for individual students and require thinking outside the box to apply their learning and solve problems (Wendt et al., 2018). Another adaptive learning program is SuccessMaker®. It provides prescriptive math interventions and uses student progress on games to forecast future performance.

Additionally, it provides real-world math problems and performance tasks that force students to think critically. Because the program is primarily an intervention program, teachers can monitor student progress and use the forecast to provide individualized instruction necessary for success (Pearson, n.d.). SuccessMaker® is adaptive and continuously adjusts math content based on student performance. Lastly, *Imagine Math* is an adaptive program that provides instruction through tutorials and problem-solving activities but also incorporates games. Each student works on a personalized pathway based on the results of a beginning-of-the-year benchmark assessment. Students who feel comfortable with certain concepts may opt to test out of a pathway. Lessons in pathways provide scaffolding to support mastery, and students are encouraged to use journaling to explain their thinking and provide justifications. The program also includes access to a live tutor 24 hours a day that are certified and bilingual (Imagine, n.d.).

Intelligent Adaptive Learning

Intelligent adaptive programs adapt to individual learners through continuous embedded formative assessments (DreamBox, 2012). DreamBox® Learning differs from the programs mentioned above in that it uses an intelligent adaptive mode of instruction. "Intelligent adaptive learning adapts to each learner, builds on each learner's prior personal knowledge and goals, empowers learners to make self-directed choices, continually assesses to form an increasingly rich mental model of the learner, and continuously utilizes assessment data to individualize instruction appropriately" (DreamBox, 2012). The program adapts lessons, hints, levels of difficulty, and sequence. The program utilizes interactive manipulatives which appear to be game-like. In addition to analyzing right and wrong answers, DreamBox® also analyzes student strategies to determine if additional support is needed. Regardless of which mode of instruction students use, each of the programs provides supplemental tools that may be beneficial to student achievement. The integration of technology, namely computer-assisted instruction, supports comprehension and motivates students to learn the content (Serin & Oz, 2017).

Computer-Assisted Instruction: Embedded Learning and Instructional Theory

Several learning and instructional theories may link to the use of computer-assisted instruction. The theories that strongly correlate to computer-assisted instruction are behaviorism and personalized learning.

Behaviorism

Ivan Pavlov's theory of behaviorism, namely classical conditioning, is connected to the use of computer-assisted instruction. In behaviorism, learning takes place as a response to a stimulus in the environment (Merriam & Bierema, 2014; Jarius & Wildemann, 2017). With classical conditioning, two stimuli link together to yield a new response, and a change in behavior determined whether learning had occurred. One stimulus is considered neutral, and the other elicits a natural reaction (Jarius & Wildemann, 2017). In Pavlov's classic experiment involving dogs, the dogs were conditioned to associate the sound of a bell with the presence of food. So, when a bell rang, the dogs would expect food. It is noted that "key components of a behaviorist approach to learning are part of our everyday vocabulary" (Merriam & Bierema, 2014, p. 27). For example, in some CAI programs, namely, *Imagine Math*, students are "rewarded" with points to purchase avatars when they complete a lesson. After completing 30 lessons, students receive a gift card to buy food at a local restaurant. Students completing the lessons are the neutral stimulus and the reward system, points and gift cards, elicits a response. Even with the presence of a reward system, computer-assisted instruction has shifted from a behaviorist approach to more of a constructivist approach as computer technology has become more erudite (Lowe, 2001).

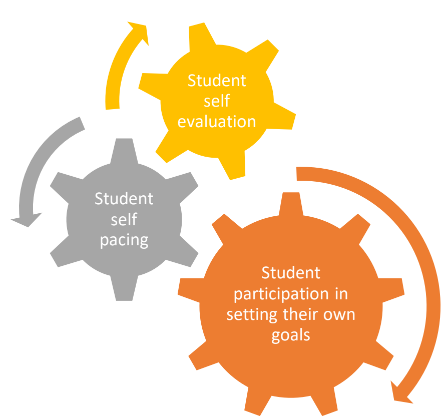
Personalized Learning

Computer-assisted instruction is "a method of instruction that uses the computer as a tool to assist in identifying and meeting the needs of individual learners" (Anderson, 1986). The goal of CAI is to learn and retain content with instruction that is student-centered. The computer program determines where a student is with regards to content knowledge by administering some form of diagnostic assessment. It then analyzes the results and customizes instruction to assist in filling in gaps in learning and connecting prior knowledge to concepts to be learned. Although teachers create different learning experiences for students in their classrooms, it becomes difficult to differentiate when there is limited instructional time in the classroom, and class size is significant (Seo & Bryant, 2009).

Personalized learning is linked to the use of computer-assisted instruction. It can be described as student experiences customized to their individual needs, interests, and skills that empower them to take ownership of their learning (Childress & Benson, 2014). It challenges traditional instruction by creating individual pathways for students to consider that may include small group work, one-on-one time with the teacher, individual and group projects, and moving away a teacher leading a common lesson with the whole class. Personalized learning may sometimes be referred to as individualized instruction and is comprised of three components: student participation in setting their own goals, self-pacing, and involvement in the evaluation process (Miller, 1976).

Figure 3

Components of Personalized Learning



Personalized learning allows students to work at different paces and different places in the learning environment. This is not feasible in a traditional classroom; however, in a blended learning environment, students can be actively engaged in experiences that are interactive. According to Grant and Basye (2014):

> By elegantly blending assessment with daily classroom instruction, technology-based learning platforms can serve as the cornerstone of revolutionary educational change. They have the potential to personalize the learning process, support teachers in enacting best teaching strategies, and help students meet ambitious and rigorous standards (p. 52).

In the blended learning environment, a combination of technology with face-to-face instruction, students can control the time and pace of their learning (Tucker, 2013). Using technology to personalize instruction can engage and empower students and foster collaboration between and among students. When students advance at their own pace, teachers are free to devote time, attention, and instruction to other individual students or other groups of students experiencing similar setbacks (Childress & Benson, 2014).

Effects of Computer-Assisted Instruction

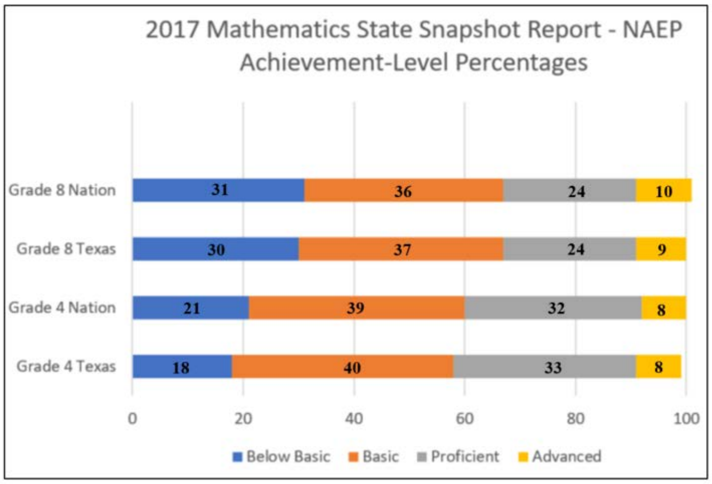
Technology has permeated every aspect of modern life, and school districts are no exception. To boost student's academic performance, districts have devoted a large percentage of their budgets towards educational technology and programs (Cheung & Slavin, 2013). Studies conducted on the use of computer-based or computer-assisted instruction report positive effects on students. Results of the studies concluded that students learned more in classes that included computer-assisted instruction and in less time than with traditional teaching (Kulik & Kulik, 1987; Mautone et al., 2005; Aliasgari et al., 2010).

Elementary Students

In elementary school, learners face many challenges with completing tasks and staying focused. Hill (2015), a journalist and freelance writer, believes there is a direct correlation between a student's age and their attention span. Most children have a concentration rate of 2 – 5 minutes for every year old they are. For example, a child that is six years old would be able to focus for 12 – 30 minutes, at most. That time may be shortened due to various distractions in the environment. The idea of a shortened attention span is concerning when you look at how fourth-grade students are performing in mathematics in Texas and the nation. The percent of Grade 4 students in Texas who performed below proficient was 56 percent in 2017 on the National Assessment of Educational Progress (NAEP) and 60 percent in the nation, while the percent Grade 8 students who performed below proficient was 67 percent in the state as well as in the nation (NAEP, 2018).

