2018

ALEKS Constructs as Predictors of High School Mathematics Achievement for Struggling Students

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This is to certify that the doctoral study by

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has been found to be complete and satisfactory in all respects,
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Abstract

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MA, Central Connecticut State University, 2003

BS, Wesleyan University, 1998

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Education

Walden University

August 2018

Abstract

Educators in the United States (U.S.) are increasingly turning to intelligent tutoring systems (ITS) to provide differentiated math instruction to high school students. However, many struggling high school learners do not perform well on these platforms, which reinforces the need for more awareness about effective supports that influence the achievement of learners in these milieus. The purpose of this study was to determine what factors of the Assessment and Learning in Knowledge Spaces (ALEKS), an ITS, are predictive of struggling learners' performance in a blended-learning Algebra 1 course at an inner city technical high school located in the northeastern U.S. The theoretical framework consisted of knowledge base theory, the zone of proximal development, and cognitive learning theory. Three variables (student retention, engagement time, and the ratio of topics mastered to topics practiced) were used to predict the degree of association on the criterion variable (mathematics competencies), as measured by final course progress grades in algebra, and the Preliminary Scholastic Assessment Test (PSATm) math scores. A correlational predictive design was applied to assess the data of a purposive sample of 265 struggling students at the study site; multiple regression analysis was also used to investigate the predictability of these variables. Findings suggest that engagement time and the ratio of mastered to practiced topics were significant predictors of final course progress grades. Nevertheless, these factors were not significant contributors in predicting PSATm score. Retention was identified as the only statistically significant predictor of PSATm score. The results offer educators with additional insights that can facilitate improvements in mathematical content knowledge and promote higher graduation rates for struggling learners in high school mathematics.

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Dedication

I dedicate this study to my loving husband, Gregory Mills, and other family members and friends who contributed much support towards this accomplishment.

Acknowledgments

I extend special thanks to my committee members, Dr. Tammye Turpin, Dr. Jennifer L. Brown, and Dr. Michael Cass (who was displaced by Hurricane Harvey), and my University Research Reviewer, Dr. Barbara Schirmer, for their continuous support and guidance throughout the development of this study.

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Chapter 1: Introduction to the Study

Educationalists view mathematics as one of the most difficult subjects to master in education, and many individuals across the United States demonstrate challenges with attaining proficiency in mathematics concepts and skills. U.S. high school graduates are among these nonproficient math learners, with many requiring remediation in higher education, according to Johnson and Samora (2016). The rapid infusion of intelligent tutoring systems (ITS) in high school mathematics courses has provided educators with unprecedented opportunities to engage learners in active learning (Dani, 2016; Fine, Duggan, & Braddy, 2009; Icoz, Sanalan, Cakar, Ozdemir, & Kaya, 2015; Liu, Rogers, & Pardo, 2015) and potentially address nonproficiency issues. Such platforms aid teachers with assessing, instructing, monitoring, modifying, and differentiating instruction to address the diverse needs of students.

Nonetheless, many learners at risk of failing high school mathematics continue to experience difficulties in such milieus (Gasevic, Dawson, Rogers, & Gasevic, 2016; McManis, & McManis, 2016). Their lack of self-management and self-regulation skills exacerbates the challenges these students face in these settings. It is therefore imperative that stakeholders are aware of effective supports that influence the achievement of struggling learners in these learning platforms. Accordingly, in this study, I sought to determine the predictability of the constructs of a commonly used ITS program known as the Assessment and Learning in Knowledge Spaces (ALEKS) on struggling students' achievement in a high school Algebra 1 course and to determine what ITS program variables are the best predictors to support these learners' success in this arena. Such findings may inform effective interventions to maximize struggling learners' performance in similar learning environments now and in the future.

In the following sections, I offer background information on the scope and focus for this study as related to the problem at the local, national, and international levels. After presenting the problem statement and purpose of the study, I state the research questions and hypotheses for the study and then present an overview of the study's theoretical foundation and methodology. The assumptions, scope and delimitations, limitations, and significance of the study follow. The chapter concludes with a summary of key points.

Background

Technological advancements have contributed to the increased application of computer-based instruction and adaptive tutors to aid the success of learners in the United States. Of these systems, intelligent tutors have been the most frequently applied in recent years (Kulik & Fletcher, 2016). These tutoring and assessment systems are capable of identifying and gauging individualized learning. Elnajjar and Naser (2017) asserted that adaptive techniques affiliated with ITS shows promise in supporting the learning of students in blended settings. These systems incorporate cognitive theories along with artificial intelligence to infer students' knowledge (Johnson & Samora, 2016; Kulik & Fletcher, 2016) as well as make intelligent decision to coach them toward improved learning. Educationalists incorporated these programs in blended learning settings to determine what students know and to motivate and engage them in rigorous activities that would enhance their performance outcomes.

Educators incorporate ITSs in blended learning settings to assist the teaching and learning processes, promote diversification, and to foster andragogic practices for learning. Such application provides educationalists with encouraging outlooks for the use of one-to-one learning devices (Johnson & Samora, 2016) to facilitate independent learning and differentiated instruction. Accordingly, a growing number of learners are being exposed to ITSs on a yearly basis (Chen & Yao, 2016). These students are required to demonstrate self-management and self-regulation skills to facilitate their progress in these settings. Nonetheless, the blended learning arena has provided instructors with challenges in managing and promoting struggling learners. The heuristics that educators require to assess students' disengagement are not readily available or easily transferable in the online platform (Liu, Froissard, Richards, & Atif, 2015). Still, the recent fields of education data mining (EDM) and learning analytics (LA) have optimized the potential for improved knowledge and understanding of such behaviors. Through advancements in these fields, practitioners are able to measure and analyzed large amounts of students' behavioral data from ITS databases to garner greater insights related to students' who are at risk for failure in these online modalities, and to develop and apply modifications to improve their performance in these settings (Gasevic et al., 2016; Holstein, McLaren, & Aleven, 2017; Icoz et al., 2015; Liu et al., 2015a, 2015b; San Pedro, 2017). Accordingly, educators view these new developments in teaching and learning models as a panacea for despondent results (Johnson & Samora, 2016) in struggling students' mathematical achievement across the United States.

However, few researchers have conducted studies to assess the effect of ITS adaptive instruction on high school students' mathematics achievement or identify ITS variables that are most effective at predicting these learners' success in blended learning mathematics courses. A few of these investigations suggest a need for further evaluation of ITS and various system factors (including time on ITS content information) that might improve the effectiveness of the individualized teaching and learning processes (Dani, 2016; Icoz et al., 2015; San Pedro, 2017). Accordingly, in conducting this study, I sought to contribute to this knowledge base by investigating factors of the ALEKS ITS online software that are predictive of struggling students' mathematics competency. Such insights can facilitate greater success for learners who are at risk for failure in these milieus, improve mathematical content knowledge, promote higher graduation rates, and increased job opportunities.

Problem Statement

My objective was to determine what factors of ALEKS are predictive of struggling learners' performance in a blended-learning Algebra 1 course at an inner city technical high school located in the northeastern United States. There is a gap in practice on what ALEKS measures are the best predictors of learners' future mathematics achievement. Few researchers have assessed the impact of ALEKS on the math achievement of high school students, and only one group of researchers (Bringula et al., 2016), based on my review of the literature, have examined the relationship between variables measured in ITS instruction on students' mathematics attainment at this level. With minimal understanding of the ALEKS variables that are predictive of students' achievement in this environment, it was unclear whether this ITS was being used by educators to optimize the instructional and learning processes at the site of this investigation.

Evidence of the Problem at the Local Level

Analysis of math state testing data (EdSight, n. d.), math course grades, and math SAT scores (EdSight, n. d.) reveal that struggling students at this research site were not making adequate progress in math. These performances are consistent with struggling students' declining mathematics scores at the national and international level (NCES, n. d.). In an attempt to address this concern, school leaders implemented, in Fall 2015, a blended learning, mastery-based instructional model that integrated the ALEKS ITS online instruction with algebra course instruction. These online tutoring systems provide instructors with the opportunity to monitor students' behavioral data from ITS databases to garner information related to students who are at risk for falling behind in these online platforms, and to modify instruction to improve their performance in these environments (Baker, 2016; Gasevic et al., 2016; Holstein et al., 2017; Icoz et al., 2015; Liu et al., 2015a, 2015b; San Pedro, 2017). Although this information is available, I concluded, based on my research, that an investigation was needed to identify possible ALEKS constructs that might be predictive of students' mathematical success.

The struggling learners at this institution were consistently performing at subpar levels on the state's summative assessments. The district employs the school performance index (SPI) as a standardized measure of student achievement on various state assessments. The educators, at the study site, apply the SPI to describe students' average performance on summative assessments in various subject areas (EdSight, n. d.). According to EdSight (n. d.), these scores range for 0-100, and the acceptable score that indicates proficiency in math is at least 75 (equivalent to a "C" or better average) in student performance. Table 1 depicts the results of students' state assessment scores for the last 2 years.

Table 1

Students' Performance Index Scores on State Mathematics Standardized Assessments

Academic year	School's (SPI) target	School's SPI for at-risk students	State average for at-risk students	State average for all students
2015-2016	75	35	50	61
2014-2015	75	36	47	59

Note. Data were obtained from EdSight (n. d.).

The data indicate that students at this research site were performing well below the state's benchmark for math achievement as compared to other students throughout the state. Also, examination of the data reveals that struggling students, in this northeastern high school, were performing at a lower level of achievement as compared to struggling high school students statewide.

Additionally, students at this location were demonstrating inadequate performance on the mathematics portion of the SAT exam. According to EdSight (n. d.), approximately 4% (7/178) of the 11th- and 12th-graders met the 530 proficiency benchmark on this assessments during the 2015-2016 academic year, and 3% (6/183 and 6/172) attained this benchmark during the previous 2 school years. Educationalists apply the proficiency benchmark to determine the score at which students entering college have a 75% chance of earning a "C" or higher in their first-semester math courses (College Board, 2017a). On average, few students from the site of this investigation attained this proficiency. The school's guidance coordinator has confirmed that the percentage of students from this site who demonstrate success on the college readiness exam consistently hovered below the 10 % index mark, and many students were ill-prepared to succeed in math courses during their first semester of college.

Evidence of the Problem at the National and International Level

Struggling students' mathematics performance at this location was also of concern at the national and international level as high school learners continued to demonstrate low mathematics achievement on both national and international standardized assessments. The national average math scores for 12th-grade at-risk students demonstrated a decline in scores from previous averages in 1995, according to the NCES (n. d.). Results from the Trends in International Mathematics and Science Study (TIMSS) indicate a decline in struggling students' mathematics performance between 1995 and 2015 (NCES, n. d.). The NCES (n. d.) asserted that students who fell within the 75th percentile range for free or reduced lunch demonstrated a 15% decrease in achievement scores on the advanced mathematics TIMSS scores in 2015 as compared to scores in 1995. Accordingly, I concluded from this data that additional supports and research interventions were needed to assist struggling learners' in realizing success in mathematics.

Evidence of the Problem from the Professional Literature

Educators from school districts with limited resources within the United States have begun to employ technology to address the problems related to content mastery in mathematics (McManis & McManis, 2016). Hence, an increasing number of educators are electing to infuse e-learning mathematics into their academic courses (Hachey, Wladis, & Conway, 2015). Nonetheless, students at risk for failure in mathematics continue to struggle even in these environments (Butzler, 2016; Gasevic et al., 2016; James, Swan, & Daston, 2016).

Many researchers addresses the benefits and challenges associated with struggling learners in the blended learning and e-learning educational setting (Butzler, 2016; Chen & Yao, 2016; Cigdem, 2015; Foster, Anthony, & Clements, 2016; Gasevic et al., 2016; James et al., 2016; McManis & McManis, 2016; Salminen, Koponen, & Rasanen, 2015; Steele, Bozick, & Davis, 2016). Several of these investigators asserted that the application of computer-assisted instructional (CAI) programs in blended settings support the achievement of struggling students (Foster et al., 2016; McManis & McManis, 2016; Salminen et al., 2015; Steele et al., 2016). However, few researchers reported on the effect of instruction of the ALEKS ITS on high school students' mathematics achievement or that identify what ITS variables are the most effective at predicting struggling learners' success in blended learning math settings.

To date, a small number of investigators have examined the relationship between variables measured in ITS instruction and high school learners' achievement in mathematics. One group of researchers Bringula et al. (2016), based on my review of the literature, have assessed the relationship between high school students' prior mathematical knowledge on time spent tutoring, total hints requested, and the number of completed quizzes in a SimStudent ITS program, and discovered that prior knowledge demonstrated a significant and consistent positive influence on learner-interface interactions (time spent tutoring, number of hints requested by the program, and number of quizzes conducted). Based on this information, I anticipated that a better understanding of this relationship could result in improvements in the application of ITS software for specialized instruction. I concluded that further evaluation of ALEKS is needed at this level of education to identify factors that might improve the effectiveness of personalized learning in this environment. When conducting such research, the authors should consider including various sample size (Dani, 2016) of diverse groups and across grade levels.

Nevertheless, according to the district specialists at the site of this investigation, despite the fact that many students were still at risk for failure in the area of mathematics, no in-depth examination of the instructional data was conducted to identify components of the ALEKS program that are related to improving the mathematics achievement of learners. In addition, no examination relating to the impact of ALEKS training on learners' mathematics achievement had been conducted. Accordingly, the district and school leaders concurred that such an investigation was needed to support the mathematics achievement of struggling learners at this study's location.

Purpose of the Study

The purpose of this quantitative study was to conduct a correlational predictive investigation to determine the factors of the ALEKS ITS that are predictive of struggling students' achievement in a blended learning high school mathematics courses and to determine what ITS program variables are best predictors of struggling learners' success in this arena. Specifically, I evaluated the influence of the predictor variables (student engagement time, retention, and the ratio of topics mastered to topics practiced) on struggling students' performance as it pertains to the development of academic competency in mathematics (the criterion variable). I included three predictor (independent) variables from the ALEKS data logs (retention, engagement time, and the ratio of topics mastered to topic practiced) and two criterion (dependent) variables (students' final Algebra 1 progress grades and PSAT math performance scores) for analysis. Predictor scores were gathered from archival data related to the first 2 consecutive years of implementation in the ninth-grade math classes (the 2015-2016 and 2016-2017 academic years) while the criterion scores were obtained after students had completed their first year in the ALEKS ITS.

A description of each variable follows:

*Engagement Time (*depicted as *ET in data tables)* is a predictor variable that was obtained from the ALEKS database. This continuous variable reflects the combined (active and inactive) time logged in the program and is recorded in hours and minutes each time an individual logs in and out of the ITS during instructional (during school) and non-instructional (outside of school) periods.

Retention is a continuous predictor variable that was acquired from the ALEKS database. The ALEKS software records when students initiate a knowledge assessment, and tracks students' progress between each assessment. The retention scores for individual learners reflect the average percentages in gains and losses between these assessment scores.

The *Ratio of Topics Mastered to Topics Practiced* is a continuous predictor variable that was obtained from two factors within the ALEKS program (mastered and practiced topics). Hence, this variable denotes the quotient of total topics mastered and those practices for participants during their first year of instruction in the ALEKS Algebra 1 course.

