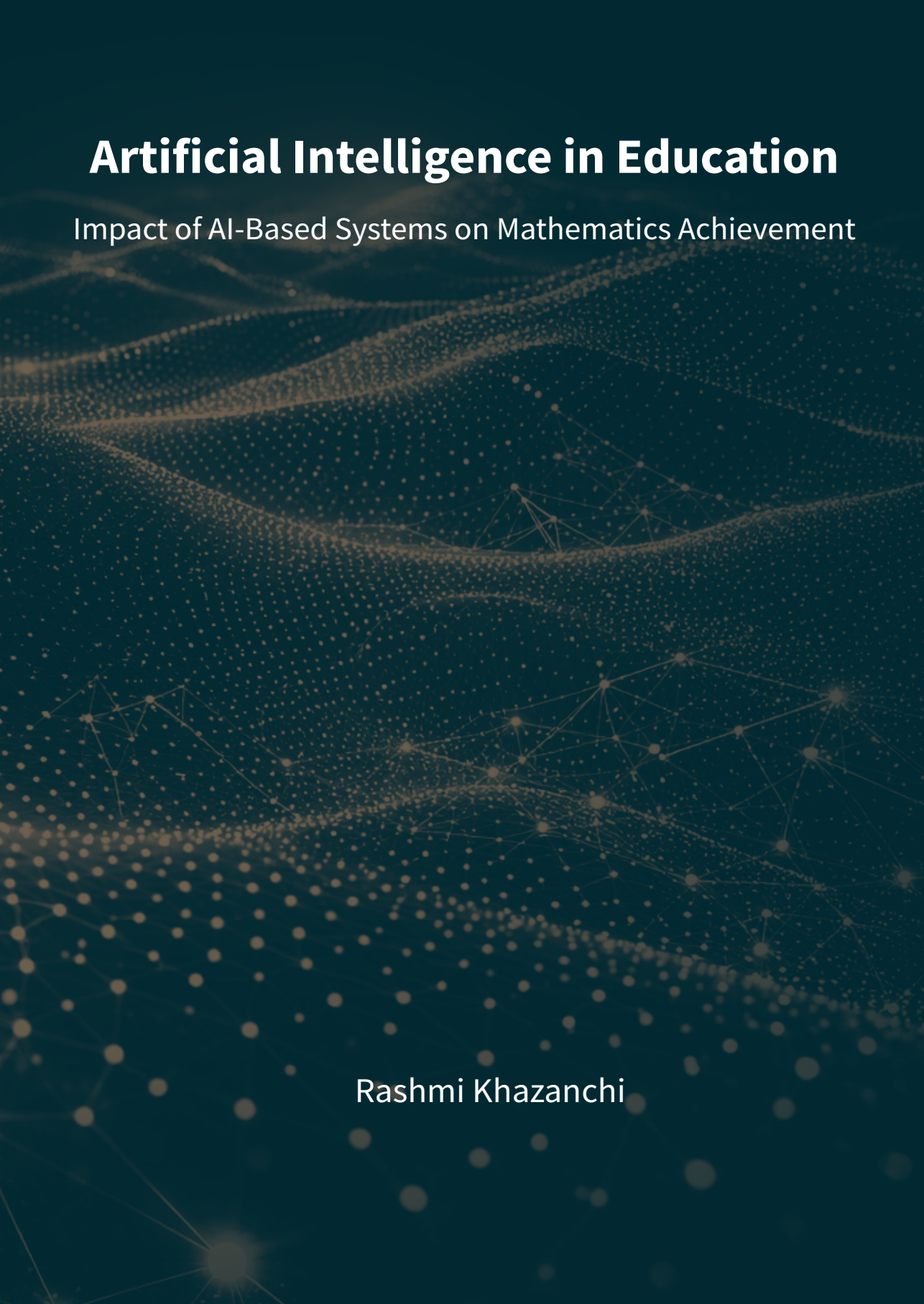
Artificial Intelligence in Education

Impact of AI-Based Systems on Mathematics Achievement



Rashmi Khazanchi

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The research reported in this thesis was carried out at the Open Universiteit in the Netherlands at the Faculty of Education, formerly known as Welten Institute – Research Centre for Learning, Teaching and Technology,



and under the auspices of SIKS, the Dutch Research School for Information and Knowledge Systems.