Figure 4

2017 Mathematics State Snapshot Achievement-Level Percentages



When learners fail at basic mathematical concepts in elementary school foundation classes, it is an indication of a significant problem that has nothing to do with the learner (Lashley, 2017). Student attention, engagement, and effort are crucial to learning mathematics (Becker, 2000). To grasp the student's attention, schools and teachers have begun to supplement traditional instruction with computer-assisted instruction (Lashley, 2017). There is hope that students' capacity to apply what they have learned and to solve problems will increase with a rise in the use of computer-assisted instruction in more sophisticated learning situations (Johnson et al., 1985).

Computer-assisted instruction has caught the attention of international researchers. Several international studies sought to determine the effects of computer-assisted instruction on the achievement, attitudes, and performance of fourth-grade students. One study conducted on fourth-grade students in North Cyprus suggested that computer-assisted instruction is an excellent supplementary method of instruction. The study resulted in an increase in student performance in units on the multiplication and division of natural numbers; however, students did not do as well on the unit involving fractions (Pilli & Aksu, 2013). Additionally, students exposed to computer-assisted mathematics program Frizbi Mathematics 4 outperformed students who were given traditional instruction. Another study conducted on fourth-grade students in Guyana showed a significant difference between the academic performance of students exposed to computer-assisted instruction and those given traditional instruction in favor of using the computer (Lashley, 2017).

Secondary Students

With the introduction of technology in the classrooms, many secondary schools have opted to use a significant amount of their budget to purchase individual laptops or tablets for students. The district in this study is among those districts that have initiated a one-to-one program for students. The program essentially provides every high school student with a laptop computer as a 21st-century learning tool with the goal of extending the program to middle and elementary school students in the future (Houston Independent School District [HISD], 2013). The purpose of the one-to-one initiative is to give students equitable access to a rigorous instructional program. Using the laptops, along with computer-assisted instruction, can empower students to collaborate and take ownership of their learning.

A study on the influence of computer-aided mathematics instruction on the performance of public secondary schools in Kenya found a strong correlation between the use of computer-assisted instruction and student performance in mathematics. They stress that teachers and students should be appropriately trained on the use of computers prior to integrating and implementing computer-assisted instruction and note that how teachers perceive technology in the classroom has a substantial effect on student achievement and performance (John et al., 2018).

A study on the effectiveness of using computer-assisted instruction as a supplement on selected algebra topics was conducted in central Illinois. The participants were all eleventh and twelfth-grade students enrolled in a two-year geometry or algebra course. The study was necessitated due to students graduating from high school and entering college with deficits in mathematics. Several factors were cited as reasons for the gaps, including math anxiety, lack of resources, and negative attitudes toward mathematics. Results concluded that students gained knowledge and skills for factoring and solving problems involving radical expressions and exponents, and students performed better on the posttest after treatments with computer-based instruction (Bassoppo-Moyo, 2010). Both studies showed positive results with using computer-assisted instruction.

Students with Learning Disabilities

School districts have a substantial number of students labeled with a learning disability (LD). Approximately 6% of school-age children are identified as having LD (Fuchs et al., 2007). Students suffer from a variety of issues, including attention deficit hyperactive disorder (ADHD). Capturing and keeping student’s attention becomes a daunting task, especially in inclusion classes where the population is so diverse. With the lack of qualified special education and certified mathematics teachers, the use of supplementary computer-assisted instruction is critical to meeting the needs of the students (Xin et al., 2017). Several methods of instruction commonly used among various special education populations— “drill and practice, individualized instruction, different starting points, and immediate feedback”—are standard features of educational software (Schmidt et al., 1985, p. 494). The incorporation of games, visuals, immediate feedback, and access to a live tutor within computer-assisted programs are ideal for working with learning disabled students. In a study involving exceptional students, CAI showed positive effects on student achievement (Schmidt et al., 1985). Moreover, students with learning disabilities who used the Please Go Bring Me-Conceptual Model-Based Problem Solving (PGBM-COMPS) intelligent tutor program outperformed those taught by traditional instruction (Xin et al., 2017).

In classrooms where instructional time is limited, and the number of students is significant, computer-assisted instruction is encouraged (Seo & Bryant, 2009). CAI programs differentiate for learners by adapting instruction to fit the needs of the individual based on their learning styles. It can assist teachers challenged with tailoring instruction to diverse students. However, in a meta-study of computer-assisted instruction studies in mathematics for students with learning disabilities, the results did not show definite effectiveness on student performance (Seo & Bryant, 2009).

Lack of Clarity About Effectiveness of CAI

While there have been various studies conducted that conclude the use of computer-assisted instruction is beneficial and useful for students, there are other studies that show no statistical significance in using computer-assisted versus traditional instruction. In a review of the literature concerning computer-assisted mathematics instruction for students with specific learning disabilities, the effectiveness of CAI was unclear (Stulz, 2017). Five meta-analyses that compared computer-based instruction to traditional classroom instruction found there was little difference between the two (Lowe, 2001). The use of technology in middle school is controversial, and the effectiveness of computer-assisted instruction is relative to teachers' experience in technology and attitudes of teachers and students (Guerrero et al., 2004).

Importance of Algebra

In the state of Texas, there is a set of standards given to public schools for instruction in grades K – 12, known as the Texas Essential Knowledge and Skills (TEKS). The current TEKS for mathematics was adopted in 2012, and these standards dictate what students should know and be able to do. The study of algebra is a requirement for students to graduate high school, and students start preparation beginning as early as Grade 3.

Robert Moses, the founder of the Algebra Project, asserts that "algebra has become a gatekeeper for citizenship and economic access and as the world becomes more technological, the reasoning and problem solving that algebra demands are required in a variety of workplace settings" (Blair, 2003, p. 1). In elementary school, teachers begin to help students connect the arithmetic to algebraic reasoning and thinking by allowing students to model, explore, argue, conjecture, and test their ideas while they practice computational skills. In middle school, teachers provide rich opportunities for students that allow them to connect their personal experiences with concepts and ideas they are learning. In high school, students would continue to build their algebraic reasoning and thinking by using their "funds of knowledge" to make connections to big ideas in algebra (Walkington et al., 2014).

Algebraic reasoning and thinking involve analyzing patterns and relationships, generalizing situations based on observable patterns, and examining how things change. It builds on students' understanding of numbers and their relationships (Ketterlin-Geller et al., 2007). In elementary, students study patterns of shapes, colors, and numbers. They categorize things that are similar and make generalizations about new ideas introduced to them. In middle school, students begin to connect patterns to symbolic work with expressions and equations and focus mainly on proportionality. In high school, students connect the concept of proportionality to interpret and analyze functions and make connections to multiple representations. Algebraic reasoning and thinking continue well beyond high school.

When students use algebraic reasoning, they primarily look for patterns in situations and then try to generalize from familiar to unfamiliar situations. Algebraic reasoning is present in many areas of our lives and is also an intricate part of many careers. Construction workers and architects use algebraic reasoning to design buildings and bridges and to determine the amount of material needed for construction to occur. Bankers use algebraic thinking to determine interest rates. Software developers create codes using algebraic reasoning. Scientists use algebra in a variety of fields to solve complex problems. Anesthesiologists use algebra to determine the amount of medicine to administer to patients based on their weight and prior medical history. Algebra is also helpful in daily life, from using functions to determine profit and loss of business to calculating the number of miles per gallon of gasoline when planning a road trip (Ketterlin-Geller et al., 2007).

Algebra, or algebraic reasoning and thinking, is essential for various reasons. It is the foundation for all mathematics, and it prepares students for college and careers in numerous professions (Blair, 2003).

Summary

The use of technology provides teachers with the necessary tools to differentiate for every student (Grant & Basye, 2014). Computer-assisted instruction presents opportunities for students to work at their own pace as well as collaborate with other students in a non-threatening environment, thereby freeing up the teacher to work with individuals and small groups that require additional assistance.

Studies conducted on the effectiveness of computer-assisted instruction concluded that students typically learned more in classes where they received instruction via the computer versus traditional instruction. Additionally, students reported enjoying classes more when they received computer assistance and learned lessons in less instructional time (Kulik & Kulik, 1987).

Although many studies showed positive occurrences with the implementation of computer-assisted instruction, still others showed little to no difference between the use of computer-assisted versus traditional instruction (Stulz, 2017; Lowe, 2001). Various factors influence the effectiveness of implementing computer-assisted instruction in the classroom (Guerrero et al., 2004; Lowe, 2001).