The PSAT, which was a continuous criterion variable in the study, is a standardized aptitude test that is administered by the College Board to assess the general intelligence of students in Grades 9 and 10 (Warne, 2016). It is also known as the National Merit Scholarship Qualifying Test (NMSQT). The mathematics section of the PSAT measures a student's conceptual understanding and reasoning skills in numeracy (College Board, 2017a). This section includes topic objectives that are relevant to Algebra 1 and Geometry courses. The College Board (2017b) asserts that a mathematic grade-level benchmark score of 480 (indicating students who are performing at or above grade level) is established to track students' yearly progress towards attaining the SAT benchmark (addressed earlier in the problem statement).

Students' Final Progress Grades (SFPG) is a continuous criterion variable that was ascertained from the school's guidance department. This variable reflects the combination of the scores for the Algebra 1 course requirements into one final percent averages, with higher scores reflecting increased progress with learning. Accordingly, this criterion variable denotes students' final progress grades as tracked by the amount of weekly topics completed (60% of final grade), weekly time logged (10% of final grades), district assessment scores (15% of final grade), and notebook checks (15% of final grade) as specified by members of the math department at the study site.

Research Questions and Hypotheses

I sought to answer the following broad research questions:

RQ1: Is engagement time, retention, and the ratio of topics mastered to topics practiced (in ALEKS) for students identified as at risk for failure in mathematics predictive of final Algebra 1 course progress grades?

RQ2: Is engagement time, retention, and the ratio of topics mastered to topics practiced (in ALEKS) for students identified as at risk for failure in mathematics predictive of PSAT math scores?

In conducting this investigation, I assessed the relationship of the predictor variables (student retention, engagement time, and the ratio of topics mastered to topics practiced) to students' math achievement (the criterion variable) as measured by PSAT mathematics performance and final progress course grades. I implemented a correlational predictive design to evaluate research outcomes. Using this design, I was able to investigate the collective and individual association between the three identified factors on mathematics competencies as defined by the ALEKS ITS online program theories and measured by the ALEKS data logs.

Answers to the research questions facilitated the identification of the best learning indicators to support instructional practices in these milieus. Teachers at the research site may be able to apply this information to deliver effective teaching and learning strategies to better address the needs of their students. Accordingly, the following alternative hypotheses were tested:

H_a1: Engagement time, retention, and the ratio of topics mastered to topics practiced (in ALEK) will be significant predictors of final Algebra 1 course progress grades, $\alpha \leq 0.05$.

H_a2: Engagement time, retention, and the ratio of topics mastered to topics practiced (in ALEK) will be significant predictors of PSAT math scores, $\alpha \leq 0.05$.

The null hypotheses were the following:

H_01: Engagement time, retention, and the ratio of topics mastered to topics practiced (in ALEK) will not be significant predictors of final Algebra 1 course progress grades, $\alpha \leq 0.05$.

H_02: Engagement time, retention, and the ratio of topics mastered to topics practiced (in ALEK) will not be significant predictors of PSAT math scores, $\alpha \leq 0.05$.
I conducted a multiple regression analysis to test the hypotheses. A correlation coefficient (r) and z-scores (R^2) were applied to determine the significance of engagement time, retention, and the ratio of topics mastered to topics practiced on students' performance on final Algebra 1 course grades and/or PSAT scores.

Theoretical Foundation

Knowledge Space Theory

The theoretical framework for this study stems from the mathematical cognitive sciences behind ALEKS known as knowledge space theory (KST; McGraw-Hill Education, 2017). The origin of this theory encompasses the work of Jean-Paul Doignon and Jean-Claude Falmagne whose goal was to improve the psychometric approach to assessing individual competencies (Doignon & Falmagne, 2015). These theorists described the KST as the collection of all possible state of knowledge that exists within the mathematical domain (Craig et al., 2013). A few researchers (Craig et al., (2013), stated that this theory incorporates the compilation of various sets of problems as related to mathematical concepts and problem-solving skills, and facts. Accordingly, Doignon and Falmagne's ideas on the KST underscore the diagnosis of students' math competencies (state of knowledge) based on their mastery of particular items on adaptive knowledge assessments that are comprised of 25-30 problem types (McGraw-Hills, 2017). Craig et al suggested that the program can identify what information students already know and can apply; what they are ready to do; and what they are unable to accomplish and adjust problem types based on the analysis of all collected information. Thomas and Gilbert (2016) asserted that this adaptive ability of ITSs is underpinned by the theoretical foundations of the Zone of Proximal Development (ZPD) and the Cognitive Learning Theory (CLT).

Zone of Proximal Development

Lev Vygotsky (1978) introduced the idea of the ZPD and identified student' intellectual development has not only what learners can do, but also what they can do with assistance. Vygotsky stated the following:

> We give children a battery of tests or a variety of tasks of varying degrees of difficulty, and we judge the extent of their mental development on the basis of how they solve them and at what level of difficulty…., if the child barely misses an independent solution of the problem-the solution is regarded as indicative of his mental development. This "truth" was familiar and reinforced by common sense. Over a decade even the profoundest thinkers questioned the assumption; they never entertained that notion that what children can do with the assistance of others might be in some sense even more indicative of their mental development than what they can do alone. (p. 3)

Through the acquisition of the learners' ZPD, educators can apply ITS scaffolding methods to support learning processes by aligning new learning with what students already know and can do, and concentrate lessons around what students are prepared to learn with guidance. Through these practices, educators can minimize learning anxiety by ensuring that appropriate tasks are presented with attention to students' background knowledge (Chounta, McLaren, Albacete, Jordan, & Katz, 2017). Instructors can use the program to construct and identify new knowledge based on the explorations and discoveries of what students are ready to learn. Accordingly, educationalists can incorporate ITSs to guide and consultant students' academic learning.

Cognitive Learning Theory

Various theologians contributed to the cognitive principles. A few of these theorists include Thorndike, Lindeman, Rogers, Maslow, and Dewey's conceptualization of scientific thinking (Knowles, Holton, & Swanson, 2005). The principle of cognitive theory places the learner's mental inquiry at the center of learning, according to Knowles et al. (2005). These researchers stated that learners' mental inquiries are influenced by intrinsic and extrinsic experiences and the student's surrounding environment. Knowles et al. (2005) aligned this theory with student-centered learning environments, as opposed to conventional education where instruction is teacher-centered and students are required to conform to the pedagogic processes. The students garner educational acumen to achieve personal objectives. Leaners demonstrate this understanding in the practices associated with adult learning (andragogy) where learning is directly influenced by the students and their experiences. Hawkins et al. (2017) stated that through the acquisition of these background experiences, learners are able to maximize their self-actualization and the ability to be a self-directed learner. The latter promotes the personalization of new information by stimulating a deep sense of value and meaning that facilitates personal growth (Hawkins et al, 2017). Learners apply this awareness to cultivate a greater connectedness to new topics and to drive motivation for furthering one's education. Hence, educators can incorporate personalized learning to promote reflection between learning and experiences and facilitate active interaction to assess the trials and errors of new knowledge. Program developers and educators apply these insights to underscore the development and implementation of one-to-one adaptive learning with the use of adaptive ITS programs.

Educationalists combine and apply the three philosophies in blended-settings to optimize their abilities to differentiate instruction and effectively address the needs of learners. Based on these theories, one would predict that students who are provided with instruction at a level geared to them would make considerable advances in mathematics achievement and would demonstrate the acquisition of the current mathematical standards as they relate to 21st-century skills.

Nature of the Study

I implemented a correlational methodology with a predictive design to evaluate the outcomes of this research. A correlation predictive methodology allows for the opportunity to predict the relationship between two or more variables (see Creswell, 2012). This design will facilitate the predictions about one variable from the other. This approach applies predictor variables to forecast the behavior of criterion measures (Boundless, n. d.). Unlike other quantitative studies that assess the probable cause and effect between variables, a predictive correlation study does not infer causation (see Creswell, 2012). I identified the predictor variables from the framework of the ALEKS ITS online program, and students learning patterns were assessed from the data logs obtained by the software. I employed a multiple regression analysis to investigate the collective and individual strength, and the degree of association between the predictor variables (student retention, engagement time, and the ratio of topics mastered to topic practiced) on the criterion variable (mathematics competencies) as measured by the PSAT scores and final progress grades in algebra.

Definitions

The definitions and abbreviations of major terms used within this study are, as follows:

Assessment and learning in knowledge spaces (ALEKS): An ITS that is used to assist students with improving their learning deficiencies in various course subjects. The ITS is a web-based math curriculum based tutoring system that applies artificial intelligence to assess, identify, and monitor students' mastery of mathematical objectives. The ALEKS computer-assisted courses are applied in blended learning settings to foster and promote students' learning, understanding, and skills in various high school mathematics subjects (McGraw-Hills, 2017).

Artificial intelligence (AI): AI is the science behind intelligent computer programs which liken machines to demonstrate human-like intelligence and characteristics.

At-risk/struggling learners: According to NEA (2002-2015), students who continue to demonstrate low academic success due to language barriers, race/ethnicity, disabilities, socioeconomic, and other demographics are categorized as at risk for failure. This definition was applied to define struggling learners throughout this investigation. Such definition typifies approximately 80% of students at this location (EdSight, n. d.).

Blended learning: Chen and Yao (2016) define blended learning as a combination of traditional face-to-face and e-learning experiences. The e-learning setting provides students with the ability to self-pace, self-manage, and self-direct their learning. Various blended learning and e-learning courses are employed in educational milieus to drive positive outcomes for learners. This teaching and learning setting provides instructors and learners with unprecedented opportunities for learning in and outside classroom milieus. According to Chen and Yao (2016), blended-learning environments facilitate improved understanding, connect learners and resources, promote active learning, and enhance critical thinking and communication skills.

Computer-assisted instruction (CAI): A dynamic instructional process whereby instructional materials are delivered through the means of a computer program that monitors students' learning patterns.

Education data mining (EDM): The field of education relating to methods of analyzing large amounts of educational data to garner insights on students' behaviors and teaching and learning practices in these settings (Baker, 2016).

Intelligent tutoring systems (ITS): Types of Computer based-instructional programs the use artificial intelligence to monitor and provide instant support and feedback to students as they work through mastery of learning objectives (Icoz et al., 2015).

Knowledge space theory (KST): The cognitive science behind ALEKS created by Doignon and Falmagne that describes all possible mathematical competences. The theory employs assessment techniques to determine an individual state of knowledge and modifies instruction to meet their individual needs (Doignon & Falmagne, 2015).

Learning analytics (LA): A related field of EDM, that uses statistical methods to analyze students' learning patterns (in educational settings) and applies new insights to improve the instructional and learning processes in these environments (Zacharis, 2015).

Mastery-based learning: An instructional method premised on a metric of success that incorporates students' individual demonstration of competencies including task completion and levels of achievement (Connecticut State Department of Education, 2002-2017).

National Center for Education Statistics (NCES): A federal agency related to the United States Department of Education's Institute of Education Sciences that is responsible for collecting, analyzing, and publishing educational statistics.

National Education Association (NEA): A professional interest group that represents public education in the United States and offers publications that inform and engage public schools and other stakeholders.

Preliminary Scholastic Assessment Test (PSAT): A standardized test used as a preparatory assessment for the SAT, and to identify qualifying National Merit Scholars. The test is administered by the College Board and the National Merit Scholarship Corporation (NMSC) in the United States (College Board, 2017a).

Scholastic Assessment Test (SAT): A standardized college entrance tests used to make college and university admission decisions. The College Board administers the test in the United States (College Board, 2017b).

School Performance Index (SPI): A standardized measure that describes students' average performance in a particular subject area on various state assessments. Scores range for 0-100, and the acceptable score that indicates proficiency in math at this district is 75 (i.e., equivalent to a “C” or better average) or higher in students’ performance (EdSight, n. d.).

Trends in International Mathematics and Science Study (TIMSS): A series of international measures that assess the mathematics and science knowledge of students from around the world and provide timely and reliable data to compare the achievements of U. S. students with students in other countries (NCES, n. d.).

Assumptions, Scope and Delimitations, and Limitations

The purpose of this investigation was to determine the predictability of the ALEKS program constructs on students’ math achievement. I instituted a correlational predictive design to assess the predictability of the predictor variables (student retention, engagement time, and the ratio of topics mastered to topics practiced) to students’ math achievement (the criterion variable) as measured by PSAT mathematics performance and final progress course grades. I concentrated primarily on a purposive sample of 265 ninth- and 10th-grade high school students at an urban technical high school in the northeast United States. These participants worked in the ALEKS ITS program during the 2015-2016 and 2016-2017 academic year, the first 2 years of implementation. Students in other cohorts and from other locations did not participate in this research. Including such participants in the study may pose possible threats to external validity (see Creswell, 2012). Creswell (2012) stated that purposive sampling techniques promote possible selection bias in research studies.

I assumed that mathematics teachers at this location applied the ALEKS mastery-based curriculum effectively in the classrooms and students were actively engaged in the ITS during class time. I also assumed that selected participants were fully versed in the use of the ALEKS ITS program in and outside of active learning in the math course. However, threats to internal validity existed as engagement time in the ALEKS ITS was recorded as the total time a student is logged into the program irrespective of their active or inactive performances. For example, a student can make no attempt to learn or master topics while logged into the program and will accrue idle time that is collected in the student's overall engagement time total (Dani, 2016). The accumulation and combination of these time differential in ALEKS may have impeded the validity of findings germane to student learning. Additionally, the students' ability to work in the program outside of school hours might compromise findings as some students might obtain assistance from their parents or older siblings during these timeframes. The latter delineates some students attaining more assistance than others. Such activities could have threatened the accuracy of the ALEKS measures.

Educationalists across the United States have employed various ITSs in learning institutions to enhance students' achievements. Instructors use ITSs to provide specific types of adaptive CAI to remediate and improve the cognitive achievements of their learners (Bartelet, Ghysels, Groot, Haelermans, & Maassen van den Brink, 2016). Erumit and Nabiyev (2015) suggested that ITS programs aim to identify, guide, and improve students' understanding towards attaining desired behavior. Nonetheless, due to the unique nature of the sample, choice of methodology and the choice of predictor variables for this study, results may not be generalized beyond the specific population from which the sample was drawn or to other ITS programs other than ALEKS.

Significance

In this study, I sought to expand the knowledge base on the topic that identifies what ALEKS measures are the best predictors of students' future mathematics achievement by analyzing information generated by students' data log in the ITS. To date, few researchers have assessed the impact of ALEKS on the math achievement of high school students and only one group of researchers (Bringula et al., 2016), based on my review of the literature, have examined the relationship between variables measured in ITS instruction and mathematics achievement. It is anticipated that a better understanding of this relationship could result in changes in the way in which ITS is employed and what emphasis is placed on various areas of instruction. For example, the findings from this investigation might justify an increase in engagement times or the need for additional retention reviews in ALEKS. Educators could apply this information to improve the quality and effectiveness of combining such ITSs with best teaching practices to foster better educational outcomes for struggling learners', and technology developers can incorporate such findings to improve the working efficiency of the ALEKS ITS software program. These actions could result in struggling students mastering more math concepts at a quicker pace, thus, increasing the likelihood of greater math proficiency. Several positive social changes that might occur as a result of this investigation include: (a) reduction in failure rates, (b) higher graduation rates, (c) a greater range of job and future education choices, (d) and greater success in these milieus. The latter may also contribute to the productivity of the current and future society.