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Impact of AI-Based Systems on Mathematics Achievement

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The future depends on what we do in the present.

Mahatma Gandhi

Contents

General Introduction **1**
Outline of the Thesis 4

I Exploring AIED: Intelligent Tutoring Systems 7

1 Impact of Intelligent Tutoring Systems **9**
1.1 Introduction 10
1.2 Background 11
1.2.1 Skills Gap in Mathematics Education 11
1.2.2 Intelligent Tutoring Systems 12
1.2.3 Learning Theories underpinning the ITSs 12
1.2.4 ALEKS ITS 13
1.2.5 Research Agenda 13
1.2.6 Research Questions 14
1.3 Method 14
1.3.1 Research Variables 14
1.4 Results 15
1.5 Discussion 17
1.6 Conclusions 20

2 Measuring Efficacy of ALEKS **21**
2.1 Introduction 22
2.2 Background 24
2.2.1 Skills Gap in Mathematics Education 24
2.2.2 Intelligent Tutoring Systems 24
2.2.3 Learning Theories underpinning the ITSs 25
2.2.4 ALEKS ITS 25
2.2.5 Previous Research using ALEKS 26
2.2.6 Research Aims 27
2.3 Method 27
2.3.1 Research Variables 28
2.3.2 Results 29
2.3.3 Discussion 31
2.4 Conclusions 33

II Exploring AIED: Adaptive Learning Systems 35

3 Effect of AI-Based Systems on Mathematics Achievement 37
3.1 Abstract . . . 38
3.2 Introduction . . . 39
3.3 Background and Theoretical Framework . . . 41
3.3.1 AI-Based Learning Systems . . . 41
3.3.2 Edmentum Exact Path . . . 43
3.3.3 Theoretical Framework . . . 45
3.4 Methodology . . . 46
3.4.1 Study Design and Tool Selection . . . 46
3.4.2 Participant Selection and Ethical Considerations . . . 46
3.4.3 Sample Size and Group Composition . . . 46
3.4.4 Study Duration and Instructional Methods . . . 47
3.4.5 Assessment Development and Administration . . . 48
3.4.6 Student Engagement Measurement . . . 48
3.4.7 Data Analyses . . . 48
3.5 Results . . . 48
3.6 Discussion . . . 54
3.7 Limitations and Future Directions . . . 58
3.8 Conclusion . . . 60

III Systematic Literature Review 63

4 Impact of Artificial Intelligence-Based Systems on Mathematics Achievement: A Systematic Review 65
4.1 Introduction . . . 67
4.2 Background . . . 68
4.2.1 AI-Based Systems . . . 68
4.2.2 AI-Based Systems in K-12 Classrooms . . . 69
4.2.3 AI-Based Systems in Mathematics . . . 70
4.3 Data and Methods . . . 71
4.3.1 Data Collection and Selection . . . 71
4.3.2 Information Sources and Search Strategy . . . 71
4.3.3 Inclusion and Exclusion Criteria . . . 72
4.3.4 Data Preprocessing . . . 73
4.3.5 Data Classification and Analysis . . . 74
4.4 Results . . . 75
4.5 Discussion . . . 84
4.5.1 Types of AI-Based Systems in Mathematics and Education Level 84
4.5.2 Impact of AI-Based Systems on Students' Mathematics Performance . . . 86
4.5.3 Achievement Gap in Mathematics of Students from Low Socioeconomic Backgrounds . . . 89

4.6 Conclusions 90
4.7 Limitations and Future Directions 91

General Discussion **94**
Main Findings 94
Limitations of the Thesis 100

List of Tables **136**

List of Figures **139**

Summary **141**

Samenvatting **147**

सारांश **153**

Acknowledgements **157**

SIKS Dissertation Series **159**

General Introduction

Artificial Intelligence (AI) is transforming the world in unprecedented ways. AI is increasingly revolutionizing healthcare, industries, human interaction, and is reshaping education in ways that were never imagined before. AI refers to the ability of machines to mimic human intelligence (Milana et al., 2024). It is not merely limited to machine learning and data processing, but extends beyond these functions, enabling machines to solve complex problems and make decisions (Milana et al., 2024). Artificial intelligence in education (AIED) is an emerging interdisciplinary field that integrates AI technologies in education to enhance teaching and learning processes (Hwang et al., 2020).