Chapter III

Methodology

A large urban district purchased a computer-assisted instruction program for use in area schools to address the issue of students entering high school mathematics classrooms with gaps in their content knowledge. The goal of the program was to provide differentiated instruction to help students increase their content knowledge.

Methods

The purpose of this quantitative, correlational study is to analyze the effects of implementing the computer-assisted instruction program, *Imagine Math*, in Algebra 1 classes. The study sought to determine whether there is a relationship between the number of lessons passed in the program and the scores on the State of Texas Assessment of Academic Readiness Algebra 1 End of Course exam.

To answer the research questions, a quantitative methodology was chosen for this study. The methodology utilizes statistical analysis to answer questions and explore patterns to determine whether a relationship exists (Rudestam & Newton, 2014). A quantitative methodology was chosen because the data are numerical and are needed to determine the relationship between lessons passed in the *Imagine Math* program and the scores on the STAAR End of Course exam for Algebra 1. As a result, correlational design was employed because it is a quantitative design with the capabilities of examining relationships between numeric values (Creswell, 2014).

The central question addressed in this study: What is the relationship between the number of successfully completed computer-assisted Algebra I mathematics instruction lessons and performance on the State of Texas Assessment of Academic Readiness? The following sub-questions were used to address the central question:

1. What is the correlation between total *Imagine Math* lessons passed and the STARR Algebra 1 assessment for various demographics represented?
2. How does total *Imagine Math* lessons passed predict the STARR Algebra 1 assessment after controlling for gender, grade level, and ethnicity?
3. What are the different aspects of the relationship between the number of *Imagine Math* lessons passed and the STARR Algebra 1 assessment?

The null-hypothesis for the research question is as follows: The data will show no statistically significant relationship between the number of lessons passed in *Imagine Math* and students' scale scores on the STAAR end-of-course assessment for Algebra 1 students.

Participants and Settings

The district selected for this study is a large urban district located in southeast Texas. The district serves approximately 210,000 students and includes 280 schools, which consist of 8 early childhood, 160 elementary, 38 middle, 37 high, and 37 combined/other campuses (See Table 2).

Table 2

District Campuses and Enrollment

Academic Level	Number of Schools	Enrollment	% of All Students
Early Childhood Centers	8	3,524	1.68
Elementary	160	100,793	48.05
Middle	38	33,054	15.76
High	37	47,785	22.78
Combined/Other	37	24,616	11.73
Total	**280**	**209,772**	**100**

Note. Combined/Other = combination of middle/high or elementary/middle, alternative, and charter schools.

The targeted course for the *Imagine Math* program at schools involved in this study was Algebra 1. Students selected for inclusion in data collections were all those who completed an Algebra 1 class in the 2018-2019 school year for the first time. The group represented in this study was comprised of approximately 4,800 students of mixed gender and grade level, socio-economic status, and ethnicity representative of the large urban school district. The breakdown of students by grade level, gender, and ethnicity are illustrated in Tables 5, 6, and 7.

Figure 5

Algebra 1 Students by Grade Level

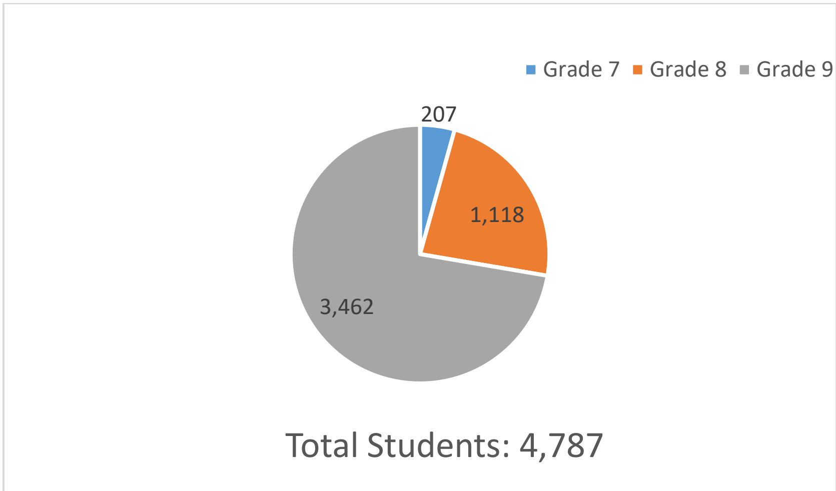


Figure 6

Algebra 1 Students by Gender

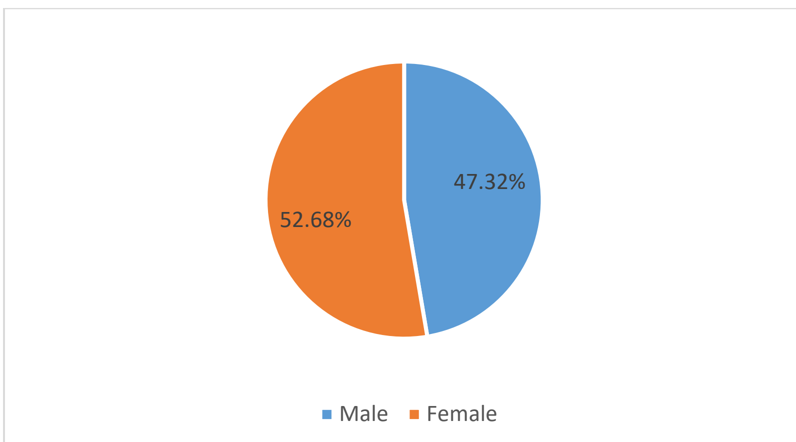
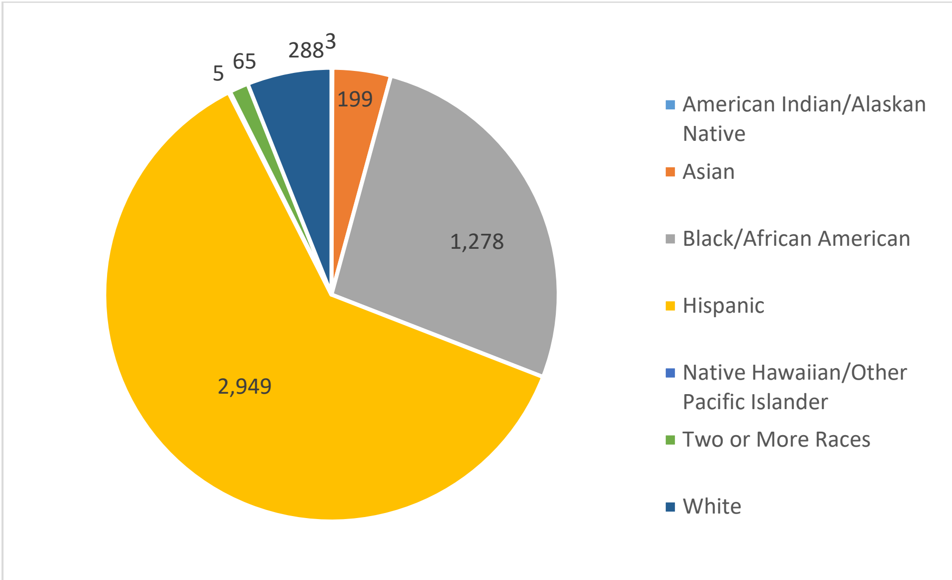


Figure 7

Algebra 1 Students by Ethnicity



This research utilized archival data from middle and high school campuses in an urban community located in southeast Texas. The campuses selected were those who offered an Algebra 1 course. Consent for participation in this study was not needed since archival data was used. No direct identifiers will be obtained. All previously collected data will be de-identified for this study.

Procedures

During the 2018-2019 school year, data were collected on the use of the computer-assisted instruction program, *Imagine Math*. Data were analyzed to determine students included in the study. Student data were selected based on the criterion that they were enrolled in an Algebra 1 course for the first time and that they had completed lessons in the *Imagine Math* program. The number represented was initially about 12,800 students. Students who completed an Algebra 1 course in the 2018-2019 school year but did not complete or pass any lessons in the *Imagine Math* program were excluded from the study, decreasing the number of participants to 4,787 students.

Once permission to conduct this research was granted by the local school district and the University of Houston, archived data from the 2018-2019 school year were used to begin analyzing the results. Data were stored on secured district servers in Microsoft Excel. The researcher was able to determine whether there was a relationship between the computer-assisted instruction program, *Imagine Math*, and students' scale scores on STAAR using the results found in this research.