Summary

This chapter provided background information on the scope and focus for this investigation. Chapter 2 of this study contributed a review and analysis of rich information on relevant research topics related to artificial intelligence and adaptive learning. The section commences with discussions pertaining to CAI, followed in tandem with literature conversations related to ITS and the ALEKS program.

Chapter 2: Literature Review

In the current study, I sought to identify what ALEKS constructs are best predictors of struggling students' achievement in mathematics. My particular focus was on ascertaining the predictability of students' retention, engagement time, and topics mastered to topics practices on struggling students' success in high school Algebra 1 and PSAT math scores at the study site. Few researchers have investigated the effects of ALEKS on the mathematical achievement of high school students or the relationship of ITS factors to students' mathematical success at this level of instruction, according to my review of the literature. Additional insight on the topic of focus may help educators to maximize the pedagogic process for the application of this ITS program to support struggling learners in math classrooms at this location.

Accordingly, in this chapter, I thoroughly reviewed relevant literature in an effort to establish the significance of this research and provide a base to support the findings of this investigation. The chapter begins with an overview of the search strategies used to locate pertinent articles for this topic, followed by a section on the theoretical foundations that underpinned the study. The literature review section includes arguments supporting the call for personalization in education and conversations on CAI programs and ITSs that pertain to trends in teaching and learning in mathematics. The literature review concludes with discussions related to ALEKS and its application in math at the high school level.

Literature Search Strategy

I used Walden University Library resources to conduct an extensive search on current (2015 to 2018) full-text, peer-reviewed articles relevant to the topic. I commenced with an initial search in ERIC and PsycINFO (and later in SAGE Journals, ScienceDirect, and Education Sources) for themes related to *computer-assisted instruction and student achievement*, which resulted in over 1,400 journal, reports, magazines, and books published from 1965 to 2018. The ensuing literature encompassed seminal works as well as recent peer-reviewed articles. I limited these search results to current (2015 to 2018) full-text peer-reviewed documents, which produced 95 journal articles. These sources provided helpful information on the application of diverse types of CAI programs across various levels of mathematics education and possible influences on instruction, learning, and achievement. In another search, I used the Boolean phrases *computer-assisted instruction (learning) and mathematics* and *online learning and student achievement*. These results were predominantly academic journal articles and reports that provided insights on the application of CAI (including ITSs) in math settings at all levels of instruction which was later narrowed to the high school level. The latter search yielded 24 results that addressed the instructional level of focus for this study. I later modified the search by replacing *mathematics* with *mathematics achievement* and found seven journal articles. These articles provided information on the impact of online education technologies on the math achievement of high school students.

I proceeded to conduct additional explorations to include the American Doctoral Dissertation and Education Sources using Boolean phrases such as *intelligent tutoring* *system and mathematics achievement and high school*, which resulted in nine articles including project studies, journal articles, and reports. These sources provided rich information on the institution of ITSs to support the instruction and learning of mathematics at the high school level. Nonetheless, the number of articles was reduced to two items once limiters such as full-text, peer-reviewed, and published since the year 2015 to 2018, were applied. To locate additional studies, I turned to Google Scholar, a search engine which was accessed via Walden University Library. In addition to the phrases listed above, I used the terms and phrases *ALEKS and students' mathematics achievement (secondary education)*, *ALEKS and factors for improved achievement*, *the theory behind intelligent tutoring systems*, *computer-assisted instruction and the Zone of Proximal Development*, *intelligent tutors and the cognitive theory*, and *adaptive learning in mathematics*. These searches resulted in over 15,000 results for dissertations, reports, books, and journal articles published since 2016. These items were tracked to the Walden Library to substantiate their credibility as acceptable sources with the use of appropriate limiters. The latter search provided extensive literature surrounding CAI, ITS, and ALEKS in various levels of education, predominantly at the postsecondary level of education.

Theoretical Foundation

The theoretical foundation for this study centered on the work of Doignon and Falmagne (2015), which was based in the KST. These theologians applied this theory to divide a subject domain into infinite structures of knowledge states and allows for the general description of what students know, do not know, and are ready to learn (Craig et al., 2013; Huang, Craig, Xie, Graesser, & Hu, 2016; McGraw-Hills, 2017). Computer scientist incorporate this theory in ALEKS to supports the determination of a student's state of knowledge at each point of learning through the use of adaptive knowledge assessments that are comprised of approximately 30 question types (Huang et al., 2016). A knowledge state refers to the complete set of problems in a particular domain that a student is proficient in solving (Doignon & Falmagne, 2015). Huang et al. (2016) asserted that a student's probability of knowledge state increases when that student responds correctly to a problem type that is contained within that knowledge domain. Such actions permit these computer programs to adapt to the learner's state of knowledge.

Thomas and Gilbert (2016) stated that the adaptive capability of online learning and assessment platforms are based on discussions relating to Vygotsky's ZPD and the CLT. The CLT evolved from works by Thorndike, Lindeman, Rogers, and Maslow and from Dewey's conceptualization of scientific thinking (Knowles, Holton, & Swanson, 2005). These adaptive processes are also grounded in artificial intelligence (Kulik & Fletcher, 2016). According to Kulik and Fletcher (2016), these platforms guide learners towards discovering solutions to problems by providing appropriate scaffolding and feedback from knowledgeable databases. Chounta et al. (2017) stated that Vygotsky's ZPD supports the acquisition of knowledge by aligning course content with what individuals are ready to learn with guidance, and Thomas and Gilbert (2016) discussed the importance of addressing the learner's needs and experiences. Accordingly, these three theories are not divergent but work in concert to support computer-assisted instructional environments.

These theologians provide the roots that facilitated the development of various technological platforms that assist teaching and learning processes, promote diversification, and foster andragogic practices for learning. Numerous adaptive learning programs, including ALEKS, are based on these foundations. These systems infuse cognitive theory and adaptive techniques to infer students' knowledge (Johnson & Samora, 2016; Kulik and Fletcher, 2016). Such learning milieus place the individual at the center of learning that is driven by active engagement towards personal growth (Hawkins, Collins, Herman, & flowers, 2017). Accordingly, these theoretical foundations create awareness that cultivates a greater connectedness to new topics and instills the motivation for continued learning. Such personalized learning promotes reflection between learning and experiences (Hawkins et al, 2017) and facilitates active interaction to assess the trials and errors of new knowledge. These individualized learning opportunities encourages educators and students to participate in meaningful learning experiences that promote students' success in such learning milieus.

Literature Review Related to Key Concepts and Variables

Technology for Personalized Learning

According to Johnson and Samora (2016), the advancements in technology, increasing need for differentiated instruction, rising cost of education, despondent student performances on international assessments, and the lack of proper student preparation for higher education, has substantiated the claim for revamping traditional views of education and the accountability systems. The "New" Commission Report which galvanized the path for the infusion of computer-aided instruction in education, formally addressed these concerns (Pellegrino, 2006). Pellegrino (2006) declared that technology could act as a panacea to address the shortcomings of traditional instructional and assessment methods by stating as follows:

> By building statistical models into technology-based learning environments for use in classrooms, teachers can assign more complex task, capture and reply students' performances, share exemplars of competent performances, and in the process gain critical information about student competence. Without question, computer and telecommunication technologies are making it possible to create powerful learning environments and simultaneously assess what students are learning at very fine levels of detail, with vivid simulations of real-world situations, and in ways that are tightly integrated with instruction. (p.10)

Johnson and Samora (2016) stated that the application of some form of personalization may increase the quality of education. Other researchers have discovered that students who were tutored one-to-one by human tutors performed 2 standard deviations higher than students exposed to traditional instruction (Johnson & Samora, 2016; Kulik & Fletcher, 2016). Such findings reflects a change in grade from a "C" to an "A". Other researchers reported that students who were taught by CAI tutors demonstrated an increase in achievement of 0.80 standard deviation higher than those who participated in traditional instruction settings (Johnson & Samora, 2016) or approximately 0.3 standard deviation (a change from the 50th to the 62nd percentile) above usual levels (Kulik & Fletcher, 2016). Kulik and Fletcher (2016) noted that ITSs demonstrated and effect size of 0.66 standard deviation (a change from the 50th to the

75th percentile) on students' performance outcomes. These authors' meta-analysis included 50 studies that evaluated the impact of ITSs on students' achievement. Their claims were substantiated by Zheng, Warschauer, Lin, and Chang (2016) meta-analytical study that discovered significant positive finding on the effects of one-to-one laptop programs on students' academic achievement. Such findings implied that one-to-one tutoring programs were most beneficial, when compared to traditional instruction, for improving learning.

Accordingly, learners are being increasingly exposed to ITSs on a yearly basis (Chen &Yao, 2016; McManis & McManis 2016; Shute & Rahimi, 2017). Elnajjar and Naser (2017) asserted that ITSs provide new strategy for learning and instruction that is applied more prevalently at the postsecondary level and such application shows promising academic effects for learners at this stage of education (Escueta, Quan, Nickow, & Qreopoulos, 2017). However, a few researchers have observed an increase in the application of such technological modalities at the K-12 levels of education over recent decades (Shute & Rahimi, 2017). Nevertheless, the idea of including computer tutoring systems in educational settings is not new. Infusing these systems in education milieus dates back to approximately fifty years ago (Kulik & Fletcher, 2016). Instructors include these computer tutors in the instructional setting to monitor students' working behavioral and to gather information germane to students' who are at risk for falling behind in these online platformsand while supporting the effectiveness of teaching and learning practices (Baker, 2016; Gasevic et al., 2016; Holstein et al., 2017; Icoz et al., 2015; Liu et al., 2015a, 2015b; San Pedro, 2017). Currently, Educators apply CAI and

ITSs in educational milieus to support the personalized learning needs of students and to promote differentiated instruction.

Computer Assisted Instruction and Intelligent Tutoring Systems

Liao and Lin (2016) described CAI as the use of a computerized learning system to deliver instruction to learners. Young et al. (2017) defined CAI as a technologically advanced form of instruction that is delivered primarily through the use of a computer program. These instructional tools include the use of web-based and software programs, as well as mobile devices (Hawkins et al., 2017) to foster particular learning skills that are relevant to specific subject areas. According to Shute and Rahimi (2017), the first of these programs appeared in the 1960s and applied a systematic didactic form of instruction to solicit desired behaviors for learning. These systems used a scientific form of programmed instruction (related to large discrete components) and were referred to as computer-assisted instruction (Kulik & Fletcher, 2016; Shute & Rahimi, 2017). Shute and Rahimi stated that it was not until the 1970s to the 1990s that such systems began incorporating formative and summative assessments with ongoing effective feedback to assess students' knowledge based on correct and incorrect responses, and to support teaching and learning practices. These more advanced tutors (beginning with CAI which later developed into ITSs) assimilated AI and CLT with an advanced data management system to provide learners with step-by-step guidance towards solving problems (Kulik & Fletcher, 2016). Educators apply these software programs in learning settings to provide students with unlimited access to learning and offer instant assessments that incorporate instructional simulations and educational tools (Dani & Nasser, 2016). Nonetheless, these technological modalities include a wide range of program type.

Today's evolution of CAI tutoring systems encompasses online and multimedia, and ITS software programs (Liao & Lin, 2016). However, essential differences exist between traditional CAI and today's ITS tutors. Current ITSs encompass more adaptability when compared to earlier models of CAI systems. Kulik and Fletcher (2016) stated that CAI tutors deliver framed instructional segments while ITSs prescribe blocks of guided instruction which relies on organized knowledge databases that interact with learners. These researchers, along with other scholars, shared additional descriptors of ITSs that include three models. The authors described (1) the domain model, which contains the core concept to promote understanding and application of course skills and objectives; (2) the student model, which tracks a learner's state of knowledge and predicts their performance; and (3) the pedagogical or teaching model, which identifies and applies the appropriate learning activities to address personal instructional needs (Kulic & Fletcher, 2016; Wang et al., 2015). These models work collaboratively to provide numerous data related to students' learning patterns and achievement in various academic courses.

According to Slater, Baker, Almeda, Bowers, and Heffernan (2017), these ITSs apply Bayesian Knowledge Tracing and Performance Factor Analysis to draw inferences of students' knowledge. Other researchers asserted that these knowledge tracing methods allows for the identification of appropriate problems to predict the probability that students will correctly apply a skill and are most consistent at estimating student knowledge (Tariq, Kolchinski, & Davis, 2016). Dani and Nasser (2016) stated that ITSs "have the ability to integrate more than one medium, provide authentic and concurrent learning activities and provide academic content-based support to a large student body" (p. 153). Accordingly, educators view ITSs as CAI software programs that help students practice and develop specific educational skills. The goal of program developers is for these platforms to achieve the same effect as human tutors by instituting ongoing scaffolding and appropriate feedback to support learning outcomes. Accordingly, educationalists apply these software systems, by way of the Internet, to analyze multidimensional characteristics of students' learning and problem-solving skills across various content areas.

Increasing Application of CAI and ITSs in Mathematics

Computer-aided instruction and tutoring programs are emerging in blended learning settings as an effective tool to support achievements in mathematics courses (Hachey et al., 2015; Soliman & Hilar, 2016; Young, 2017) and to support low achieving students (Chappell et al., 2015; Hawkins et al., 2017; Higgins, Crawford, Huscroft-D'Angelo, & Horney, 2016; Kessler, Stein, & Schunn, 2015; Xin et. al., 2017). These modalities include, but are not limited to, ALEKS, Cognitive Tutor, Catchup Math, Math XL, and SuccessMaker (Brasiel, Jeong, Ames, Lawanto, & Yuan, 2016), as well as iTutor, ASSISTments, and the Building Block Software program. The research addressing the impact of CAI and ITSs on student mathematics success is predominantly quantitative, and results have been mixed. Nonetheless, the findings relevant to this topic have demonstrated a small to moderate positive effect size on learning outcomes

(Hawkins et al., 2017; Young, 2017). A few researchers have observed an increase in effect size when CAI is applied as a supplemental, rather than a core instructional tool (Hawkins et al., 2017). Several investigators (Hawkins et al., 2017) and (Young, 2017) stated that CAI may not serve students best as a replacement for core instruction but may be more beneficial when applied to supplement effective educational practices. Haelermans and Ghysels (2017) experimental study on the supplemental use of an individualized digital practice tool on 337 seventh grade students while at home, improved their numeracy skills. Brasiel et al. (2016) depicted similar findings in a quasi-experimental evaluation on the supplemental application of CAI on students' achievement in K-12 mathematics courses. Jeong et al. (2015) conducted a correlational evaluation of a large sample of 8000 secondary students and found that ITSs showed promise in promoting mathematics understandings in secondary students. These results were substantiated by De Witte, Haelermans, and Rogge's (2015) descriptive study that incorporated an instrumental variable design and discovered a positive effect of CAI programs on students' learning outcomes in secondary math courses.