Traditionally, teachers are responsible for delivering lessons, providing feedback, and assessing student performance within limited time frames, often focusing on standardized test outcomes (Black & Wiliam, 2018). Traditional pedagogical methods present challenges, as students come from diverse backgrounds and have varying prior knowledge, cognitive skills, and learning needs. The rapid advancement of technology has caused a shift in pedagogical practices, with teachers now adopting a more student-centered approach. Rather than simply imparting knowledge, teachers are taking on the role of facilitators, guiding and supporting students in their learning process (Stone & Burriss, 2019). With the rapid advancements in technology, educational institutions are focusing on restructuring curricula to equip students with the skills needed to navigate a rapidly changing world.

The U.S. National Council of Teachers of Mathematics (NCTM) has established comprehensive standards for mathematics education, emphasizing the importance of building on students' prior knowledge and experiences. Effective mathematics instruction requires teachers to assess students' understanding, support their learning, and provide challenges that foster critical thinking (Mainali, 2025). Students are expected to learn mathematics by actively engaging in the learning process, building new knowledge, connecting it with prior understanding, and gaining new experiences. With the shift in traditional pedagogical approaches, assessment methods are also evolving. Assessments are now continuous and ongoing throughout the learning processes (Collins & Halverson, 2010).

Mathematical knowledge and skills play a crucial role in academic success and significantly impact an individual's overall quality of life (Fung et al., 2018). National and international benchmark assessments indicate that U.S. students are lagging in mathematics. International benchmarks, such as the 2024 Trends in International

Mathematics and Science Study (TIMSS), reveal that U.S. students performed at or below the international average in mathematics. Among the 58 participating countries and 5 benchmarking entities, U.S. 4th graders ranked 27th with a score of 517, while Singapore led with a score of 615. At the 8th-grade level, 44 countries and 3 benchmarking entities participated, U.S. students ranked 22nd with a scale score of 488, while Singapore led with a scale score of 605 (von Davier et al., 2024), further highlighting global disparities in mathematics achievement. The most recent data from the National Assessment of Educational Progress (NAEP) indicate that less than half of the students in the 4th and 8th grades were at the desirable levels of proficiency, similar to the TIMSS's result (Mainali, 2025; NAEP, 2024).

Student engagement is critical when academic curricula are heavily influenced by standardized assessments and test performance (Kong et al., 2003). Fung et al. (2018) demonstrated that students who actively engaged in mathematical learning activities tend to achieve greater academic success. Engagement refers to a multidimensional construct encompassing emotional (affective), behavioral, and cognitive elements, each reflecting different aspects of a student's involvement in the learning process (Appleton et al., 2008; Fredricks et al., 2004).

Affective engagement refers to students' emotional responses to learning, with higher affective engagement linked to increased academic achievement (Buckley et al., 2004). This is particularly relevant in mathematics, a subject often perceived as challenging or boring (Grootenboer & Marshman, 2016). Behavioral engagement includes actions such as making an effort, asking questions, and working with peers on problem-solving tasks. Students who demonstrate strong behavioral engagement tend to attend class regularly, participate in academic activities, and put forth more effort to complete challenging assignments (Fine et al., 2009). Cognitive engagement refers to students' investment in understanding content through the use of deep learning strategies and persistence in academic tasks. Research has shown that cognitively engaged students exhibit greater improvements in mathematics achievement (Fung et al., 2018).

Research suggests that many students struggle with learning mathematical concepts, often due to ineffective traditional teaching practices, large student-to-teacher ratios, and an unfriendly classroom environment. In traditional classrooms, teachers typically manage the entire learning process, limiting opportunities for differentiation and student-centered learning. As evident by national and international benchmarking, many students have difficulty grasping and applying core mathematical concepts (Mainali, 2025).