Data Collection Procedures

The researcher used archival data from the 2018-2019 *Imagine Math* for the number of lessons passed in Algebra 1 and the spring 2019 scale scores for the STAAR Algebra 1 end-of-course exam. All data were readily available to the researcher in their role as district Curriculum Specialist for Secondary Mathematics. Permission from the school district was obtained before performing any research or conducting any analysis of data.

Data were collected through an electronic medium. As part of their job, the researcher collected data on student usage in the *Imagine Math* program for each middle and high school in the district. A report that details usage in the program by campus was generated every month and disseminated to members of the Secondary Mathematics Curriculum department. From those reports, the data determined for inclusion in the study were information on the amount of *Imagine Math* lessons that students passed.

Each year, the state of Texas sends a report to districts that detail students' scores for the STAAR end-of-course assessment. The report is broken down by student performance per campus. Student performance is reported using vertical scale scores. A scale score for the STAAR test "is a conversion of the raw score onto a scale that is common to all test forms for that assessment" (TEA, 2019).

Table 3

STAAR End-of-Course Performance Standards for Algebra 1

Performance Standard	Scale Score
Did not meet grade level	< 3550
Approaches grade level	3550
Meets grade level	4000
Masters grade level	4333

Note. Students whose scale scores fall below 3550 do not meet grade level and must retest.

The reports are released by the district and stored in Analytics for Education (A4E) dashboards located in the learning management system and is accessible by district employees. Also included in this study was data for first time Algebra 1 test-takers.

Reports for both *Imagine Math* and STAAR were formatted into a Microsoft Excel spreadsheet and then imported into the Mathematica software, IBM SPSS Statistics, so that statistical measures could easily be computed.

For the purpose of this study, all students enrolled in an Algebra 1 course for the first time in the 2018-2019 school year were selected from the 38 middle school, 37 high school, and 37 combined/other campuses. Students enrolled in Algebra 1 who did not pass any lessons or did not work within the program were excluded from the study.

Instrumentation

The data collection instrument employed in this correlational research was secondary data from existing student usage log records stored in the *Imagine Math* platform from the 2018-2019 school year. Additional data used were secondary data detailing students' performance on the STAAR end-of-course assessment for Algebra 1 administered in the spring of 2019. STAAR data were stored in the learning management system – Its Learning. The data instrument used in the collection of secondary data was an Excel spreadsheet.

Data Analysis Procedures

After data was collected, an analysis was conducted using correlation and linear regression. A scatterplot of STAAR scale scores against the number of lessons passed in *Imagine Math* was plotted. Visual inspection of the scatterplot was used to determine whether there was a linear relationship between the variables with the number of lessons passed in *Imagine Math* representing the independent variable.

Linear regression was then run to determine the correlation and association between the variables and outliers were identified. To further assess linearity, a scatterplot with a superimposed regression line was plotted. The correlation coefficient of the linear regression was reviewed to evaluate the strength of the relationship between the two variables. The scatterplot and linear regression were then examined to determine whether a negative or positive correlation existed between the number of lessons passed in *Imagine Math* and performance on the STAAR end-of-course assessment. Scatterplots and linear regressions for individual grade bands in Algebra 1, as well as ethnicity and gender, were also created to ascertain whether there was a stronger correlation between the variables based on the grade the student was in when taking the Algebra 1 course.

Summary

The purpose of this quantitative, correlational study was to determine if a relationship existed between the number of lessons passed in the computer-assisted program, *Imagine Math*, and students' scores on the State of Texas Assessment of Academic Readiness End-of-Course exam for Algebra 1. Using statistical analysis, this study sought to determine whether the use of a computer-assisted instruction program showed significant associations to a students' score on the end-of-year assessment given by the state of Texas.

The targeted course for the *Imagine Math* program at schools involved in this study was Algebra 1. Students selected for inclusion in data collections were all those who completed an Algebra 1 class in the 2018-2019 school year for the first time. Data were analyzed to determine students to be included in the study. Student data were selected based on the criterion that they were enrolled in an Algebra 1 course for the first time and passed lessons in the program. A scatterplot of STAAR scale scores against the number of lessons passed in *Imagine Math* was plotted. Linear regression was then run to determine the correlation and association between the variables and outliers were identified. The scatterplot and linear regression were then examined to determine whether a negative or positive relationship existed between the number of lessons passed in *Imagine Math* and performance on the STAAR end-of-course assessment.

Chapter 4 of this study includes the analysis of the data. Chapter 5 consists of the discussion of the findings, conclusion of the study, and a summary of the data. The researcher then discusses recommendations for further research.

Chapter IV

Results

The purpose of this study was to examine the relationship between using the computer-assisted instruction program, *Imagine Math*, and student performance on the STAAR Algebra 1 end-of-course assessment. In addressing the research question, the study tested the following null hypothesis: The data will show no statistically significant relationship between the number of lessons passed in *Imagine Math* and the scores on the STAAR end-of-course exam for Algebra 1 students.

Research Questions

The central question: What is the relationship between the number of successfully completed computer-assisted Algebra 1 mathematics instruction lessons and performance on the State of Texas Assessment of Academic Readiness?

Sub-questions:

1. What is the correlation between total *Imagine Math* lessons passed and the STARR Algebra 1 assessment for various demographics represented?
2. How does total *Imagine Math* lessons passed predict the STARR Algebra 1 assessment after controlling for gender, grade level, and ethnicity?
3. What are the different aspects of the relationship between the number of *Imagine Math* lessons passed and the STARR Algebra 1 assessment?

Participants

As stated in Chapter Three, the district selected for this study is a large urban district located in southeast Texas that serves approximately 210,000 students. The targeted course for the *Imagine Math* program at schools involved in this study was Algebra 1. Students selected for inclusion in data collections were all those who completed an Algebra 1 course for the first time in the 2018-2019 school year and passed lessons in the *Imagine Math* program. The group represented in this study was initially comprised of 12,787 students of mixed gender and grade level, socio-economic status, and ethnicity representative of the large urban school district shown in Table 4. Students who completed an Algebra 1 course in the 2018-2019 school year but did not complete or pass any lessons in the *Imagine Math* program were excluded from the study, decreasing the number of participants to 4,787.

Table 4

Student Count by Grade Level, Ethnicity and Gender

Ethnicity	Male	Female
Grade 7		
American Indian or Alaskan Native (Non-Hispanic)	0	0
Asian (Non-Hispanic)	16	12
Black or African American (Non-Hispanic)	15	16
Hispanic Latino of any race	47	52
Native Hawaiian or Other Pacific Islander (Non-Hispanic)	0	0
Two or More Races (Non-Hispanic)	5	4
White (Non-Hispanic)	22	18
Grade 8		
Ethnicity	Male	Female
American Indian or Alaskan Native (Non-Hispanic)	0	1
Asian (Non-Hispanic)	66	49
Black or African American (Non-Hispanic)	84	129
Hispanic Latino of any race	261	358
Native Hawaiian or Other Pacific Islander (Non-Hispanic)	3	0
Two or More Races (Non-Hispanic)	11	19
White (Non-Hispanic)	62	75
Grade 9		
Ethnicity	Male	Female
American Indian or Alaskan Native (Non-Hispanic)	2	0
Asian (Non-Hispanic)	28	28
Black or African American (Non-Hispanic)	442	592
Hispanic Latino of any race	1126	1105
Native Hawaiian or Other Pacific Islander (Non-Hispanic)	0	2
Two or More Races (Non-Hispanic)	13	13
White (Non-Hispanic)	62	49

Results

Data were analyzed to determine if a relationship existed between the number of lessons passed in Imagine Math and students’ scale scores for the STAAR Algebra 1 end-of-course assessment. The researcher used archival data from the 2018-2019 *Imagine Math* for the number of lessons passed in Algebra 1 and the spring 2019 scale scores for the STAAR Algebra 1 end-of-course assessment. The data used included all students who completed an entire year of Algebra 1 for the first time in the 2018-2019 school year.