According to Chappell et al. (2015) and Kulik and Fletcher (2016), the findings on the effectiveness of these adaptive tutors on students' mathematics achievement have been inconclusive. The latter is corroborated by studies that reported little to no effect of such modalities on student success. For example, Craig et al. (2013) randomized experiment reported no significant difference between struggling students who participate in ALEKS after-school tutoring program (at the middle school level) and those who did not, as measured by the Tennessee Comprehensive Assessment Program (TCAP).

Similar results were discovered in Xin et al. (2017) pre-test post-test comparative study (at the elementary level) that investigated the possible effects of an ITS- Please Go Bring Me-Conceptual Model-Base Problem Solving- and reported no statistically significant difference between groups. Young et al. (2017) implemented a second-order meta-analysis and argued that results on this topic may fluctuate depending on the methodology and theoretical, and conceptual variances; the type of program and teacher preparation and training activities; and the intensity of the program application across studies. These nuances in the literature have resulted in calls for further research on this topic to substantiate future claims (Brasiel et al., 2016; Young et al., 2017).

Support for Struggling Learners

The NEA (2002-2015) categorizes at-risk or struggling students as learners who continue to demonstrate low academic success due to language barriers, race/ethnicity, disabilities, socioeconomic, and other demographics. These students enter the learning environment with more learning disadvantages when compared to their non-categorized peers. Jacob, Berger, Hart, and Loeb (2016) posited that struggling or at-risk students may require more guided instruction in mathematics than their non-struggling counterparts. However, a survey research employed by Elnajjar and Naser (2017) asserts that the alignment between adaptive technology and ITSs show promise in supporting students' achievement in learning settings. Dai and Huang (2015) confirmed these finding in a comparative analysis of three models of instruction (traditional instruction, e-learning, and blended learning) and found that the e-learning model was most effective in improving the achievement levels of low performing students. These software programs act as a human instructor, to some extent, and provide one-to-one instruction for personalized teaching (Wang et al., 2015). As a result, it would seem that the application of these online platforms as a remediation tool in educational settings would benefit struggling learners (Liao & Lin, 2016).

The body of literature on the affordances and constraints of computer tutoring on the learning performances of struggling learners is extensive (Butzler, 2016; Chen & Yao, 2016; Cigdem, 2015; Foster, Anthony, & Clements, 2016; Gasevic et al., 2016; James et al, 2016; McManis & McManis, 2016; Salminen, Koponen, Rasanen, & Aro, 2015; Steele, Bozick, & Davis, 2016). However, few researchers have assessed the impact of CAI and ITS systems on struggling students' mathematics success and results have been inconsistent (Chappell et al., 2015). Several investigators assert that the application of computer-assisted instructional programs supports the achievement of students who are at risk for failure in various academic subjects (Foster, Anthony, & Clements, 2016; McManis & McManis, 2016; Salminen et al., 2015; Steele et al., 2016). Wang et al. (2015) conducted a quasi-experimental study and found that the iTutor, an ITS, was effective in improving the mathematics skill acquisition of students with low-level prior knowledge. Chappell et al. (2015) incorporated a mixed method study to assess the impact of a synchronous online tutoring system (Power Teaching math) on struggling middle school students' mathematics achievement and discovered that such tutoring application contributed to significant gains in students' posttest performances.

Nevertheless, struggling learners continue to experience challenges in these environments (Butzler, 2016; Gasevic et al., 2016; James et al., 2016). In the CAI and

ITS online instructional environments, instructors can encourage learners to control, manage, and take ownership of their learning. Cigdem (2015) asserted that these settings allow teachers to create more student-centered and active learning opportunities for the application of students' metacognitive skills to develop motivation and action for learning. However, struggling students lack the self-regulation learning skills that are essential for success in these technical platforms (Butzler, 2016; Duffy & Azevedo, 2015). Greene et al. (2015) stated that students perceived self-efficacy is one of the variables that drive motivation for learning and performance. Duffy and Azevedo (2015) viewed motivation as an essential factor for the application of self-regulation strategies and reaction to scaffolding in online learning settings. These researchers conducted an experimental study that incorporated an ITS (MetaTutor) to examine their views and found that prompts and feedback within CAI environments fostered the increased use of self-regulated learning strategies and viewing time during learning sessions. However, the authors also concluded that these variables did not significantly support improvements in achievements or comprehension outcomes (Duffy & Azevedo, 2015).

Based on these findings, I concluded that students who demonstrate deficiencies in such self-regulation learning skills may not perform effectively in online learning platforms; and such theories may support the opinions of Gasevic et al. (2016) and Zacharis (2016) that reflected a high attrition rate among students in CAI and ITS learning settings. Additional conclusions from Duffy and Azevedo (2015) implied that students' dominant achievement goal interacted with their responses to scaffolding conditions. For example, students who applied a performance-approach by striving to outperform peers demonstrated improved performance to scaffolding when compared to learners who used a mastery-approach and strived to improve personal competency (Duffy & Azevedo, 2015). Howard, Ma, and Yang (2016) asserted that a misalignment between student and teacher expectations for the application of technology may foster learners' disengagement in learning. Accordingly, it is important that struggling students understand and determine which strategies are most beneficial to address their personal needs for academic success (Butzler, 2016). I concluded that the learners at the site of this investigation should be made aware of those variables that best support their success in the blended learning and e-learning settings. It is imperative that learning institutions provide these students with the proper supports to facilitate their achievement in these learning milieus.

Before introducing these modalities into classrooms, Hawkins et al. (2017) stressed the importance of aligning CAI tools with the curriculum and grade-level standards, as well as students identified levels of performance with effective instructional strategies to motivate and engage students. These researchers posit that educationalists consider the degree of engagement, appropriate pacing, opportunities for progress assessment and reports, and the level of suitable practice and immediate feedback when selecting CAI tools for instruction. According to Young (2017), CAI promotes instrumental understanding and the ability to apply mathematical rules and procedures by providing didactical functions to practice skills. Instrumental understanding is one of the common understandings that can be observed in mathematics (Young et al., 2017). Young et al. (2017) declared that these CAI programs provide more opportunities for drill and skill development and practice to enhance procedural knowledge development. Accordingly, I concluded that such findings may maximize the effective applications of CAI platforms to promote the achievements of learners who are at risk for failing high school mathematics.

ALEKS

The ALEKS web-based program is an ITS that is designed to apply mathematical instruction and ongoing assessments to monitor and manage students' knowledge acquisition. Similar to other ITSs, the computer platform gathers data related to learners' working behavior pattern and provides appropriate feedback and guidance to support their learning needs (Dani, 2016). Educationalists can obtain and apply this data to differentiate instruction to address the needs of students. The program provides learners with (1) individualized sequence of problems to solve, (2) implements knowledge checks to assess their understanding (implemented continuously and at the end of course goals), and (3) provide guidance via instructional practice review to promote learning and understanding of problem-solving skills (McGraw-Hills, 2017). Nonetheless, ALEKS provides the same level of instruction to all students irrespective of their diverse learning styles and provides instructors with the opportunity to upload external video presentations to assist students' visual and auditory learning demands (Dani & Nasser, 2016).

The ALEKS software program uses a curriculum-based approach (Johnson & Samora, 2016) which minimizes adjustments to school districts' curriculum practices. Hence, educators can apply ALEKS in blended settings to is deliver an entire mathematics curriculum via individualized instruction (McGraw Hill Education, 2017); and apply problems that are within the learners ZPD to facilitate the knowledge, skills, and behavior that promotes conceptual understanding (Dani & Nasser, 2016) and mathematical thinking. Similar to most ITSs for numeracy, program developers created ALEKS to address the current problems relevant to students' mathematical achievement. Educators at the postsecondary level of instruction apply this ITS to improve the remediation problems associated with learning mathematics (Johnson & Samora, 2016) and to promote competency-based education at the K-12 level of education. However, unlike other ITSs that provides procedural step-by-step guidance when completing a problem, ALEKS only provide feedback on the final answer (Dani, 2016; Dani & Nasser, 2016). Dani (2016) asserted that the inability for students to demonstrate strategies for problem-solving within the ALEKS program may limit the software's capability to measure meta-cognition for learning.

The body of research on the effectiveness of the ALEKS software program is limited. Most of these investigations center on the impact of ALEKS on students' math achievements at the postsecondary level. Nonetheless, recent studies have been growing at the secondary levels of instruction and results have been mixed. Several of these studies show promising effects related to the ALEKS ITS on struggling students' math achievement

A pilot study was instituted by Hu et al. (2012) to investigate the effectiveness of the ALEKS ITS on improving the mathematical skills of struggling sixth-grade students in an after-school setting. The participants included 266 sixth-grade students and four math instructors who were randomly assigned to an ALEKS centered or a teacher-centered condition. The researchers applied a state standardized assessment to measure student performance outcomes and listed the following research questions (p. 23).

1. How does computer-mediated learning from ALEKS compare to learning from a human teacher in an after-school program when assessing student achievement on the Tennessee Comprehensive Assessment Program?
2. How does the after-school program compare to students not included in the program in raising student achievement on the Tennessee Comprehensive Assessment Program?

The authors reported the findings from the first of a 3-year study. The investigators applied a *t*-test analysis and multiple regression evaluations to analyze pre and post standardized test scores and ALEKS data logs. The results indicated no significant differences between pre and post-standardized test scores. However, the regression examination predicted 29% of the observed variance for students' post-standardized test scores. These findings revealed that higher post-test scores were predicted by participants' pre-test scores, attendance, and gender; while experimental treatment and race reported insignificant results.

Brasiel et al. (2016) conducted a mixed method study with the use of a quasi-experimental and survey design to assess the impact of 11 CAI mathematical software programs on student achievement gains. The exploration included 200,000 K-12 students who participated in the quasi-experimental method and 2,933 instructors who completed survey responses. This study was the first assessment of a 2-year impact inquiry. A state standardized assessment was applied as a measure of student achievement performance. The authors sought to answer the following research questions:

1. To what extent are there improvements in mathematics achievement for students using the selected technology products?
2. How are the educational technology products being used by teachers with their students (e.g., homework, intervention, supplemental material to support instruction)?
3. What are some common areas of satisfaction, concern, and barriers to implementation?
4. How are teachers using the performance management features of the product? (p. 2791)

The authors used a baseline comparison and logistic regression analysis to analyze quantitative data and a thematic approach was instituted to assess survey responses. The investigators identified six products that met the established criteria to conduct an impact analysis and two modalities (ALEKS and iReady) that demonstrate statistically significant achievement variations ($p < .05$). Further results indicated that teachers were satisfied with the technologies ability to manage performance assessments and engage and empower students in learning activities. Nonetheless, obstacles related to teacher attitude and experience with technology, and infrastructure relevant these platforms, were noted by the researchers.

Sullins et al. (2013) applied an examination to determine if individualized instruction in the ALEKS ITS will increase students' performance on a state standardized assessment. The researchers solicited middle school students (from grades 6, 7, and 8) who participate in a supplemental application of the ALEKS ITS during the academic year. The authors conducted two studies. The objective of the first study was to identify if mastery of ALEKS goal topics correlated with success on the Tennessee Comprehensive Assessment Program, a state standardized assessment. The second study replicated and expands on the findings from the first study and included a new sample from a different district. A total of 218 students from two school districts participated in the first study. The practitioners instituted a correlation analysis to compare the percentage of students' mastered topics in ALEKS with achievement scores. The results indicated a positive and statistically significant relationship between both scores at each grade level. Specifically, the researchers identified a significant positive correlation between the ALEKS mathematical categories measure and learners' standardized mathematics category measures (including Numbers and Operations, Algebraic Thinking, Graphs and Graphing, Data Analysis and Processing, Measurement, and Geometry).

The second study that was carried out by Sullins et al. (2013) assessed the relationship across and within grade levels. This examination involved 321 middle school students (from grades 5, 6, and 7) and included those measures applied in the first study. The results confirmed the findings of study 1 and revealed a positive statistically significant correlation between and within these scores. The authors suggest that students' proficiency in ALEKS can be a potential predictor of future performance on the Tennessee Comprehensive Assessment measure. The researchers did caution these results based on the lack of rigorous analysis and methodology within the research.

A more recent study that was carried out by Brasiel et al. (2016) used a mixed-method study to evaluate the effectiveness of 11 online mathematics educational technology products on the achievements of 200,000 K-12 students during the 2014-15 academic year. The research addressed the following questions (p. 209):

1. What is the impact of the supplemental use of mathematics educational technology on student proficiency on the state assessment?
2. What common themes do teachers report from the implementation of the educational technology in their classroom?

The practitioners applied a quasi-experimental design was instituted to tackle the first question. The participants were separated into a technology group (with one-to-one application) and a traditional instructional (business-as-usual) group. The results from the logistic regression analysis of 44, 497 students favored the use of the technological products, and the ALEKS ITS was identified as one of the programs that demonstrated a statistically significant positive impact on struggling students' achievement. To answer the second question, the investigators applied a qualitative self-reported survey to garner teachers' perspective on the use of educational technology in the classroom. The survey data were obtained from 2, 933 teachers and a thematic approach was incorporated to identify commonalities. Teachers overall response to the use of the technology in the classroom was positive. The findings indicated that 57% of the teachers were satisfied with the software products and 10% were satisfied with their students' engagement when using these modalities. However, only 34% of the instructors reported using the performance management features within the products to monitor students' progress.

The authors reflected disappointment at the small percentage of responders who applied the management feature to support students and guide instruction as this was one of the primary function of the mathematical platforms.

In contrast to the above findings, some researchers postulate that ALEKS provides minimal to no advantage to learning in traditional classrooms. Craig et al. (2013) reported insignificant finding in their experimental study that assessed the effectiveness of the ALEKS ITS on improving the mathematical skills of struggling middle school students. A sample of sixth-grade individuals was recruited to participate in a 25-week afterschool program. The participants included 253 sixth-graders from a large disadvantaged minority population and five teachers that were randomly chosen from a group of 25 instructors. The students were randomly assigned to a teacher-centered and an ALEKS centered classroom in an after-school setting. The authors applied a state examination to measure students' performance outcomes. Teachers were also asked to rate students conduct, involvement, and need for assistance, based on a three-point scale ranging from poor to excellent (not involved to actively involved) and a 2-point scale reflecting no help to more help than usual. A *t*-test analysis was conducted on all scores, and no significant difference was observed between struggling students who participate in ALEKS after-school tutoring program and those who did not. However, students in the ALEKS-led condition required significantly less assistance in mathematics from teachers than their counterparts (ALEKS-led: $M = 0.05$, $SD = 0.11$; and Teacher-led: $M = 0.65$, $SD = 0.27$).

In a similar study involving ALEKS at the secondary level, Huang et al. (2016) conducted an experimental evaluation of 533 sixth-grade students (from five middle schools) to explore the effects of ALEKS on mathematics achievement. The research question for this study addressed the mathematics performance gap in education and the prospects of ITSs towards reducing this gap. The investigation focused on data from the last 2-years of a 3-year study that placed students in an after-school setting. The participants were randomly assigned to an ALEKS ITS led and a teacher-led condition. The researchers conducted a *t*-test analysis and observed no significant difference in scores between the two conditions (even though scores favored the ALEKS ITS condition). Nonetheless, the authors reported encouraging results for the application of ALEKS to aid the education of struggling youth. The practitioners concluded that White males and females, and African American males and females performed differently on the math state test in the teacher-led condition; and students who had varied individual differences demonstrated similar performances in the ALEKS ITS setting.