To address these challenges, the Common Core State Standards for Mathematics were introduced in 2010 to establish a unified and rigorous set of expectations aimed at preparing all students for college and careers (NCTM, 2011). These standards emphasize conceptual understanding, problem-solving, and the use of multiple solution strategies, moving beyond rote memorization and procedural fluency. While the Common Core offers a coherent and research-based approach to mathematics instruction, many teachers have not received adequate professional

development to implement these standards effectively (Mainali, 2025). Inconsistent pedagogical training, a lack of supportive classroom environments, and systemic inequities in curriculum design and delivery continue to hinder educational progress, particularly for underrepresented and underperforming student populations (Mainali, 2025).

Research consistently highlights that AI-based systems can enhance mathematics achievement, especially when compared to traditional teacher-led instruction (Craig et al., 2013; VanLehn, 2011; Wang et al., 2023). These systems offer personalized and adaptive learning experiences, allowing students to engage with content at their own pace and according to their individual needs (D'Mello & Graesser, 2023; Outhwaite et al., 2017; VanLehn, 2011). AI-based systems have shown a positive impact on mathematics achievement among underachieving students. Underachievement refers to students whose academic performance falls significantly short of what their cognitive ability predicts based on standardized assessments (Bluemink et al., 2024). In this context, AI-based systems have the potential to support student learning, address achievement gaps, and transform mathematics instruction across diverse educational settings.

AI-based learning systems can enhance mathematics achievement, especially when compared to traditional teacher-led instruction (Craig et al., 2013; VanLehn, 2011; Wang et al., 2023). These systems offer personalized and adaptive learning experiences, allowing students to engage with content at their own pace and according to their individual needs (D'Mello & Graesser, 2023; Lin et al., 2023; VanLehn, 2011). AI-based systems have shown a positive impact on mathematics achievement among underachieving students. Underachievement refers to students whose academic performance falls significantly short of what their cognitive ability predicts based on standardized assessments (Bluemink et al., 2024). In this context, AI-based systems have the potential to support student learning, address achievement gaps, and transform mathematics instruction across diverse educational settings.

In this thesis, two types of AI-based systems included are Intelligent Tutoring Systems (ITS) and Adaptive Learning Systems (ALS). Early versions of ITS were based on a fixed architecture and were considered intelligent in terms of determining what to teach (content), whom to teach (learner), and how to teach (instructional methodologies) (Self, 1974). The architecture of ITS typically includes four components: the Domain Model, Student Model, Tutor Model, and User Interface Model (Bagheri, 2015). These systems are designed to deliver instructions and immediate feedback without requiring any human interaction (Psotka et al., 1988).

The Domain model defines the subject matter or content to be taught. The Student Model tracks information about the learner and updates dynamically as the learner interacts with the system. The Tutor model determines instructional strategies, and the User Interface model is responsible for the appearance and interaction styles with learners.

ALS represent a newer generation of ITS, focusing on conceptual instructions rather

than problem-solving alone. ALS can adapt content, instructional delivery, and assessments to individual learners based on their prior knowledge, readiness to learn, and learning preferences (Wang et al., 2023). Their architecture often incorporates adaptive hypermedia technologies, which provide personalized access to online information (Bagheri, 2015).

Outline of the Thesis

This doctoral thesis is organized into three parts, each examining the impact of AI-based systems. Part I explores the impact of Intelligent Tutoring Systems (ITS) on the mathematics achievement of underachieving students. Part II investigates the effectiveness of AI-based systems in enhancing mathematics achievement in a rural context. Part III presents a comprehensive literature review spanning 2008 to 2023, focusing on the role of AI-based Intelligent Tutoring Systems in enhancing mathematics outcomes in K-12 classrooms.

Part I focuses on the impact of ITS on mathematics performance and includes Chapters 1 and 2. These chapters highlight that students in the United States are underperforming in mathematics, as shown by national and international benchmarking data. The issue is more pronounced in the rural areas, where challenges such as a shortage of qualified teachers, limited funding and resources, generational poverty, and low parental education levels are prevalent. These disparities were further compounded by learning loss during the COVID-19 pandemic. To help bridge the achievement gap and enhance mathematics learning, a rural high school implemented Assessment and LEarning in Knowledge Spaces (ALEKS), an ITS, as a supplemental instructional tool. In Chapter 1, we investigated the impact of ALEKS on mathematics learning among 8^{th} graders by comparing pretest and posttest outcomes between traditional teacher-led instruction versus ALEKS-led instruction from the two consecutive years. Chapter 2 extends this analysis by further evaluating ALEKS as a supportive instructional tool. In addition to comparing teacher-led and ALEKS-led instruction, this phase of the study also examined five years of End-of-Grade (EOG) assessment results without ALEKS against one year of results with ALEKS integration, providing a broader view of its effectiveness.