Reports for both *Imagine Math* and STAAR were formatted into a Microsoft Excel spreadsheet and then imported into the Mathematica software, IBM SPSS Statistics, so that statistical measures could be easily computed. An analysis was conducted using correlation and linear regression. A scatterplot of STAAR scale scores against the number of lessons passed in *Imagine Math* was plotted with *Imagine Math* as the independent variable. Linear regression was then run to determine the correlation and association between the variables. The correlation coefficient, r, of the linear regression was reviewed to evaluate the strength of the relationship between the two variables. The scatterplot and linear regression were then examined to determine whether a negative or positive correlation existed between the number of lessons passed in *Imagine Math* and performance on the STAAR end-of-course assessment.

Data were analyzed using a hierarchical regression that examined the relationship between grade level, gender, ethnicity, and the total number of *Imagine Math* lessons passed and students’ performance on the STAAR end-of-course assessment. Additionally, quantile regression was run for all students in Grades 7-9 to explore different aspects of the relationship between the number of *Imagine Math* lessons passed and scale scores on the STAAR Algebra 1 end-of-course assessment.

Table 5 shows the descriptive statistics for all students taking Algebra 1 in grades 7–9. The scale scores ranged from 1420 to 6181 for all students with an average scale score of 4176. The number of *Imagine Math* lessons ranged from one to 136, with an average of 10 lessons passed.

Data for 4,787 students were analyzed to determine if a relationship existed between and students' scale score on the STAAR Algebra 1 End-of-course assessment (M = 4176.65, SD = 626.515) and the number of *Imagine Math* lessons passed (M = 10.02, SD = 13.469).

Table 5

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Scale Score	4,787	1420	6181	4176.65	626.515
Total *Imagine Math* Lessons Passed	4,787	1	136	10.02	13.469
Valid N (listwise)	4,787				

Table 6 shows the Pearson's correlation between the data. Pearson's r data analysis revealed a moderate positive correlation, $r = .39$. Students who passed more *Imagine Math* lessons reported higher scale scores. Pearson's r ranges in value from -1 to +1. The further r is from zero, the stronger the correlation. A weak correlation is $| r | \leq .30$, moderate correlation is $.30 < | r | < .70$ and a strong correlation is $| r | \geq .70$.

Table 6

Correlations

		Scale Score	Total *Imagine Math* Lessons Passed
Scale Score	Pearson Correlation	1	.389**
	Sig. (2-tailed)		.000
	N	4,787	4,787

Note. ** Correlation is significant at the 0.01 level (2-tailed).

Hierarchical Regression

Hierarchical regression was utilized to understand the effect of the number of lessons passed in *Imagine Math* on students' STAAR Algebra 1 scale scores. Table 7 shows the model summary of the data.

Table 7

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.520[a]	.271	.270	535.265	.271	591.296	3	4783	.000
2	.581[b]	.338	.337	510.155	.067	483.429	1	4782	.000

Note. a. Predictors: (Constant), Gender, Grade level, Ethnicity
b. Predictors: (Constant), Gender, Grade level, Ethnicity, Total *Imagine Math* lessons passed

Model 1 is the starting model and reflects the variables gender, grade level, and ethnicity compared to a model with no independent variables. This model is statistically significant, $p < .001$. The addition of total *Imagine Math* lessons passed in Model 2 led to a statistically significant increase in R^2 of .067, $F(1, 4782)$, $p < .001$. The full model of gender, grade level, ethnicity, and total Imagine Math lessons passed to predict students' scale scores on the STAAR Algebra 1 end-of-course assessment was statistically significant, $R^2 = .338$, $F(4, 4782) = 609.059$, $p < .001$, adjusted $R^2 = .337$. The standardized coefficients, β values, were grade level (-.440), gender (.075), ethnicity (.000) and total *Imagine Math* lessons passed (.269), for $p < .001$. See Table 8 for full details on each regression model.

Table 8

Hierarchical Multiple Regression Predicting Scale Scores from Grade Level, Gender, Ethnicity, and Total Imagine Math Lessons Passed

	STAAR Scale Score Performance			
	Model 1		Model 2	
Variable	B	β	B	β
Constant	9140.3**		8339.5**	
Grade Level	-579.8*	-.510	-499.7**	-.440
Gender	106.9	.085	94.6**	.075
Ethnicity	4.3	.007	-.1**	.000
Total *Imagine Math* Lessons Passed			12.5	.269
R^2	0.271		0.338	
F	591.29**		609.059**	
ΔR^2	.271		.067	
ΔF	591.29**		483.429**	

Note. $N = 4,787$. * $p < .05$, ** $p < .001$.

Quantile Regression

Quantile regression was used to explore different aspects of the relationship between the number of *Imagine Math* lessons passed and scale scores on the STAAR Algebra 1 end-of-course assessment. Tables 9 and 10 show the model quality and parameter estimates by different quantiles with Quantile-25, Quantile-50, and Quantile-75, each accounting for more than 8% of the explained variability in scale scores.

Table 9

Model Quality

	Model Quality[a,b,c]			
	q = 0.25	q = 0.5	q = 0.75	q = 0.95
Pseudo R Squared	.087	.088	.087	.063
Mean Absolute Error (MAE)	537.3337	447.3896	546.8446	1077.1448

Note. a. Dependent variable: scale score
b. Model: (Intercept), total *Imagine Math* lessons passed
c. Method: Simplex algorithm

Table 10

Parameter Estimates by Different Quantiles

Parameter Estimates by Different Quantiles[a,b]				
Parameter	q = 0.25	q = 0.5	q = 0.75	q = 0.95
(Intercept)	3578.182	3928.400	4314.377	5037.678
Total *Imagine Math* Lessons Passed	19.273	19.267	18.623	17.864

Note. a. Dependent variable: scale score
b. Model: (Intercept), Total *Imagine Math* lessons passed

Table 11 shows parameter estimates by individual quantile levels. Levels analyzed were quantile-25 (0.25), quantile-50 (0.50), quantile-75 (0.75), and quantile-95 (0.95).

Table 11

Parameter Estimates by Individual Quantile Levels

Parameter Estimates[a,b]					
Quantile-25					
Parameter	Coefficient	Std. Error	t	df	Sig.
(Intercept)	3578.18	12.513	285.96	4785	.000
Total *Imagine Math* Lessons Passed	19.273	.745	25.86	4785	.000
Quantile-50					
(Intercept)	3928.40	12.398	316.86	4785	.000
Total *Imagine Math* Lessons Passed	19.27	.739	26.09	4785	.000
Quantile-75					
(Intercept)	4314.38	16.747	257.63	4785	.000
Total *Imagine Math* Lessons Passed	18.62	.998	18.67	4785	.000
Quantile-95					
(Intercept)	5037.68	36.237	139.02	4785	.000
Total *Imagine Math* Lessons Passed	17.864	2.158	8.28	4785	.000

Note. a. Dependent variable: scale score
b. Model: (Intercept), Total *Imagine Math* lessons passed

The regression equation for Quantile-25 can be interpreted as predicted scale score = 3578.18 + (19.27 x total number of *Imagine Math* lessons passed) with students’ scale scores ranging between 3553 and 3602, accounting for 8.7% of the explained variability in scale scores.

The regression equation for Quantile-50 can be interpreted as predicted scale score = 3928.40 + (19.27 x total number of *Imagine Math* lessons passed) with students' scale scores ranging between 3904 and 3952, accounting for 8.8% of the explained variability in scale scores.

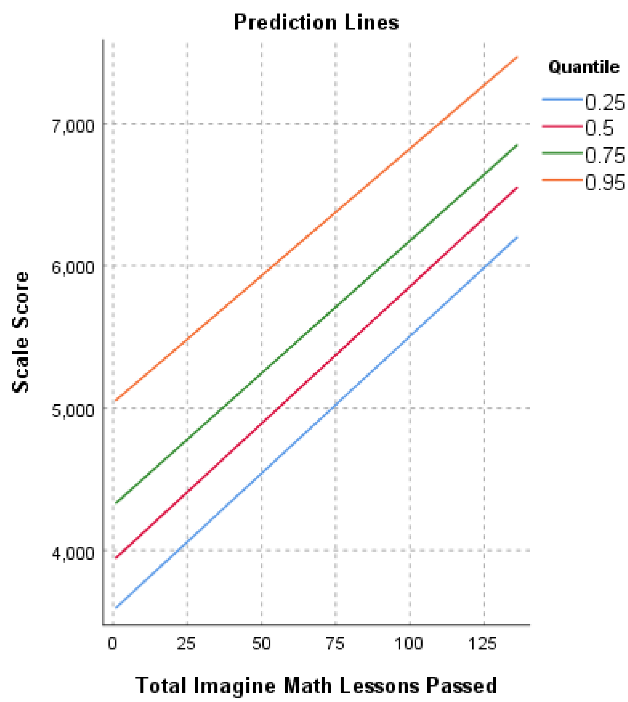
The regression equation for Quantile-75 can be interpreted as predicted scale score = 4314.38 + (18.62 x total number of *Imagine Math* lessons passed) with students' scale scores ranging between 4281 and 4347, accounting for 8.7% of the explained variability in scale scores.