Most of the above studies were implemented at the middle school level of instruction. Few investigators have assessed the influences of the ALEKS ITS on struggling students' mathematics performances at the high school level of instruction, and that may identify program construct that may be predictive of students' success. A possible explanation for such limitations may be the constraints associated with the ability to conduct large data analysis. However, recent developments in the field of large data have opened up numerous possibilities of such investigations.

Data Mining and learning analytics

Computer tutoring supports the diversification of instruction to facilitate teaching and learning processes in and outside the classroom, provides timely feedback to students and flexible learning plans, and offers managerial assistance for synchronous and asynchronous educational processes (Chappell, Arnold, Nunnery & Grant, 2015). Such personalization is bolstered by the emerging field of large data analysis. This field facilitates the use EDM and LA to optimize understanding of student learning patterns and behaviors in various CAI learning environments, and to support the identification of learning problems linked to the timely signs of students at risk for academic failure and attrition (Gasevic et al., 2016). According to Henrie, Halverson, and Grahm (2015), technology records summative and formative data on students' system interactions and can provide pertinent data on their engagement in learning. The behavior and progress data can be recorded directly through these modalities (Hu, Wu, & Gu, 2017). Gasevic et al. (2016) posit that "the interpretation of these patterns can be used to improve our understanding of learning and teaching processes, predict the achievement of learning outcomes, and inform support interventions and decisions on resources allocation" (p. 68). Most research in EDM and LA has coalesced around predicting the achievement and retention of students at risk of failing particular CAI courses; and to identify common variables that individually or collectively inform a general model (Gasevic et al., 2016). Nonetheless, the literature on this body of research is limited, and studies are commonly applied at the postsecondary level to assess the impact of ITSs on students' academic success. Some studies have been employed at the secondary level; however, these studies largely involve other ITS modalities (similar to ALEKS).

For example, a correlational study of Bringula et al. (2016) assessed the relationship between high school students' prior mathematical knowledge on time spent tutoring, total hints requested, and the number of completed quizzes in a SimStudent ITS program. The investigation sought to answer the following questions (p. 464):

1. What is the mathematics performance of the students before and after the intervention period?
2. How do students interact with the simulated student in terms of time spent tutoring, number of hits requested, and number of quizzes conducted?
3. Does prior knowledge of mathematics influence, singly or in combination, interactions of students with the simulated student?

The participants were involved in 1-hour SimStudent sessions over a 3-day intervention period. These respondents included 139 (of 236) first-year high school students who were enrolled in the Introductory Algebra course, and who completed both the test examinations and the three-day intervention period. The authors applied two measures for this investigation. The evaluation included three Introductory Algebra pre and post-test that were used to gain an understanding of students' knowledge (as related to linear equations), and data logs related to students' interaction were collected from the SimStudent (i.e., time spent tutoring, number of hints requested by the program, and number of quizzes conducted) were correlated. Results indicated that 11 % of the variability in the time spent tutoring, 5% of the variability in the number of quizzes conducted, and 3% of the variability in the number of hints requested were due to students' prior mathematical knowledge. The authors concluded that prior knowledge demonstrated a significant, consistent, positive influence on learner-interface interactions (i.e., time spent tutoring, number of hints requested by the program, and number of quizzes conducted) with the ITS program. Nonetheless, recommendations were made to extend the intervention period for future studies.

Zacharis (2015) assessed data generated in the data logs of a computer management system (Moodle) to determine a realistic model for predicting struggling students' performance in blended learning mathematics courses. The author sought to determine the relationship between students' final course grades and their interaction in online modalities. The study addressed two research questions (p. 48).

1. Which online activities correlated significantly with student grades?
2. Which course learning management system tracking variables form the best model predicting student success?

The practitioner accumulated 29 potential explanatory variables and identified 14 variables with significant association to students' course grades. These variables were selected for application in a stepwise multivariate regression analysis. The participants of the study included 134 college students who were enrolled in an introductory Java programming course that was instituted over a 12-week period. The research findings indicated that reading and posting message (37.6%), content creation contribution (10.4%), quiz effort (2.5%), and the number of files viewed (1.5%) predicted 52% of the variance in student final course grade. Reading and posting messages contributed the greatest variance (37.6%) in students' scores.

Dani and Nasser (2016) conducted a study of ALEKS at the higher education level to determine potential identifiers of students' academic success in foundational mathematics. The researchers embarked on addressing the following questions:

1. Does the ability to work individually effect students' marks in the coursework and the final exam?
2. Does the proficiency of English affect the ability to study individually? (p. 157)

The participants included a sample of 152 college students who were divided into three clusters (numbered one –three) based on derived attributes. Students in cluster one demonstrated the highest ratio of weekly topics mastered to topics practiced (averaging 80%). Leaners in cluster three symbolized the lowest values (averaging 53%) within this variable (cluster average percentages represented 80%, 66%, and 53%). The research measures involved students' activity data from the ALEKS data logs. The ALEKS factors included learners' score on initial assessments, the ratio of weekly topics mastered to topics practiced, number of progress test (knowledge assessments), final exam score, and whether students completed the course before the 12-week period or not. A Chi-square, ANOVA test, and Regression analysis were employed to address the research questions. Results indicated that student ratio of topics mastered to practiced was predictive of students' academic success in the course. This component represented a significant moderately strong, positive correlation with student final exam marks. The authors indicated that the ratio of topics mastered to topics practices represented 16% of the variance in students' final exam scores. Further results indicated that learners' English language proficiency affected their ability to learn independently.

Dani (2016) implemented a quantitative investigation at the postsecondary level to determine potential identifiers (within ALEKS) of students' academic success. This study sought to expand on findings from the previous study carried out by Dani and Nasser (2016). The research aim was to:

1. Develop a model to determine which factors affect academic achievement
2. Examine students' perceptions about tutoring and cognitive effects on ALEKS and their learning study habits.
3. Examine if their study habits and perceptions have an effect on their ability to master topics. (p. 9)

The respondents included 58 students who were enrolled in a foundational mathematics course over a 12-week period. The researchers implemented a cross-sectional design to triangulate the measures of students' ALEKS data logs and survey responses. The study implemented Chi-square, correlational and regression analysis, and pair *t*-test to address the research questions. The findings suggest that learners prior knowledge and derived attitude (a ratio of topics mastered to topics practiced) were predictive of final course marks (R^2 = 42%). Further results indicated that students who selected topics sequentially demonstrated better retention of mathematical content than students who progress randomly through topics. These findings afford instructors the opportunity to monitor the progress of struggling students who are unable to maintain proper pacing and provide guidance in the selection of appropriate (sequential) topics.

Review and Synthesis

The use of the ALEKS ITS in blended learning settings provides personal learning settings that are customized to address the individual needs of learners. Nonetheless, the body of research that explores what factors of ITSs that are best predictors of struggling students' performance is limited. Although studies exist at the postsecondary level that addresses ALEKS factors (ratio of topics mastered to topics practiced) to be predictive of students' mathematics success, very limited research investigations have been conducted at the secondary level. One of such studies (Bringula et al., 2016) indicated that 11 % of the variability in the time spent tutoring, 5% of the variability in the number of quizzes conducted, and 3% of the variability in the number of hints requested were due to students' prior mathematical knowledge. The authors concluded that prior knowledge demonstrated a significant, consistent, positive influence on learner-interface interactions (i.e., time spent tutoring, number of hints requested by the program, and number of quizzes conducted) with the ITS program. The authors recommended that future investigations extend the intervention period for similar conditions. Dani and Nesser (2016) study at the postsecondary level identified ALEKS constructs and determined which factors were best predictors of students' success. These ALEKS factors included learners' score on initial assessments, the ratio of weekly topics mastered to topics practiced, number of progress test (knowledge assessments), final exam score, and whether students completed the course before the 12-week period or not. A Chi-square, ANOVA test, and Regression analysis were employed to address the research questions. Results indicated that student ratio of topics mastered to topics practiced was predictive of students' academic success in the course.

It is imperative that practitioners investigate if these findings are transferable across various ITSs and sample populations. If such associations exist, then ALEKS could provide the means for effective and efficient application of such factors to improve the performances of students who are at risk for failure these settings. Additionally, Baker (2016) and Icoz et al. (2015) posit that the combination of large data analysis and human decision-making can facilitate a more realistic design of ITSs that can collect, analyze, and report important information related to various student learning constructs. The author asserts that new insight can support the enhanced design of online tutoring systems and instructors can apply this information to support the needs of students in the learning arena. Therefore, the current state of learning analytics and the effective use of data management systems can drive improved instruction and achievements for struggling learners (Gasevic et al. 2016; Holstein et al. 2017; Liu et al., 2015a, 2015b; San Pedro, 2017).

It is anticipated that a better understanding of the variables that predict learners' success could result in changes in the way in which ITSs are employed and what emphasis is placed on various areas of instruction. For example, study findings might justify more extended engagement times or the need for additional retention reviews; educators could apply this information to increase the quality and effectiveness of combining ITSs with best teaching practices to foster improved educational outcomes for struggling learners, and technology developers can incorporate such findings to improve the working efficiency of the ALEKS ITS software program. These actions could result in struggling students mastering more math concepts at a quicker pace, thus, increasing the likelihood of greater math proficiency. This research aims to fill the gap in practice by investigating which ALEKS constructs are best predictors of struggling students' success in a high school blended-learning mathematics course.

Summary and Conclusions

Chapter 2 provided an extensive review and analysis of rich information on relevant research topics related to artificial intelligence and adaptive learning. The section began with discussions related to the need for personalized instruction followed by developments pertaining to CAI and ITSs and concluded with literature conversations related to ALEKS. Topics relevant to the characteristics of the ALEKS ITS programs were identified in the literature and contributed to the conceptual framework for this study. These constructs include the ratio of topics mastered to topic practiced (a ratio reflecting the probability of each student's total mastered to total practiced topics during the specified timeframe for this study), retention (demonstrated by the percentage gains on progress knowledge assessments), and engagement time (total time in ALEKS during the investigation period). Review of the literature revealed limited research pertinent to the predictability of ALEKS constructs on struggling students mathematical success at the high school level.

Chapter 3 presented the methodology for this study; it includes the research design, strategies for data collection, and the analytical processes through which an improved understanding of ALEKS constructs and students' mathematical success was obtained.

Chapter 3: Research Method

In this chapter, I address the methodology for this study of the predictability of ALEKS ITS constructs on struggling students' mathematical achievement. The purpose of this quantitative study was to determine if engagement time, retention, and the ratio of topics mastered to topics practiced, all of which are variables that are measured in the ALEKS computer-assisted math instruction program, are predictive of struggling students' mathematics performance. This research had a correlational perspective that involved a multiple regression analysis. In the subsequent sections of this chapter, I address the participants, instruments, data collection procedures, and data analysis that underpinned the approach for this research investigation.

Setting

The setting for the study was an urban technical high school located in a low socioeconomic community in the northeastern United States. All ninth-grade students had been placed in (one of three) Algebra 1 blended learning mastery-based math classes where one-to-one devices had been implemented and the ALEKS ITS software program incorporated as the predominant form of instruction. The classrooms were assembled in a stationary format where students worked in collaborative groups when learning in the program before reporting to testing stations that were allotted for knowledge assessments and district mathematics evaluations. Students worked in the online program for the entire instructional period and also had the opportunity to work in the program outside of school hours as well. In this environment, teachers acted as facilitators to assist students as needed and to apply the ALEKS managerial tools to monitor students who may need additional support.

Upon logging into the ALEKS interface, students are offered an initial assessment that evaluates the learner's state of knowledge. Once this initial step is accomplished, each subsequent log-in directs students to their pie chart that reflects their learning progress towards achieving their course completion (refer to Figure 1 for visual display). A student can choose to work towards gaining new topics or to review topics already learned (Dani & Nessar, 2016). Each slice of the ALEKS pie chart depicts a different set of mathematics objectives that replicates the learner's knowledge state depending on what he or she understands and is ready to learn (McGraw Hill Education, 2017). The program sequentially delivers math topics; however, students can also choose to work on any ready-to-learn topics within a given domain group (i.e., goal topics; Dani & Nasser, 2016). Once presented with a topic, students can request an explanation to support their learning or proceed to solve the problem on their own. In addition to the latter, instructors required all students to write notes to facilitate their learning needs.

Figure 1. ALEKS pie chart depicting learners' status and course content.

Students are recognized in the program as having learned a topic after three consecutive correct responses to a problem type. According to Dani (2016), these processes allow students to work at their own pace and monitor their learning. Instructors assign students a knowledge assessment once they have learned 10 or more topics. Nonetheless, ALEKS also assigns a progress assessment base on topics mastered and time spent in the software (Dani & Nasser, 2016). Accordingly, students are provided with progress assessments after completion of approximately 20-25 topics, and 10 hours of login time (McGraw Hill Education, 2017). Learners may gain or lose topics in their pie chart based on their performances on provided progress assessments. These working behaviors are logged and tracked in the ALEKS database and can be applied to assess students' learning within the online program (Dani & Nasser, 2016).

Research Design and Rationale

I included three predictor variables from the ALEKS data logs (retention, engagement time, and the ratio of topics mastered to topic practiced) and two criterion variables (students' final Algebra 1 progress grades and PSAT math performance scores) for analysis. I gathered the predictor scores from archival data germane to the first 2 consecutive years of implementation in the ninth-grade math classes (the 2015-2016 and 2016-2017 academic years), and the criterion scores were obtained after students completed their first year in the ALEKS ITS program. According to Creswell (2012), this time differential for collecting the data is characteristic of a predictive correlational study. This methodology allowed me to apply a multiple regression analysis to investigate the combined and individual strength and the degree of association between the predictor variables on the criterion variables.

Quantitative Research

Quantitative research methodologies involve applying objective processes to assess observations and measure results involving one or more groups (see Creswell, 2012). The epistemological viewpoint for these methods emphasizes objectivism, empiricism, and positivism and understanding the world through scientific methods (Park & Park, 2016). Park and Park (2016) stated that a quantitative research approach is characterized by a review of the previous literature to formulate concepts and testable research questions and hypotheses, the application of descriptive and inferential statistical practices for data collection and analysis, validation of processes, and the generalization of findings. These methods include surveys, experiments and quasi-experiments, and correlational (casual-comparative) studies (see Creswell, 2012). Researchers using these designs are able to evaluate causes, trends, and associations between variables (see Creswell, 2012). The underlying research question(s) is the primary basis for the investigative inquiry, however (Kopf, Hsu, Shows, & Albinsson, 2016).

I used quantitative methods to assess the predictive abilities of struggling students' engagement time, retention, and the ratio of topics mastered to topics practiced (the predictor variables) in ALEKS on their final Algebra 1 progress grades and mathematics performance on the PSAT (the criterion variables). Other quantitative methods can be used to assess cause and effect capabilities (e.g., experimental and quasi-experimental studies) or beliefs and trends (survey research; see Creswell, 2012). In contrast, I sought to predict the relationship between and among continuous variables within a single group. A predictive correlational methodology affords the opportunity to predict the association between two or more variables after the intervention has already occurred (Lodico, Spraulding, & Voegtle, 2010). Using this approach involves applying predictor variables to predict the behavior of criterion measures (Boundless, n. d.). Predictions can then be drawn about one variable from the other. These features made a predictive correlational methodology the best choice for this study.