Part II, Chapter 3 explores the effect of AI-based systems, Edmentum Exact Path on both mathematics achievement and student engagement (affective and cognitive) within a socioeconomically disadvantaged population from the rural area. Edmentum Exact Path is an ALS that was implemented by the high school in Southern Georgia. Based on the results of this study, this chapter also outlines the study's limitations and proposes directions for future research.

Part III, Chapter 4, presents a systematic review of the literature examining the use of AI-based systems in K-12 classrooms. This systematic review investigates the types of AI-based systems implemented and the educational levels at which they are applied, the variation of its implementation based on socioeconomic status, and

their overall impact on mathematics achievement. Conducted as per PRISMA guidelines, this review included 42 peer-reviewed research articles published between 2008 and 2023, sourced from six major digital databases. The findings indicate that AI-based systems mostly have positive outcomes on students' mathematics achievement. The chapter concludes with implications for practice and recommendations for future research.

The thesis concludes with a General Discussion that summarizes the findings of the studies presented, focusing on the impact of AI-based systems on mathematics achievement. This section also reflects on the practical implications of the research and outlines directions for future studies.

Part I

Exploring AIED: Intelligent Tutoring Systems

Chapter 1

Impact of Intelligent Tutoring Systems

Abstract: The educational landscape has changed considerably in the past decade. The focus has shifted from using traditional teaching methods to integrating technology in today's curricula. Much of the emphasis is on fostering 21st-century skills by using technology in new and innovative ways. Student engagement is a crucial component of learning. Intelligent Tutoring Systems (ITSs) are computer software that uses artificial intelligence to provide adaptive, customized learning based on students' needs. This quasi-experimental research study explored the effect of ITSs, such as ALEKS, on underachieving students' mathematics achievement among 8th-grade students. This research study compared the results of pretest and posttest between teacher-led instructions versus ALEKS-led instructions from the two consecutive years. During the first year, only McGraw's curriculum "Reveal" was used with no use of ALEKS. In the second year, the school implemented ALEKS as a supplemental tool in a mathematics support class for fifty minutes every other day for a year to provide instruction to struggling students along with McGraw's curriculum "Reveal." On the contrary, the findings of this study revealed that students who received teacher-led instructions showed greater mathematics achievement than those who used ALEKS-led instructions. This research also explored the challenges posed by using ITS in the classroom.

This chapter is based on:

Khazanchi, R., Di Mitri, D., & Drachsler, H. (2022, April). Impact of intelligent tutoring systems on mathematics achievement of underachieving students. In *Society for Information Technology & Teacher Education International Conference* (pp. 1524-1534). Association for the Advancement of Computing in Education (AACE). https://www.learntechlib.org/d/220916/

1.1 Introduction

In the 21st century, artificial intelligence (AI) and intelligent digital technologies are being developed, which can be deployed to provide more adaptive and personalized education and deliver high-quality educational opportunities to all. Artificial Intelligence in Education (AIED) challenges traditional pedagogical practices and alters how we learn, communicate, and collaborate. Traditionally, teachers are responsible for teaching, providing feedback, and assessing the knowledge of several students within a limited time so that they can obtain good scores on standardized assessments (Black & William, 2018). Such a traditional approach is challenging for teachers, as students have different prior knowledge, backgrounds, cognitive skills, and learning needs. Moreover, there is a shift in teaching pedagogies in contemporary education due to rapidly evolving technology and future job requirements. In the present scenario, teachers should play the role of facilitator in student-centered learning processes rather than dispensing knowledge.