The regression equation for Quantile-95 can be interpreted as predicted scale score = 5037.68 + (17.86 x total number of *Imagine Math* lessons passed) with students' scale scores ranging between 4966 and 5108, accounting for 6.3% of the explained variability in scale scores.

Figure 8 shows the prediction lines for the total *Imagine Math* lessons passed against scale scores for STAAR Algebra 1 end-of-course assessment. Regression equations were written for each quantile within a confidence interval of 95%.

Figure 8

Prediction: Total Imagine Math Lessons Passed

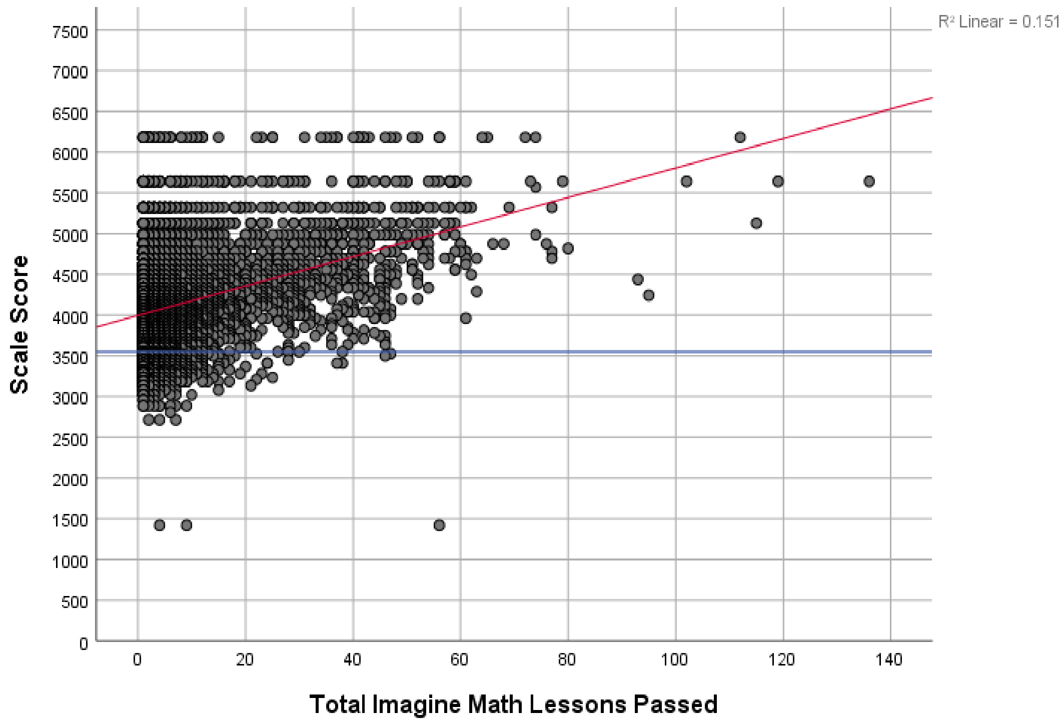


Data for each quantile showed a positive correlation between the number of *Imagine Math* lessons passed and students' scale scores on the STAAR Algebra 1 end-of-course assessment. While there is a positive relationship between the variables, the relationship is moderate, with a Pearson's *r*-value of .39.

Figure 9 displays a visual representation of the data as a scatterplot with minimum passing scale score superimposed to show students who did not meet passing standards.

Figure 9

Simple Scatter with Fit Line



Note. The horizontal line represents the minimum scale score needed to pass Algebra 1 STAAR end-of-course assessment.

Individual Grade Levels

The data was broken into subsets to determine if a relationship existed between the number of lessons passed in *Imagine Math* and students' scale scores on the STAAR end-of-course assessment based on students' grade level.

Grade 7. Scale scores ranged from 1420 to 6181 for students in Grade 7 with an average scale score of 4709, and the number of lessons passed ranged from one to 102, with an average of 15 lessons passed. Data for 207 students were analyzed to determine if a relationship existed between and students' scale scores on the STAAR Algebra 1 end-of-course assessment (*M* = 4709.51, *SD* = 654.36) and the number of *Imagine Math* lessons passed (*M* = 15.31, *SD* = 20.16). Pearson's *r* data analysis revealed a weak positive correlation, *r* = .23. Students who passed more *Imagine Math* lessons reported higher scale scores. The average number of lessons passed in *Imagine Math* was statistically significant to predict students' scale scores on the STAAR Algebra 1 end-of-course assessment, *F*(1, 205) = 11.22, *p* < .001 and number of lessons passed accounted for 5.2% of the explained variability in scale scores.

Grade 8. Scale scores ranged from 3325 to 6181 for students in Grade 8 with an average scale score of 4738, and the number of lessons passed ranged from one to 136, with an average of 17 lessons passed. Data for 1,118 students were analyzed to determine if a relationship existed between and students' scale score on the STAAR Algebra 1 end-of-course assessment (*M* = 4738.26, *SD* = 554.58) and the number of *Imagine Math* lessons passed (*M* = 16.54, *SD* = 18.28). Pearson's *r* data analysis revealed a moderate positive correlation, *r* = .31. Students who passed more *Imagine Math* lessons reported higher scale scores. The average number of lessons passed in *Imagine Math* could statistically significantly predict students' scale scores on the STAAR Algebra 1 end-of-course assessment, *F*(1, 1116) = 116.03, *p* < .001 and number of lessons passed accounted for 9.4% of the explained variability in scale scores.

Grade 9. Scale scores ranged from 1420 to 6181 for students in Grade 9 with an average scale score of 3963, and the number of lessons passed ranged from one to 95, with an average of 8 lessons passed. Data for 3,462 students were analyzed to determine if a relationship existed between and students' scale scores on the STAAR Algebra 1 end-of-course assessment (*M* = 3963.42, *SD* = 503.67) and the number of *Imagine Math* lessons passed (M = 7.60, SD = 9.88). Pearson's r data analysis revealed a weak positive correlation, r = .30. Students who passed more *Imagine Math* lessons reported higher scale scores. The average number of lessons passed in *Imagine Math* could statistically significantly predict students' scale scores on the STAAR Algebra 1 end-of-course assessment, $F(1, 3460) = 341.50$, $p < .001$ and number of lessons passed accounted for 9.0% of the explained variability in scale scores.

Gender

The data was broken into subsets to determine if a relationship existed between the number of lessons passed in *Imagine Math* and students' scale scores on the STAAR end-of-course assessment based on students' gender.

Males. Scale scores ranged from 2714 to 6181 for male students with an average scale score of 4113, and the number of lessons passed ranged from one to 136, with an average of 9 lessons passed. Data for 2,265 students were analyzed to determine if a relationship existed between and students' scale score on the STAAR Algebra 1 end-of-course assessment (M = 4113.26, SD = 642.86) and the number of *Imagine Math* lessons passed (M = 9.43, SD = 13.04). Pearson's r data analysis revealed a moderate positive correlation, r = .44. Students who passed more *Imagine Math* lessons reported higher scale scores. The average number of lessons passed in *Imagine Math* could statistically significantly predict students' scale scores on the STAAR Algebra 1 end-of-course assessment, $F(1, 2263) = 530.67$, $p < .001$ and number of lessons passed accounted for 19.0% of the explained variability in scale scores.

Females. Scale scores ranged from 1420 to 6181 for female students with an average scale score of 4233, and the number of lessons passed ranged from one to 119, with an average of 11 lessons passed. Data for 2,522 students were analyzed to determine if a relationship existed between and students' scale scores on the STAAR Algebra 1 end-of-course assessment (M = 4233.58, SD = 605.97) and the number of *Imagine Math* lessons passed (M = 10.55, SD = 13.82). Pearson's r data analysis revealed a moderate positive correlation, r = .35. Students who passed more *Imagine Math* lessons reported higher scale scores. The average number of lessons passed in *Imagine Math* could statistically significantly predict students' scale scores on the STAAR Algebra 1 end-of-course assessment, $F(1, 2520) = 339.99$, $p < .001$ and number of lessons passed accounted for 11.9% of the explained variability in scale scores.