Methodology

Population

The target population for this investigation included all students from lower socioeconomic background in a northeastern U.S. state who were attending urban high schools and who are at risk for failure in math. Approximately 530,000 students from this state were enrolled in K-12 learning institutions at the time of this investigation, and an estimated 31,000 individuals represented the selected population that was germane to this investigation (EdSight, n. d.). The guidance coordinator at the study location stated that 585 of the individuals from this site were represented in the selected population.

Sampling and Sampling Procedures

I used purposive sampling techniques to identify and gather individuals who had completed their first year in the ALEKS Algebra 1 course and who had participated in the mathematics portion of the PSATs. Creswell (2012) asserted that purposive sampling is frequently applied in educational research because random selection and random assignment to interventions are rarely possible in these settings. The district leaders at the study site implemented the ALEKS ITS intervention at the school in Fall 2015. The author of this research solicited individuals who participated in the ITS software, achieved a final progress grade for the course, and participated in the PSAT in the Fall of their sophomore year. Individuals who were expelled, transferred in or out of the program, or missing values relevant to this investigation during this time frame were eliminated from the dataset. The data reports of the participants reflected the first and second year of the intervention was implemented in the ninth-grade Algebra 1 course (the 2015-2016 and 2016-2017 academic years).

The course groups were organized and predetermined by the district and school leaders at the study's location. I coalesced the cohorts of learners into one group and collected the data that depict the learning behaviors and mathematics achievement of these learners. Hence, for this investigation, I obtained the archival data reports for 265 ninth-graders. Of the 265 cases, 127 (47.9%) reflected the first cohort of participants and 138 (52.1 %) were from the second cohort. The ages of participants ranged between 14 and 18 years, and 143 (54%) reflected females and 122 (46%) reflected males. The ethnicity classifications for this sample included 189 (71.3%) Hispanic, 59 (22.3%) African American, 8 (3%) Caucasian, 5 (1.9%) Asian, 2 (0.8%) American Indian, 1 (0.4%) Pacific Islander, and 1 (0.4%) mixed race. Table 2 illustrates the frequency and percentages of the sample, Table 3 reflects the gender count, and Table 4 provides a numerical representation of the ethnicity classifications.

Table 2

Frequency Count and Percentages of Sample (n = 265)

Cohort	*n*	%
Cohort 1 (2015-16)	143	54
Cohort 2 (2016-17)	122	46

Table 3

Gender Count of Participants (n= 265)

Gender	*n*	%
Female	127	47.9
Male	138	52.1

Table 4

Ethnicity Classifications of Participants (n = 265)

Ethnicity	*n*	%
Hispanic	189	71.3
African American	59	22.3
Caucasian	8	3
Asian	5	1.9
American Indian	2	0.8
Pacific Islander	1	0.4
Mixed Race	1	0.4

The sample was very diverse in their experience, background knowledge, and ability level and according to the guidance counselor, at the site, a large percentage of learners were at least one to three grade levels behind in their math learning. I did not interact with participants and instead applied student archival data reports as the central analytical focus for this analysis. As a result, due to the nature of this predictive study, I did not need to obtain participant consent to conduct this investigation.

Archival Data

As I stated in the research design and rationale section, archival data were the focus of statistical analysis for this study. I obtained the data from the ALEKS ITS data logs and the guidance department at the site of this investigation. The gathered reports reflected the mathematics achievement and learning behavior of learners from one high school institution. I reported in the sampling section that the group of participants was organized and predetermined by the organization; and the ALEKS ITS intervention was a district implemented intervention for the school beginning in the Fall of 2015. Because the intervention was introduced and completed before the collection of data, I was not required to obtain informed consent from participants (National Institute of Health, NIH; Office of Extramural Research, n. d.). Nevertheless, I did solicit permission from the district superintendent and the school principal for accessing and collecting archived statistics for this investigation; and once this study's IRB approval number (03-26-18-0317860) was received, I commenced with collecting, organizing, and analyzing the data.

Instrumentation and Operationalization of Constructs

I collected the numbers for the predictor variables, students' engagement time, retention, and topics mastered to topics practiced from the data logs in the ALEKS program. To substantiate the validity of ALEKS, founders of the knowledge base theory conducted an extensive analysis to assess the reliability and validity of the AI algorithm that runs the program. To achieve this end, these researchers implemented an analysis to assess the predictive abilities of users' responses to problems not in the assessments on their observed responses (Falmagne, Cosyn, Doble, Thiery, & Uzun, 2007). The authors reported a strong positive correlation of 0.67 between the predicted and observed responses (Falmagne et al., 2007). In addition, Falmagne et al. (2007) provided additional analysis of students' learning efficacy achievement and reported a 0.92 median distribution of the conditional probabilities of learning success. These findings suggest that ALEKS provide valid assessments due to correct gauging and delivery of problem types located on the outer fringe of a student learning state. According to the authors, such observations ensures efficient learning (Falmagne et al., 2007). The following delineates the predictor, data sources, and descriptions of the scale for each variable.

Predictor Variables

*Engagement Time (*depicted as *ET in data tables)* is a predictor variable that was obtained from the ALEKS database. This continuous variable is recorded each time an individual logs in and out of the ITS irrespective of instructional and non-instructional periods. ALEKS does not provide a distinction between active and non-active time frames, and offers a 180 days range viewing limit for logged time. Accordingly, I compiled the active and inactive time for participants and used these time attributes to explain student engagement within the context of this study. Hence, I arrived at a quantitative estimate of engagement time by combining students' total log-in times in AKEKS from August 2015 to June 2016, and August 2016 to June 2017. I recorded these averages as the total hours participants spent in the Algebra 1 class during the designated time period for this study. These recorded hours ranged from 0 to 500.

*Retention (*depicted as *ren* in the data tables*)* is a predictor variable that was acquired from the ALEKS database. Unlike the *ET* construct, retention cannot be obtained directly from the software program. Nevertheless, the ALEKS program recognizes student's mastery of learned topics after they have demonstrated their competency of learned objectives on a knowledge assessment. The software records when students initiate a knowledge assessment and tracks students' progress between each assessment. Students' mastery of topics can fluctuate in gains and losses on progress between each knowledge assessment. I collected these scores and calculated the average percentages in mastered and learned topics. A comparison between participants mastered and learned topics can be used to assess the average percentage retention scores for individual learners and detect students who may require additional supports. For example, Figure 2 depicts a student that mastered nine topics on their initial knowledge assessment, then learned ten more during ALEKS instruction and achieved a total of 13 topics on their subsequent knowledge test. The latter represents 40% of students' retention in learning. I collected these retention percentage scores and an average estimate was established for each student. Hence, this continuous variable ranges from 0 to 100, with higher scores denoting students' increased retention in learning

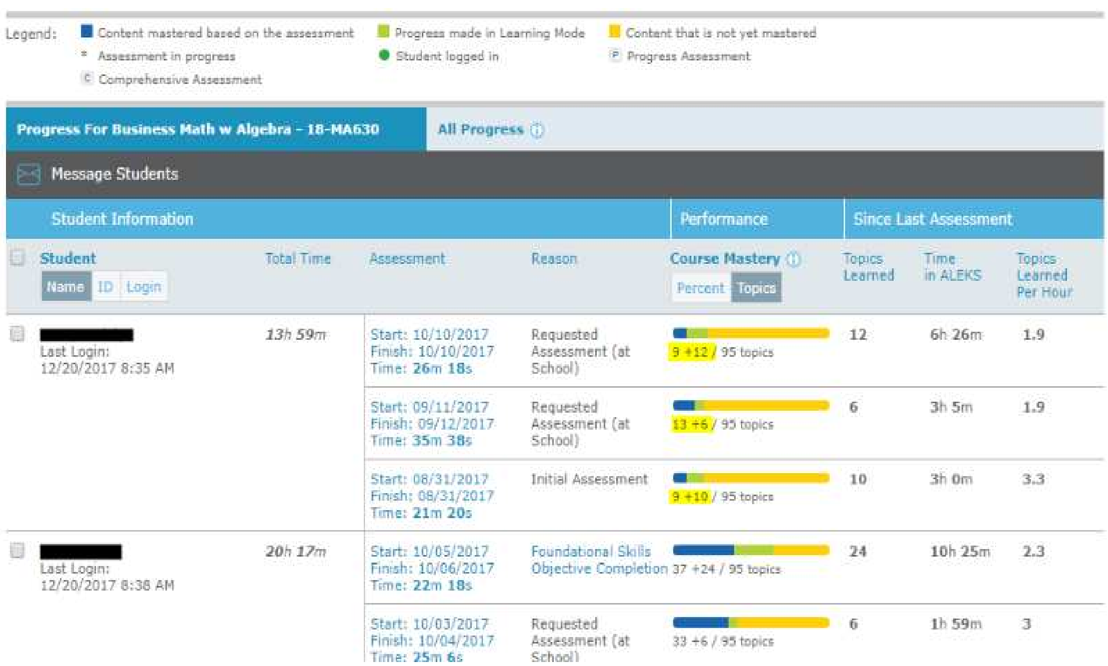

Figure 2. ALEKS progress report depicting a learner's retention after knowledge assessments.

The *Ratio of Topics Mastered to Topics Practiced* (*mtop*) is a predictor variable that was obtained from two factors in the ALEKS program. This continuous variable is an attribute that was applied by Dani and Nesser (2016) to define the learning patterns of students who worked in the ALEKS ITS platform. Dani and Nesser (2016), and Dani (2016), stated that this variable represents an abbreviation of mastered to practiced topics and denotes the measure of students ability to learn independently. These authors stated that a higher ratio of this variable indicates increased capabilities to learn independently. Accordingly, I applied this approach to calculate this attribute for this research investigation. I extracted participants total mastered and practiced topics for their respective years in the ALEKS Algebra 1 course (from August 2015 to June 2016, and August 2016 to June 2017). The combined totals were recorded as *total topics mastered (ttm)* and *total topics practiced (ttp)* in the data tables. I evaluated the quotient of students' *ttm* to *ttp* to establish a ratio of students' mastered to practiced topics. This variable range from 0 to 1 in the data tables with higher ratios reflecting increase rates of mastered to practiced topics.

Criterion Variables

The school's guidance department provided the numbers for students' PSAT math scores (PSATm) and final progress grades (FPG) for the Algebra 1 course. These numbers depict the criterion variables for this investigation. In this section, I address the data sources, nature and scale, and the validity and reliability of these measures.

The PSAT, which was a continuous criterion variable in the study, is a standardized aptitude test that is administered by the College Board to assess the general intelligence of students in grades 9 and 10 (Warne, 2016). It is also referred to as the National Merit Scholarship Qualifying Test (NMSQT). The test measures the knowledge and skills deemed to be the best indicators of college success and career readiness (College Board, 2017b). The measure may also predict students' performance on the SAT (Thum & Matta, 2015). According to Richardson, Gonzalez, Leal, Castillo, and Carman (2016), the PSAT exam is a condensed form of the SAT that provides students with feedback on current achievement skills. The exam tests learners' mathematics reasoning, critical reading, and writing skills (Richardson et al., 2016; Warne, 2016), and is a strong indicator of students' performance on the SAT (College Board, 2017a). The mathematics section of the PSAT measures a student's conceptual understanding and reasoning skills in numeracy (College Board, 2017a). The latter includes topic objectives that are relevant to Algebra 1 and Geometry courses. The College Board (2017b) asserted that a grade-level benchmark score of 480 on the mathematics test will support the identification of students performing at or above grade level and can track students' yearly progress towards attaining the SAT benchmark that was discussed in the problem statement section of the study. All college-bound high school students are invited to complete the exam in October of their sophomore year. Participants are provided with a diagnostic report detailing their estimated score range and performance on the SAT.

The College Board (2017c) asserted that the sectional scores for the PSAT/NMSQT range from 160 to 760 and those on the SAT range from 200 to 800. The 80-point range differential accounts for the variations in types and forms of the assessments (College Board, 2017a). The range of students' PSAT mathematics sectional test scores is 20 times their respective raw score that ranged from 8 to 38 (College Board, 2017c). These scores have a correlation that is greater than 0.80 with scores on the SAT and other measures of intelligence (Warne, 2016), and are directly related to math scores on the SAT College Board (2017c). For example, participants who completed the PSAT and the SAT on the same day would reflect the same score on both assessments. To ensure the validity and reliability of the SAT suite assessments (including the PSATs) the College Board frequently reviews student performance metrics and employs research-based designs to consistently evaluate test forms, prompts, questions, and items types (College Board, 2017d). A few researchers (Richardson et al., 2016) applied a multiple regression analysis to assess the predictive ability of portions of the PSAT on student advance placement performance and discovered a strong predictability between portions of the PSAT and students advance placement performance irrespective of ethnicity and socioeconomic status. Another researcher (Warne, 2016) established a conservative indicator of 0.84 as an internal reliability coefficient for each subtest of the PSAT. The author's findings also support the consistency of PSAT scores across test variations under similar conditions.

Students' Final Progress Grades (SFPG) is a continuous criterion variable that was garnered from the school's guidance department. As stated in the review of the literature, educators can apply the ALEKS platform in learning environments to monitors students' logged time and learning behavior patterns, and provides progress assessments based on their working behavior and time spent in the program (Dani & Nasser, 2016). According to researchers (Falmagne et al., 2007), the program provides valid and reliable data pertaining to students' academic performance in mathematics. The mathematics teachers at the study site can apply this information to monitor students' progress and differentiate instruction to promote personalized learning, and to track final course progress grades. Math instructors at the location of this investigation, required learners to write notes when working in the ALEKS ITS, complete a minimum of 7 to 10 topic and 7 to 10 hours per week, and to complete the ALEKS districts goal assessments with a 70% minimum score. These teachers coalesced the scores for these requirements into one final percent average that reflected the students final progress grades for the course. The latter was used to denote the students final progress grades that a range from 0 to 100 with higher scores reflecting increased progress with learning. According to the mathematics department chair at the site, students'final progress grades was calculated on a waighted average scale with 60% representing ALEKS weekly topics, 15% depicting district assessment scores, 15% indicating notebook checks, and 10% signifying ALEKS weekly logged time in the program. The department chair stated that math teachers at the site calculated the time and topic scores as a ratio of weekly topics learned to 10 expected attained weekly topics, and weekly hours gained to ten expected attained weekly hours.

Data Analysis Plan

Before initiating data analysis to address the research question, I implemented data screening and cleaning to determine if any biases existed across the variables. I used the Statistical Package for the Social Sciences (SPSS) to aid in generating scatterplots to graphically depict relationships between variables, confirm linearity and to identify outliers (Zacharis, 2015), and to run multiple regression analysis on all data pertinent to this research study.