Mathematics is a core subject and a building block for many other subjects. Most students, however, are reluctant to learn mathematical concepts due to inefficacious and traditional teaching pedagogical practices, large teacher-to-student ratio, lack of friendly atmosphere, and the high volume of prescribed books (Moradi & Amiripour, 2017). Data obtained from the national and international benchmarking assessments discloses that many students cannot grasp and apply mathematical concepts (The Nation's Report Card | NAEP, n.d.). The plethora of research studies confirms that computer-assisted Instruction in mathematics positively affects student learning compared with teacher-led or conventional teaching methods (Kulik, 2003; Morgan & Ritter, 2002; VanLehn, 2011), including underachieving students (Burns et al., 2010; Chappell et al., 2015; Outhwaite et al., 2017; Rutherford et al., 2014). The term "underachievement" is related to class performance. Student underachievement refers to poor educational performance, usually measured in scores on standardized tests, significantly lower than expected based on the student's mental ability (Smith, 2003). One factor that can predict mathematical achievement is socioeconomic status. Eamon (2005) found a direct correlation between parents' income and mathematical achievement.

Intelligent Tutoring Systems (ITSs) can support the students' thinking processes during problem solving and model complex pedagogical strategies as human tutors/teachers. ITSs, such as Assessment and LEarning Knowledge Spaces (ALEKS), SQL-Tutor, Cognitive Tutor, ASSISTments, and Andes Physics Tutoring, have shown statistically significant improvements in student learning (Craig et al., 2013; Heffernan & Heffernan, 2014; Koedinger et al., 2010; Mitrovic, 2003; Pane et al., 2014; Toner, 2011). Some ITSs can recognize students' emotions and respond accordingly (Khachatryan et al., 2014; VanLehn, 2011).

ALEKS is commonly used in higher education. Among the reviewed ITSs, we focus on ALEKS because of its potential features, such as its unique ability to accurately diagnose each student's knowledge state, provide analytics to track students'

progress, and provide actionable instructional data the teacher can use to drive their classroom instructions. Moreover, ALEKS can be used with McGraw's curriculum as a supplemental tool. Recently, ALEKS was adopted for a rural school in the United States, which is taken as a case study in this paper. The school was already implementing McGraw's curriculum in mathematics. ALEKS is a web-based intelligent tutoring system that uses AI to determine what students know and are ready to learn. ALEKS then adapts the instructions that a student is ready to learn the most. ALEKS conducts periodical assessments to ensure mastery learning (Fang et al., 2019).

There is no solid evidence yet on using ALEKS in teaching mathematics in the high school setting. A few studies examine the effectiveness of ALEKS on students' learning compared to teacher-led instructions (Brasiel et al., 2016; Conati, 2009; Graesser et al., 2018; Lippert et al., 2020; Morgan & Ritter, 2002; O'Shea, 1979). Several studies have been done at the college level to examine the effectiveness of ALEKS on student learning (Boyce & O'Halloran, 2020; Fine et al., 2009; Hagerty & Smith, 2005; Mojarad et al., 2018; Reddy & Harper, 2013; Serhan, 2017). In the past five years, no study has been conducted on underachieving students in high school settings on students' mathematics achievement using ALEKS. Therefore, this research study will add to the knowledge by examining the role of ITS's in improving students' mathematics achievement and reducing learning gaps.

1.2 Background

1.2.1 Skills Gap in Mathematics Education

The mathematical skills are relevant to 21st-century skills. The US National Council of the Teachers of Mathematics (NCTM) proposed a comprehensive set of mathematics standards related to teaching and mathematics learning. NCTM standards define effective mathematics teaching where the teacher understands what students know and are ready to learn and then supports and challenges their learning. In the current scenario, students need to have skill sets, such as adaptive experts, and on-the-go learners (Common Core, 2012; NGSS, 2013), as factual information can be retrieved easily with handy mobile devices with just a click. Therefore, educational institutions need to develop curricula focusing on communication, collaboration, knowledge application, and self-regulated learning skills (Toner, 2011).

The national and international benchmark assessments indicate that US students lag in mathematics. The Trends in International Mathematics and Science Study (TIMSS) compares US students' mathematics and science achievement to other countries. In 2019, the US 8th-graders ranked 11th among 46 participating education systems with average TIMSS mathematics scores of 515, slightly above the TIMSS average score set at 500 (Trends in International Mathematics and Science Study (TIMSS), n.d.). The National Assessment of Educational Progress (NAEP) periodically administers benchmark assessments in various subjects, including mathe-

matics for 4th, 8th, and 12th -grade students. The nation's report card reported the mathematics achievement scores of the US eighth-grade students, indicating that only 34% of students perform at or above proficiency level, which is not significantly different from 2017 scores (The Nation's Report Card | NAEP, n.d.).