Ethnicity

The data was broken into subsets to determine if a relationship existed between the number of lessons passed in *Imagine Math* and students' scale scores on the STAAR end-of-course assessment based on students' ethnicity.

American Indian or Alaskan Native. Scale scores ranged from 4495 to 4873 for American Indian or Alaskan Native students with an average scale score of 4641, and the number of lessons passed ranged from one to 16 with an average of 6 lessons passed. Data for three students were analyzed to determine if a relationship existed between and students' scale scores on the STAAR Algebra 1 end-of-course assessment (M = 4641.33, SD = 202.93) and the number of *Imagine Math* lessons passed (M = 6.00, SD = 8.66). Pearson's r data analysis revealed a strong positive correlation, r = .99. Students who passed more *Imagine Math* lessons reported higher scale scores. The average number of lessons passed in *Imagine Math* was not statistically significant to predict students' scale scores on the STAAR Algebra 1 end-of-course assessment, $F(1, 1) = 43.27$, $p > .001$ and number of lessons passed accounted for 97% of the explained variability in scale scores.

Asian. Scale scores ranged from 3367 to 6181 for Asian students with an average scale score of 4896, and the number of lessons passed ranged from one to 136, with an average of 26 lessons passed. Data for 199 students were analyzed to determine if a relationship existed between and students' scale scores on the STAAR Algebra 1 end-of-course assessment ($M = 4896.10$, $SD = 669.85$) and the number of *Imagine Math* lessons passed ($M = 26.45$, $SD = 25.02$). Pearson's r data analysis revealed a moderate positive correlation, $r = .33$. Students who passed more *Imagine Math* lessons reported higher scale scores. The average number of lessons passed in *Imagine Math* could statistically significantly predict students' scale scores on the STAAR Algebra 1 end-of-course assessment, $F(1, 197) = 23.22$, $p < .001$ and number of lessons passed accounted for 10.5% of the explained variability in scale scores.

Black or African American. Scale scores ranged from 2886 to 6181 for Black or African American students with an average scale score of 4076, and the number of lessons passed ranged from one to 119 with an average of 9 lessons passed. Data for 1,278 students were analyzed to determine if a relationship existed between and students' scale scores on the STAAR Algebra 1 end-of-course assessment ($M = 4076.14$, $SD = 539.99$) and the number of *Imagine Math* lessons passed ($M = 8.60$, $SD = 11.63$). Pearson's r data analysis revealed a moderate positive correlation, $r = .33$. Students who passed more *Imagine Math* lessons reported higher scale scores. The average number of lessons passed in *Imagine Math* could statistically significantly predict students' scale scores on the STAAR Algebra 1 end-of-course assessment, $F(1, 1276) = 160.62$, $p < .001$ and number of lessons passed accounted for 11.2% of the explained variability in scale scores.

Hispanic Latino of Any Race. Scale scores ranged from 1420 to 6181 for Hispanic Latino students with an average scale score of 4125, and the number of lessons passed ranged from one to 77, with an average of 9 lessons passed. Data for 2,949 students were analyzed to determine if a relationship existed between and students' scale scores on the STAAR Algebra 1 end-of-course assessment (M = 4125.28, SD = 600.55) and the number of *Imagine Math* lessons passed (M = 8.50, SD = 11.15). Pearson's *r* data analysis revealed a moderate positive correlation, r = .34. Students who passed more *Imagine Math* lessons reported higher scale scores. The average number of lessons passed in *Imagine Math* could statistically significantly predict students' scale scores on the STAAR Algebra 1 end-of-course assessment, $F(1, 2947) = 389.00$, $p < .001$ and number of lessons passed accounted for 11.7% of the explained variability in scale scores.

Native Hawaiian or Other Pacific Islander. Scale scores ranged from 3550 to 6181 for Native Hawaiian or Other Pacific Islander students with an average scale score of 4858, and the number of lessons passed ranged from one to 46, with an average of 26 lessons passed. Data for five students were analyzed to determine if a relationship existed between and students' scale score on the STAAR Algebra 1 end-of-course assessment (M = 4858.20, SD = 1211.27) and the number of *Imagine Math* lessons passed (M = 25.80, SD = 21.90). Pearson's *r* data analysis revealed a strong positive correlation,

$r = .96$. Students who passed more *Imagine Math* lessons reported higher scale scores. The average number of lessons passed in *Imagine Math* could statistically significantly predict students' scale scores on the STAAR Algebra 1 end-of-course assessment, $F(1, 3) = 33.82$, $p < .05$ and number of lessons passed accounted for 91.2% of the explained variability in scale scores.

Two or More Races. Scale scores ranged from 3135 to 6181 for students identified as Two or More Races with an average scale score of 4476, and the number of lessons passed ranged from one to 58, with an average of 16 lessons passed. Data for 65 students were analyzed to determine if a relationship existed between and students' scale scores on the STAAR Algebra 1 end-of-course assessment ($M = 4476.42$, $SD = 598.65$) and the number of *Imagine Math* lessons passed ($M = 16.09$, $SD = 17.08$). Pearson's r data analysis revealed a moderate positive correlation, $r = .36$. Students who passed more *Imagine Math* lessons reported higher scale scores. The average number of lessons passed in *Imagine Math* could statistically significantly predict students' scale scores on the STAAR Algebra 1 end-of-course assessment, $F(1, 63) = 9.44$, $p < .001$ and number of lessons passed accounted for 13% of the explained variability in scale scores.

White. Scale scores ranged from 1420 to 6181 for White students with an average scale score of 4567, and the number of lessons passed ranged from one to 73, with an average of 19 lessons passed. Data for 288 students were analyzed to determine if a relationship existed between and students' scale scores on the STAAR Algebra 1 end-of-course assessment ($M = 4567.15$, $SD = 723.35$) and the number of *Imagine Math* lessons passed ($M = 18.97$, $SD = 18.17$). Pearson's r data analysis revealed a weak positive correlation, $r = .25$. Students who passed more *Imagine Math* lessons reported higher scale scores. The average number of lessons passed in *Imagine Math* could statistically significantly predict students' scale scores on the STAAR Algebra 1 end-of-course assessment, $F(1, 286) = 19.19$, $p < .001$ and number of lessons passed accounted for 6.3% of the explained variability in scale scores.

Summary

It can be concluded, based on the results of this study, that the relationship between computer-assisted instruction and student's scale scores for the STAAR Algebra 1 end-of-course assessment is moderately positive based on the Pearson *r* values.

The next chapter will include a discussion of the results and provide a further investigation of the limitations that might explain reasons for the outcomes of the study as well as suggest future use of the computer-assisted mathematics instruction program, *Imagine Math* for students taking an Algebra 1 course.

Chapter V

Discussion

The purpose of this study was to examine the relationship between using the computer-assisted instruction program, *Imagine Math*, and student performance on the STAAR Algebra 1 end-of-course assessment. The study sought to answer the central research question: What is the relationship between the number of successfully completed computer-assisted Algebra 1 mathematics instruction lessons and performance on the State of Texas Assessment of Academic Readiness? by addressing the following sub-questions:

1. What is the correlation between total *Imagine Math* lessons passed and the STARR Algebra 1 assessment for various demographics represented?
2. How does total *Imagine Math* lessons passed predict the STARR Algebra 1 assessment after controlling for gender, grade level, and ethnicity?
3. What are the different aspects of the relationship between the number of *Imagine Math* lessons passed and the STARR Algebra 1 assessment?

A quantitative methodology was employed that applied correlation and linear regression to examine the relationship between using computer-assisted instruction and students' scale scores on their end-of-course assessment.

This chapter discusses the results obtained, implications for practice, limitations of the study, and future research.

Results

Correlation and linear regression were used to address the sub-question: What is the correlation between total *Imagine Math* lessons passed and the STARR Algebra 1 assessment for various demographics represented?

Students in Grades 7–9 had scale scores that ranged from 1420 to 6181 with an average scale score of 4176, and they passed between one and 136 *Imagine Math* lessons. The Pearson Correlation, *r*, for students in Grades 7–9 was .39, which indicated a moderately positive correlation. Prior research suggests that any interaction of students with computer-assisted instruction results in some positive effect on learning gains (John et al., 2018; Bassoppo-Moyo, 2010; Xin et al., 2017; Schmidt et al., 1985; Seo & Bryant, 2009).