Preliminary Testing Pertinent to Data Cleaning and Screening:

In this investigation, I sought to predict the relationship between and among continuous variables within a single group. Lodico et al. (2010) asserted that a predictive correlational methodology affords the opportunity to predict the linear relationship between two or more variables after the intervention period. Hence, I applied a multiple regression analysis to investigate the combined and individual strength and the degree of association between the predictor variables on the criterion variables.

I employed both descriptive and inferential statistics in the evaluation. Descriptive statistics describes the calculation of simple statistical measures such as mean, standard deviation, and correlational comparisons of all represented predictor variables with criterion variables within the study. Nonetheless, the validity of the study is contingent on the validity of construct measures. I conducted a missing value assessment to identify problematic data and eliminated these values from the sample set. Additionally, I utilized linear models and an ANOVA test to aid in evaluating the linearity across the domains (Triola, 2012). In this research, I applied the *Pearson r* correlation coefficient to identify the validity of each construct. The latter include an analysis of the magnitude and direction that range from -1 to 1 to describe associations. I instituted Cohen's heuristics to assist in evaluating the correlation coefficient. The Cohen's heuristics correlation provides absolute values of approximately decimal values .1, .3, and .5 to indicate small, medium and large association between variables (Shaw et al., 2016). However, Zacharis (2015) stated that these coefficients are not effective at explaining why there is a relationship or the interactions of these associations (i.e., how two variables vary together). The researcher asserted that a multiple regression analysis affords a better assessment of coefficients while controlling for other variables. As a result of these reviews, I chose to apply this analysis to address the research questions for this evaluation.

As stated in the archival data section of the study, the data for the evaluation was obtained from the data logs from the ALEKS program and the guidance department at the study site. I applied a multiple regression analysis to investigate the predictive abilities of the ALEKS constructs (engagement time, retention, and the ratio of topics mastered to topics practiced) on student achievement measures (students' final Algebra 1 course progress grades, and PSAT math scores). In this inquiry, I assessed the following research questions (where the predictor or independent variable = engagement time, retention, and the ratio of topics mastered to topics practiced; and the criterion or dependent variable = students' final Algebra 1 course progress grades and PSAT math scores):

RQ1: Is engagement time, retention, and the ratio of topics mastered to topics practiced (in ALEKS) for students identified as at risk for failure in mathematics predictive of final Algebra 1 course progress grades?

RQ2: Is engagement time, retention, and the ratio of topics mastered to topics practiced (in ALEKS) for students identified as at risk for failure in mathematics predictive of PSAT math scores?

Accordingly, the following hypotheses were tested:

H_a1: Engagement time, retention, and the ratio of topics mastered to topics practiced (in ALEK) will be significant predictors of final Algebra 1 course progress grades, $\alpha \leq 0.05$.

H_a2: Engagement time, retention, and the ratio of topics mastered to topics practiced (in ALEK) will be significant predictors of PSAT math scores, $\alpha \leq 0.05$.

The null hypotheses were the following:

H_01: Engagement time, retention, and the ratio of topics mastered to topics practiced (in ALEK) will not be significant predictors of final Algebra 1 course progress grades, $\alpha \leq 0.05$.

H_02: Engagement time, retention, and the ratio of topics mastered to topics practiced (in ALEK) will not be significant predictors of PSAT math scores, $\alpha \leq 0.05$.

I sought to reject the above null-hypotheses and to ascertain an association between the variables that is equal to zero (H_1: $p \neq 0$, H_2: $p \neq 0$, $H_{0\,(1)}$: $p = 0$, $H_{0\,(2)}$: $p = 0$, $\alpha \leq .05$: where the predictor or independent variable or = engagement time, retention, and the ratio of topics mastered to topics practiced; and the criterion or dependent variable = students' final Algebra 1 course progress grades, and PSAT math scores).

Test to Research Questions and Null-Hypotheses

According to Kirkpatrick and Feeney (2016), a multiple regression uses a linear combination of predictors to determine the equation that best predicts the criterion variable and the extent to which this equation predicts the variability in the criterion variable. Hence, I incorporated a linear model comparison to evaluate the collective and individual predictability of the predictor variables on the criterion variables (where the predictor or independent variable = engagement time, retention, and the ratio of topics mastered to topics practiced; and the criterion or dependent variable = students' final Algebra 1 course progress grades, and PSAT math scores). Kirkpatrick and Feeney (2016) asserted that the hierarchical model provides the opportunity to test if two or more predictor variables collectively predict increased variances in the criterion variable beyond what can be predicted by one alone. The latter provides a better examination of the effect size *(R^2)* between predictor and criterion variable (Kirkpatrick & Feeney, 2016). Consequently, I employed inferential statistics including a multiple regression analysis to evaluate *(R^2)* and to determine the individual and combined proportion of the variance of the predictor variables on the criterion variables.

I applied an ANOVA test of significance (*F*-test) to construct the least-square prediction equation and assess the null-hypotheses that the change in R^2 is equal to zero in the population. Zacharis (2015) asserted that this test reveals if the final regression model is significant at the .05 level. The *F*-test determines if the sum of the squares (i.e., regression) divided by the sum of squares (i.e., total) is equivalent to R^2 (Kirkpatrick & Feeney, 2016). All data were analyzed in the SPSS statistics 23 software with a .05 significance level to determine the association and strength between and among all constructs on students' achievement.

Threats to Validity

The research study concentrates primarily on ninth- and 10th-grade high school students at an urban technical high school in the northeast United States. These participants worked in the ALEKS ITS program during the 2015-2016 and 2016-2017 academic year. The first 2 years the intervention was implementation. Students in other cohorts and from other locations did not participate in this research. The latter posed possible threats to external validity. Creswell (2012) stated that purposive sampling techniques promote possible selection bias in research studies. Hence, due to the unique nature of the sample and choice of methodology, and the choice of predictor variables for this study, results may not be generalized beyond the specific population from which the sample was drawn or to other ITS programs other than ALEKS.

Threats to internal validity existed as engagement time in the ALEKS program was recorded as the total time students were logged into the program irrespective of his or her active and inactive processes. My accumulation and combination of these time differential in ALEKS may have impeded the validity of findings as they relate to students' learning. In addition, the students' ability to work in the program outside of school hours might have compromised the findings as some students could have obtained assistance from their parents or older siblings during this time frame. The latter delineates some students attaining more assistance than others. Such activities could have threatened the accuracy of the ALEKS measures.

Ethical Procedures

In this study, the students' archival data were gathered from the school and district where I am affiliated. Hence, I took all necessary precautionary steps to protect the privacy of participants per the IRB approval number for this study (03-26-18-0317860). These steps required me to obtain approval of the leaders of the the institution before initiating this exploration, selecting the most appropriate method and statistical analysis to preserve the validity and ethical standards for quantitative investigations, and eliminating any trace of data back to the study site or the participants (Lodico et al., 2010). To ensure this task, I excluded any identifiable descriptions of the research site for this investigation and linked the data to designated numbers that excluded the names of participants. I stored the collected data on a password-protected laptop and hard copies were warehoused in a locked file cabinet. Furthermore, all obtained data were shredded and disposed of following a five-year period (National Institute of Health (NIH) Office of Extramural Research, n. d.).

Summary

In chapter 3 of this evaluation, I addressed the methodology of the predictive study related to the ALEKS ITS on struggling students' mathematical achievement. I conducted a quantitative study to investigate three ALEKS constructs (engagement time, retention, and the ratio of topics mastered to topics practiced (the predictor variables) on struggling students' mathematics performance (the criterion variable). The research stems from a correlational perspective and involves a multiple regression analysis. In this chapter, I addressed the design and method for conducting a quantitative study and discussed the sample and participants. In addition, I presented the instrumentation and materials and the data collection and analysis that underpinned the approach for this research investigation. The subsequent chapter discussed the findings and reflection, and the conclusions pertinent to the analysis of the data.

Chapter 4: Results

The focus of this quantitative study was on employing a correlational predictive evaluation to analyze the data reports of 265 participants to determine what factors of the ALEKS are predictive of struggling students' achievement in a blended learning high school mathematics courses. I also sought to identify what ITS program variables are best predictors of struggling learners' success in this platform. Specifically, I investigated the influence of the predictor variables (student engagement time, retention, and the ratio of topics mastered to topics practiced) on struggling students' performance as it pertains to the development of academic competency in mathematics (the criterion variable). The research questions for this evaluation included the following:

RQ1*:* Is engagement time, retention, and the ratio of topics mastered to topics practiced (in ALEKS) for students identified as at risk for failure in mathematics predictive of final Algebra 1 course progress grades?

RQ2*:* Is engagement time, retention, and the ratio of topics mastered to topics practiced (in ALEKS) for students identified as at risk for failure in mathematics predictive of PSAT math scores?

The corresponding hypotheses were, as follows:

H_a1: Engagement time, retention, and the ratio of topics mastered to topics practiced (in ALEK) will be significant predictors of final Algebra 1 course progress grades, $\alpha \leq 0.05$.

$H_0 1$: Engagement time, retention, and the ratio of topics mastered to topics practiced (in ALEK) will not be significant predictors of final Algebra 1 course progress grades, $\alpha \leq 0.05$.

$H_a 2$: Engagement time, retention, and the ratio of topics mastered to topics practiced (in ALEK) will be significant predictors of PSAT math scores, $\alpha \leq 0.05$.

$H_0 2$: Engagement time, retention, and the ratio of topics mastered to topics practiced (in ALEK) will not be significant predictors of PSAT math scores, $\alpha \leq 0.05$.

In this chapter, I present the findings and offer my reflections and conclusion relevant to the analysis of the data. In addition, I included descriptions of the population and sample, data collection and preliminary assessments, the descriptive analysis of study variables, and a comparison of essential study measures. A full regression analysis to address both research questions and determine the predictive ability of the predictor variables on the criterion variables and a summary of the findings are all included.

Data Collection

I obtained the data for this study from the data logs in the ALEKS program and the guidance department at the study location. I used purposive sampling techniques to obtain the data reports of the participants. The sample consisted of 265 struggling students enrolled in an inner-city technical high school in the northeastern United States. The time frame for data collection and organization spanned approximately 2 weeks. The gathered reports reflected the mathematics achievement and learning behavior of 265 learners from one high school institution who had completed their first year in the

ALEKS Algebra 1 course and participated in the mathematics portion of the PSATs. The 265 participants constituted approximately 45% of the overall school population.

The identified population for this investigation included all students from a lower socioeconomic background in a northeastern U.S. state who were attending urban high schools and who were at risk for failure in math. Approximately 530,000 students from this state were enrolled in K-12 learning institutions at the time of the study, and an estimated 31,000 individuals represented the population that was pertinent to this investigation (EdSight, n. d.). According to the school's guidance coordinator, 585 of the individuals from this site represented the targeted population.

The data set for this investigation contained no missing data points within the predictor or the criterion variables. The ages of the sample cases ranged from 14 to 18 years. Of the 265 cases, 127 (47.9%) reflected the first cohort of participants, and 138 (52.1 %) depicted members from the second cohort of participants. The gender of the sample reflected 143 (54%) females and 122 (46%) reflected males. The ethnicity classifications of participants included 189 (71.3%) Hispanic, 59 (22.3%) African American, 8 (3.0%) Caucasian, 5 (1.9%) Asian, 2 (0.8%) American Indian, 1 (0.4%) Pacific Islander, and 1 (0.4%) mixed race. According to the site's guidance coordinator, the sample was very diverse in their experience, background knowledge, and ability level and a large percentage of learners were at least one to three grade levels behind in their math learning.

Results

I used the study's methodology for the preliminary analyses to answer the research questions and test the corresponding hypotheses. The preliminary analysis included missing data and preliminary demographic information, an assessment of linearity between independent and dependent variables, and pertinent descriptive analysis. I conducted a multiple regression analysis to investigate the predictive abilities of the ALEKS constructs (engagement time, retention, and the ratio of topics mastered to topics practiced) on student achievement measures (students' final Algebra 1 course progress grades and PSAT math scores).

Preliminary Testing

In this evaluation, I conducted a descriptive analysis for the three predictors or independent variables (engagement time, retention, and the ratio of topics mastered to topics practiced) for the 265 cases and discovered that the learners' engagement time had the highest mean score of 155.87 with a standard deviation of 52.67 and ranged from 49.17 to 470.95 total hours. These numbers demonstrate a large spread within the data, which indicated that some students were not spending enough time engaged in the ALEKS program. For example, some students were not logging into the program enough, while others were, perhaps, logging in but not actively working. The participants' ratio of mastered to practiced topics had the second highest mean score of 0.69 with a standard deviation of 0.08 and ranged from 0.44 to 0.87 in ratio scores. The students' retention mean score was 0.59 with a standard deviation of 0.13 and ranged from 0.12 to 0.96 in average proportional scores. Of the criterion or dependent variables (students' final Algebra 1 course progress grades and PSAT math scores), the PSAT math variable had a mean score of 388.72 with standard deviation of 49.98 and a range span from 240 to 530, and the students' final progress grade score had a mean of 79.38 with standard deviation 12.82 and a range from 41 to 100. These variables also had a large range and spread within the data. I conducted a multiple regression analysis to determine the linearity of the three predictor variables and their predictive abilities on the criterion variables. No multicollinearity existed, allowing for a clear analysis of the predictive abilities of the independent variables on the dependent variables (see Triola, 2012). Table 5 displays the descriptive statistics of pertinent study variables using measures of central tendency and variability, and Table 6 depicts the intercorrelations with these variables.

Table 5

Descriptive Statistics of Pertinent Variables

Variable	*M*	*SD*	*Min*	*Max*
ET	155.87	52.67	49.17	470.95
mtop	0.69	0.08	0.44	0.87
ren	0.57	0.13	0.12	0.96
PSATm	388.72	49.98	240	530
SFPG	79.38	12.82	41	100

Note. *M* = mean, *SD* = standard deviation, *Min* = minimum, *Max* = maximum, ET = engagement time, mtop = mastered to practiced topics, ren = retention, PSATm = PSAT mathematics scores, and SFPG = students' final progress grades.

Table 6

Intercorrelations for Pertinent Variables

Variable	1	2	3	4	5
1. ET	--	-.13*	-.15*	.43*	-.09
			*		
2. ren		--	.35**	-.02	.28*
				*	
3. mtop			--	.20*	.18*
			*	*	
4. SFPG				--	.19*
				*	
5. PSAT m					--

Note. * $p < .05$; ** $p < .01$.

Results for Research Question 1 and the Corresponding Null Hypothesis

I calculated the criterion (dependent) variable of students' final progress grades in the Algebra 1 course from the weighted averages of students' weekly learned topics ratios, active time in the ALEKS program, notebook checks, and average district assessment scores. The mean score for these averages was 79.38 with a standard deviation of 12.82 and a range from 41 to 100. In addition, I conducted a bivariate correlation to determine the relationship between the three predictors and the final progress grade scores. Students' engagement time was the strongest and statistically significant predictor of students' final progress grade scores followed by the mastered to practiced topics. A moderately strong positive relationship existed between engagement time and students' final progress grades ($r = .43$; $p < .001$), and the ratio of mastered to practiced topics depicted a slightly medium positive association with final progress grade scores ($r = .20$; $p < .001$). No statistically significant correlation existed between students' retention scores and final progress grades. Table 7 represents the correlational relationship between the three predictors on this criterion variable (SFPG).