The data for students at individual grade levels was similar to all grades. In Grade 7, scale scores ranged from 1420 to 6181, with students passing between one and 102 *Imagine Math* lessons. The Pearson Correlation, *r*, for students in Grade 7 was .23, which indicated a weak positive correlation. Students in Grade 8 had scale scores that ranged from 3325 to 6181 and passed between one and 136 *Imagine Math* lessons. The Pearson Correlation, *r*, for students in Grade 8 was .31, which indicated a moderately positive correlation. Lastly, students in Grade 9 had scale scores that ranged from 1420 to 6181 and passed anywhere between one and 95 *Imagine Math* lessons. The Pearson Correlation, *r*, for students in Grade 9 was .30 and was indicative of a weak positive correlation. All grade levels indicated a positive correlation between lessons passed and scale scores. This may be due to several factors. Students may have had limited access to technology, or teachers may have given options for using the *Imagine Math* program.

John et al. (2018) stress that teachers and students should be appropriately trained on the use of computers prior to integrating and implementing computer-assisted instruction to have positive effects on usage. It was not known whether teachers and students in this study received adequate training on the use of the program or the computer.

The results were similar for data pertaining to gender. Male scale scores ranged from 2714 to 6181, and the average number of lessons passed was nine. The Pearson Correlation, *r,* for males was .44 and indicated a moderately positive correlation. Female scale scores ranged from 1420 to 6181, with the average number of passed lessons being 11. The Pearson Correlation, *r*, for males was .35 and showed a moderately positive correlation. The results for males and females were very similar, although it was perceived at one time that males outperformed females with technology. Cam et al., (2016) contends that although gender is a crucial variable for learning and teaching activities, it is not as important enough to create a huge disparity.

The data was also used to examine the relationship between lessons passed and scale scores as it relates to ethnicity. Included in the study were data for American Indians or Alaska Natives, Asians, Black or African Americans, Hispanic Latinos, Native Hawaiians or Other Pacific Islanders, Two or More Races, and Whites.

American Indians or Alaska Natives had scale scores that ranged from 4495 to 4873, with an average of six lessons passed. The Pearson Correlation, *r*, for American Indians or Alaska Natives was .98, a strong positive correlation; however, the data was not statistically significant since there were only three students in the study. The scale score for Asians ranged from 3367 to 6181, with an average of 26 passed *Imagine Math* lessons. The Pearson Correlation, *r*, for Asians was .33, which indicated a moderately positive correlation. Blacks or African Americans had scale scores that ranged from 2886 to 6181 with an average of 9 passed lessons a Pearson Correlation, *r*, of .33, also indicating a moderately positive correlation. Hispanic Latinos' scale scores ranged from 1420 to 6181, with an average of 9 passed *Imagine Math* lessons and a Pearson Correlation, *r*, of .34. Native Hawaiians or Other Pacific Islanders had scale scores that ranged from 3550 to 6181 with an average of 26 passed math lessons and a Pearson Correlation, *r,* of .96. This is indicative of a strong correlation. Students identified as Two or More races had scale scores that ranged from 3135 to 6181, with an average of 16 passed *Imagine Math* lessons. The Pearson Correlation, *r*, for students identified as two or more races was .36, indicating a moderately positive correlation. Finally, White students had a scale score ranging between 1420 and 6181, with an average of 19 passed math lessons. The Pearson Correlation, *r*, for White students was .25 and showed a weak positive correlation.

All subgroups had data that showed a positive correlation between the number of *Imagine Math* lessons passed and students' scale scores on the STAAR Algebra 1 end-of-course assessment. A study that examined minority students' mathematics learning gains with computer-assisted instruction concluded that gender and socioeconomic characteristics were not significant predictors of learning gains, and the only significant predictor was ethnicity. It showed that CAI was more effective in raising the learning gains of Hispanics than Blacks or African Americans, which seemingly contradicts the results from this study that indicates Black or African Americans and Hispanic students had similar performance (Walker, 1987). This may warrant further investigation as there has not been much research conducted on the effects of computer-assisted instruction and students of varying ethnicity.

Hierarchical regression was used to address the sub-question: How does total *Imagine Math* lessons passed predict the STARR Algebra 1 assessment after controlling for gender, grade level, and ethnicity?

The hierarchical regression concluded that gender, grade level, and ethnicity accounted for 27% of the variability of scale scores. Adding total *Imagine Math* lessons passed yielded an additional 6.7% variability on scale scores. This outcome directly aligned with prior research that indicates any interaction with computer-assisted instruction results in positive effects on the learning gains of students (John et al., 2018; Bassoppo-Moyo, 2010; Xin et al., 2017; Schmidt et al., 1985; Seo & Bryant, 2009).

Quantile regression was used to address the sub-question: What are the different aspects of the relationship between the number of *Imagine Math* lessons passed and the STARR Algebra 1 assessment?

The data were analyzed at Quantile-25, Quantile-50, Quantile-75, and Quantile-95. It showed that there was an equal distribution across Quantile-25, Quantile-50, and Quantile-75. Each quantile accounted for approximately 8.7% of the variability in students' scale scores, while students in the highest quantile, Quantile-95, only accounted for 6.3% variability in students' scale scores.

Implications for Practice

The *Imagine Math* program was purchased in the district for teachers to use with students who demonstrated an academic gap in their mathematics learning or to enhance and build upon connections to concepts studied. The district strongly encouraged program usage with students; however, it was not known to the researcher whether there was an implementation of the suggestion. Since there is a considerable allotment spent on the program, this implies a need to scrutinize the time spent in the program. If the district continues to pay for the program, protocols and structures should be put into place to monitor the time spent in the program to ensure maximum effectiveness of student learning.

One implication for practice would be to ensure that adequate training is given to students, teachers, and parents. Since districts and campuses will begin the new school year virtually, it is imperative that parents receive training on student usage in the program so they can impress upon their children the importance of the program. Teachers need adequate training to be able to support students within the *Imagine Math* platform and address the various issues that may arise as students engage with the program.

Another implication would be to address the lack of participation from students. That may involve ensuring teachers require a minimum amount of time spent in the program. As the district spends a considerable amount of money on purchasing the program, there should be some accountability for time spent in the program as well as the number of students using *Imagine Math*. This would ensure that the district is not purchasing the program for 12,000 students, with only a fraction of those students utilizing the program.

The last implication for practice would be to differentiate how the various student population utilizes. For Tier II and Tier III students, *Imagine Math* could be used as a response to intervention to help decrease the academic gaps. For gifted students, the program could be used to extend the mathematical learning of content. Finally, students considered to be on grade level could utilize the program to help with mastery of specific mathematical topics.

Limitations and Opportunities for Future Research

This study was conducted in a large urban school district in southeast Texas; however, the findings of this study may not be generalized to other large urban school districts with different demographic composition. The study was restricted to students enrolled in an Algebra 1 course either in middle or high school. One limitation of this study is student access to technology. In 2013, the school district implemented a program to ensure every high school student would have access to a laptop to use for the school year. Implementation of the program began with a cohort of schools, and new schools were added over three years until all high schools were powered up. Every high school in the district is now “powered up,” the school district’s term for technology equality; however, middle school students either go to a computer lab or use a laptop cart shared among multiple teachers.

More information is needed to ascertain the impact of computer-assisted instruction in the school district, as teachers may or may not have promoted the use of computer-assisted instruction or participated in training on how to implement in the classroom. One future consideration for research would be to survey teachers about the classroom supports in place for the implementation of the *Imagine Math* program and how teachers, in turn, support students with computer-assisted instruction in their classrooms.

It is also crucial for students who need assistance in closing gaps or those who may need their learning extended to be able to interact within the program. Time spent in the program is vital. Another future consideration for research would be to survey teachers about the time allocations and lesson requirements for students.

Conclusion

This study attempted to determine whether a relationship existed between the number of successfully passed *Imagine Math* lessons and students' scale scores on the STAAR Algebra 1 end-of-course assessment. The data showed that passing lessons in *Imagine Math* had a positive relationship and a statistically significant effect on students' scale scores. There is no definitive proof that the relationship is strictly due to the passing of lessons in the program; however, the data showed that *Imagine Math* could be one instructional tool used to assist students in learning and mastering concepts in Algebra 1.

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