Table 7

Predictor Variables and the Criterion Variable of SFPG Score

Variable	*r*
ET	0.43**
mtop	0.20**
ren	-0.02

Note. * $p < .05$; ** $p < .01$.

After the initial descriptive and correlational analysis, I conducted a multiple regression analysis using final progress grades as the dependent variable. The participants' engagement time, retention, and mastered to practices topics were applied as independent variables. The three predictors explained approximately 25.7% of the variance in students' final progress grade scores. The R^2 for the full regression model was .26 (F (3, 261) = 30.10; $p < .001$). The participants' engagement time was the most significant predictor of students' final progress grades ($t = 8.56$; $p < .001$). Another significant contributor to the model was the students' ratio of mastered to practiced topics

($t = 5.08$; $p < .001$). In light of these findings, I chose to reject the null hypothesis for research question 1 and retained the corresponding alternative hypothesis. Table 8 provides a summary of the full regression analysis for this model.

Table 8

Summary of Full Regression for Variables Predicting SFPG (N = 265)

Variable	*B*	*SE B*	β	*t*
ET	0.46	0.01	0.11	8.55**
ren	-0.07	5.58	-6.67	-1.20
mtop	0.29	8.81	44.71	5.08**

Note. * $p < .05$; ** $p < .01$; $R^2 = .26$; *B* = unstandardized beta, *SE B* = standard error; and β = standardized beta.

Results for Research Question 2 and the Corresponding Null Hypothesis

The mean score for the criterion (dependent) variable PSATm was 388.72 with a standard deviation of 49.98 and a range from 240 to 530. I conducted a bivariate correlation to determine the association between the three predictors and the PSAT math score. The participants' retention and mastered to practiced topic scores presented a slightly moderate and statistically significant prediction of PSAT math scores, with a slight predictive edge favoring students' retention ($r = .28$; $p < .001$) over the ratio of mastered to practiced topics ($r = .18$; $p < .001$). The analysis did not reveal a statistically significant relationship between the participants' engagement time and the PSAT math score. Table 9 describes the correlational relationship between the three predictors on this criterion variable (PSATm).

Table 9

Predictor Variables and the Criterion Variable of PSATm Score

Variable	*r*
ren	0.28**
mtop	0.18**
ET	-0.09

Note. * $p < .05$; ** $p < .01$.

After descriptive and correlational analysis, I conducted a multiple regression analysis and used the PSAT math score as the dependent variable. The students' engagement time, retention, and the ratio of mastered to practiced topics were applied as independent variables. The three predictors explained approximately 8.7% of the variance in PSAT math scores. The R^2 for the full regression model was .09 (F (3, 261) = 8.27; $p < .001$). The participants' retention was the only significant predictor of PSAT math scores ($t = 3.73$; $p < .001$). In light of these findings, I elected to reject the null hypothesis for research question 2 and retained the corresponding alternative hypothesis. Table 10 illustrates the summary of the full regression analysis for this model.

Table 10

Summary of Full Regression for Variables Predicting PSATm (N = 265)

Variables	*B*	*SE B*	β	*t*
ET	-0.05	.06	-0.04	-0.77
ren	0.24	24.13	90.11	3.73**

mtop	0.09	38.08	56.00	1.47

Note. * $p < .05$; ** $p < .01$; $R^2 = .09$; B = unstandardized beta, $SE\ B$ = standard error; and β = standardized beta.

Summary

My purpose in this study was to determine the predictive ability of three predictor variables from ALEKS (retention, engagement time, and the ratio of topics mastered to topics practiced) on learners' mathematics competencies (students' final progress course grades and PSAT math score), the criterion variables. I presented two research questions and respective hypotheses. The sample included 265 struggling students who were enrolled in an inner-city technical high school in the northeastern United States. I chose to analyze the data using a combination of descriptive, inferential, correlational, and predictive methods. The findings implicated participants' engagement time as the most statistically significant predictor of students' final progress grades, followed by the ratio of mastered to practiced topics. However, the results did not identify these factors as significant contributors in predicting PSAT math score. Accordingly, the participants' retention was recognized as the only statistically significant predictor of PSAT math score. The results contribute pertinent information relevant to the application of the ALEKS ITS to support the instruction and learning of students who are at risk for failure in high school mathematics.

Chapter 5 addressed the educational implications of these results and provided recommendations for future investigations germane to this topic of focus.

Chapter 5: Discussion, Conclusions, and Recommendations

Educators have used many tutoring systems, including computer ITS, in an effort to improve high school students' performances in mathematics. It is important that these stakeholders are aware of effective supports that influence the achievement of learners in these milieus (Henrie et al, 2015). The purpose of this study was to determine what factors of the ALEKS are predictive of struggling learners' performance in a blended-learning Algebra 1 course and PSAT scores at an inner-city technical high school located in the northeastern United States. Three variables (student retention, engagement time, and the ratio of topics mastered to topic practiced) relating to the theoretical framework behind ALEKS were employed to predict the degree of association on the criterion variable (mathematics competencies) as measured by final course progress grades in algebra and the PSAT math scores. Findings suggest that the most statistically significant predictor of students' final progress grades was engagement time followed by the mastered to practiced topics. Nevertheless, these factors were not significant contributors in predicting the PSAT math score, and retention was identified as the lone statistically significant predictor of this criterion variable.

Interpretation of the Findings

The findings of this study indicate that instructional practices in ALEKS that include increased engagement time and mastery of topics, and that maximize retention in learning, may improve the authentic mathematics learning experiences of struggling students at this location. These predictors accounted for approximately 26% of the variance in students' final progress grades. This result confirms findings by Bringula et al. (2016), Dani (2016), and Dani and Nasser (2016). These researchers observed that students' ratio of mastered to practiced topics in ALEKS were significantly predictive of academic success in math courses (Dani, 2016; Dani & Nesser, 2016). They also found that time spent tutoring is significantly correlated with learners' interactions in such modalities (Dani, 2016; Dani & Nesser, 2016). Dani and Bringula et al. linked these attributes to learners' prior knowledge and derived attitude. Such information suggests that these students' prior knowledge and confidence or self-efficacy are essential factors for success in the ALEKS program.

Dani (2016) identified a statistically significant moderately strong and positive correlation between the values of mastered to practiced topics and students' final exam marks. The latter indicates that students with higher yields in this variable are able to master most of the topics they are attempting to learn. This capacity was connected to students' prior knowledge, Dani concluded. Similarly, Bringula et al. (2016) discovered that 11% of the variance in students' time spent in tutoring was due to students' prior knowledge. Dani found that learners' prior knowledge along with their levels of mastered to practiced topics facilitated a higher correlation with final exam scores. These findings indicate that students' percentages of mastered to practiced topics (in ALEKS), along with their time spent in tutoring, are essential predictor of final course grades. This information suggests that instructional practices that maximize students' engagement time in order to increase their values in mastered to practiced topics may support improved progress when learning in the ALEKS platform. For example, instructors may provide timed and topic bound instruction on a daily basis to increase the percentages in students' mastered topics and may facilitate improved learning in the ALEKS program. Such practices may support the learning of struggling students within this modality, in addition to providing opportunities to build their motivation and confidence when working in the program.

The ALEKS program gathers data pertinent to students mathematical learning patterns and applies this information to personalize learning experiences. Based on the theoretical framework underpinning it, the program can generate personalized sequences of problems that are geared towards the learners' ZPD (Thomas & Gilbert, 2016) and provide guidance via instructional practice and assessment reviews (Craig et al., 2013). Accordingly, the ALEKS ITS may support confidence building for students to problem solve and improve mastery of mathematical concepts. Nonetheless, the lack of continuous step-by-step feedback, instruction relevant to the application of student review capabilities, and a viable process to identify students' retention may limit the program's capacity to maximize the achievement, andragogic processes, and confidence building in struggling learners at the research site (see Dani, 2016; Dani & Nesser, 2016).

According to the department chair at the site, struggling students at the research location demonstrated apprehension to making errors or losing topics when working in the ALEKS ITS and when these instances occurred, students became despondent and lost confidence in their math skills and their ability to succeed. My reflection on the letter led me to conclude that such processes may be avoided if ALEKS developers incorporate more scaffolding, additional feedback related to retention as a separate construct, and better alignment review options to support students who are at risk for failure in math courses at this site. These additional supports may improve the ability of students to apply strategies for problem-solving and improve the capability of the program to measure metacognitive skills.

Dani and Nesser (2016) also discussed the topic of building students' confidence in the ALEKS program. These authors expressed the need to provide learners with additional training on how to use the system effectively. The researchers noted that such practices my remove technical barriers and improve students' ability to learn independently while promoting the andragogic skills needed to bolster students' success in the platform.

The ALEKS instructional program creates more student-centered learning opportunities to apply metacognitive skills to develop motivation and active learning (Cigdem, 2015). According to Butzler (2016) and Duffy and Azevedo (2015), many at-risk students lack the self-regulation learning skills that are essential for success in such platforms. Cigdem (2015) and Greene et al. (2015) identified learners' perceived self-efficacy as one of the factors that influences motivation for learning and performance. Hence, motivation is viewed as an essential variable for the demonstration of self-regulation strategies and learning in online learning settings (Duffy & Azevedo, 2015). This study's findings may assist struggling students in better understanding and applying strategies to address their personal needs to promote self-regulation skills. These students may also be able to build their motivation for learning in this arena.

The findings from this investigation may also further teaching and learning in the ALEKS program. Program developers and educationalists can apply gained insights to improve the application of this platform with effective instructional practices to better identify students who are at risk for failure and provide learning interventions to address their individual needs. Such actions may bolster the performances of struggling learners within these modalities.

Limitations of the Study

Various ITSs are applied in learning institutions across the United States to enhance students' achievements. These ITSs provide specific types of adaptive CAI to remediate and improve the cognitive achievements of learners (Bartelet et al., 2016). Erumit and Nabiyev (2015) noted that ITS programs aim to identify, guide, and improve students' understanding towards acquiring desired behavior. In the current evaluation, I applied a correlational design to assess the predictive impact of three predictor variables (retention, engagement time, and the ratio of mastered to practiced topics) to students' math achievement (the criterion variable) as measured by PSAT math performance and final progress course grades. In the study, I concentrated primarily on 265 students in the 9th and 10th grades at an urban technical high school in the northeastern United States. Students in other cohorts and from other locations did not participate in this research. Nevertheless, my decision to focus on a particular sample group for this investigation may have compromised the external validity of the study. Creswell (2012) stated that purposive sampling techniques promote possible selection bias in research studies. These participants worked in the ALEKS ITS program during the first 2 years of its implementation.

Several threats to internal validity existed in the study as engagement time in the ALEKS ITS was recorded as the total time a student is logged into the program irrespective of their active or inactive performances. The accumulation and combination of these time differential in ALEKS may have impeded the validity of findings germane to student learning. In addition to the latter, the students' ability to work in the program outside of school hours might have compromised the findings as some students might obtain assistance from their parents or older siblings during these time frames. The learners' ability to participate in such activities may have threatened the accuracy of the ALEKS engagement time construct. Consequently, due to the unique nature of the sample and choice of methodology, as well as the identified predictor variables for this study, results may not be generalized to other ITS programs other than ALEKS or beyond the specific population from which the sample was drawn.

Recommendations

The results from the investigation coincides with findings by Sullins et al. (2013) which suggest that learners' proficiency in ALEKS can be a potential predictor of their performance on state assessments. These practitioners applied students' mastery of topics in ALEKS as the catalyst for success. The researchers' use of this construct as the primary driving force of their research contradicts the outcomes of the current study which identify retention as the main variable to influence the state assessment measures. The contradiction in constructs between the two studies may pertain to additional factors that influence student performance at the state level. The findings from this investigation suggest that participants 'retention accounted for approximately 9% of the variance on the PSAT math score. Based on this result, I concluded that an estimated 91% of the variance was due to other factors. These additional constructs may include misalignment between students' level of performance and CAI tools and curriculum, in addition to grade-level standards and instructional strategies to promote engagement and motivation (Hawkins et al., 2017). I decided that the latter support calls for additional investigation on this topic at this level of instruction.

A few researchers, (Bringula et al., 2016; Dani, 2016), identified learners' prior knowledge and derived attitude to improved achievement in the ALEKS program. These authors used an initial assessment as a predictive construct on students' mathematics success. Dani (2016) asserted that learners' poor language skills is a factor that affects students' ability to learn independently in the ALEKS platform. The current investigation did not apply these constructs as the predictive variables for the analysis. Consequently, additional research that incorporates these elements, as well as other variables that may influence students' learning and retention in this platform is needed.

The current study centered on the predictive ability of three ALEKS factors (engagement time, retention, and the ratio of mastered to practiced topics) on the math achievement of struggling learners at the high school level. The body of research related to this field of study is limited, and results have been inconsistent (Chappell et al., 2015). As a result, I recommend that future research address other factors of ALEKS and include diverse groups and sizes, as well as the various instructional practices that may impact the application of ALEKS at this instructional level. Such insights may optimize consistency within the body of research that addresses this topic.

Implications

The findings from this study suggest that participants' engagement time and the ratio of mastered to practiced topics in ALEKS were significant predictors of struggling students' final progress grades in a high school Algebra 1 course, and retention was significantly predictive of PSAT math scores. Based on these results, I concluded that improvements in the implementation of the ALEKS program at the research site may optimize the mathematical achievement of struggling learners. Accordingly, I recommend increasing the engagement time and the number of mastered to practiced topics in ALEKS to support improvements in students' final progress course grades, and the use of ALEKS retention reviews to optimize learners' retention in mathematics and improve their performance at the state and national level. Educationalist at the site of this investigation may apply such information to increase the quality and effectiveness of combining the ALEKS ITS with best teaching practices to foster improved educational outcomes for struggling learners. The latter may include modifications in the application of the ALEKS program relative to students' prior knowledge.

Technology developers can incorporate such findings to improve the working efficiency of the ALEKS ITS software program. For example, the developers may incorporate ways to decipher learners' active and inactive time in this platform and provide addition practices to improve students' retention. The mathematics instructors at this research location can use this information to more effectively identify and address the specific learning needs of their students. These actions may result in struggling learners (at this location) mastering and retaining more math concepts at a quicker pace.

Thus, increasing the likelihood of greater success in this milieu, greater math proficiency, reduction in failure rates, higher graduation rates, improve performances on state exams, and a greater range of future job and educational choices

Conclusion

In this study, I evaluated the predictability of three ALEKS constructs on high school students mathematics success. I used a multiple regression analysis to assess the ALEKS data logs of 265 struggling high school students. The predictor variables included students' engagement time, retention, and the ratio of mastered to practiced topics and the criterion variable comprised of PSAT math score and students final course progress grade. Results indicate that engagement time followed by mastered to practiced topics were the most statistically significant predictors of final progress grade, and retention was identified as the sole statistically significant predictor of PSAT math score. ALEKS developers can apply this information to manifest changes within this technological platform, and educationalists can employ gained insights to maximize instruction and learning in the ALEKS ITS to support the mathematical proficiency of struggling learners. I concluded that such actions may bolster the self-efficacy and self-regulation skill of these struggling youth and support their future growth beyond secondary education.

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