1.2.2 Intelligent Tutoring Systems

Intelligent Tutoring Systems (ITSs) adapt the instruction as per students' needs and provide individualized instructions effectively, thus improving their mathematics performance (Craig et al., 2013; Huang et al., 2016; Pane et al., 2014). Integration of AI and its application into education led ITSs to tutor as effectively as humans. By delving deeper into the students' thinking process, cognitive science has helped develop ITS, providing personalized instruction using AI applications (Alshawwa et al., 2019). ITSs include Alef Education, Assessment and LEarning Knowledge Spaces (ALEKS), Alta, Bjyu, Century, Dreambox, iReading, Smart Sparrow, and Toppr, etc., uses a more personalized approach to learning. ITSs use AI to create intelligent software tutors to help students and make it more personalized. It is predicted that AI will have a profound impact on deeper self-learning, and by the end of the next decade, it will be capable of assisting and coaching (Holmes et al., 2019). It can customize and pace learning based on students' specific needs, interests, and educational goals. ITSs provide real-time feedback, enhance student engagement, develop a skill set, and allow students to progress faster (Mohammed & Nell'Watson, 2019).

ITS incorporates domain knowledge and pedagogical practices to engage students in complex learning and meet their comprehensive needs (Self, 1998). Student models of these systems analyze what students know and their motivation, and use it to enhance various student outcomes (Carbonell, 1970). ITSs learn how to teach and study what worked and maximize students' learning. Based on the feedback, the ITSs would improve themselves over time (Beck et al., 2000; Beck, 1997; O'Shea, 1979). In the 21st century, these evolved ITSs can support students at every step in their thinking process. ITSs can talk to students in natural language, model complex teachers, use pedagogical strategies, adapt learning, scaffold learning, and recognize and respond to emotions (Bouyias & Demetriadis, 2012; Graesser et al., 2018; Lippert et al., 2020). Research has shown positive outcomes of student learning, including ALEKS (Craig et al., 2013), Cognitive Tutor (Pane et al., 2014), ASSISTments (Koedinger et al., 2010), and SQL-Tutor (Mitrovic, 2003).

1.2.3 Learning Theories underpinning the ITSs

ITSs provide feedback based on responses. Students can use step-based hints if they face difficulty in solving a problem. Students require considerable effort to understand these hints (Wittwer & Renkl, 2008). Within educational psychology and cognitive science, Knowledge Learning-Instruction (KLI) theory connects cognitive science and educational research to educational practice (Koedinger et al., 2012). This theory suggests that the complexity of the instruction needs to align

with the complexity of the targeted knowledge. In other words, complex knowledge is built via complex instructional processes. Programmed Instructions by B. F. Skinner formed the basis of computer-assisted instructions (CAI). Computer-assisted programs are based on behavioral principles as they change the behavior of the learners. Computer-assisted programs, such as ITS, distinguish desired behavior and prepare events so that students will experience success, thus reinforcing the learning. ITSs break down the task into smaller steps and provide immediate corrective feedback based on the student's responses.

1.2.4 ALEKS ITS

ALEKS uses Knowledge Space Theory (KST) for students' assessments and learning. KST is based on a combinatorial and probabilistic model (Doble et al., 2019; Falmagne et al., 1990). When students log in to ALEKS, it offers a brief tutorial to get familiar with using answer input tools, followed by the ALEKS Assessment (pretest), which administers 20-30 questions to determine initial knowledge within a short time duration (approximately 45 minutes). ALEKS provides a pie chart, which summarizes what the student has mastered under each knowledge category and generates a list of problems that the student is ready to work on, based on KST (Xie et al., 2017). Students can work on the topic of their preference, and once they master the topic/problem type, the system adds it to their knowledge state, with a new set of problems ready to be learned. For 8th grade, mathematics learning concepts/subject matter are divided into 475 topics. Instead of providing scores for mastery of the content, it describes precisely where the student is in terms of knowledge and what they need to learn. In this scenario, the student is somewhere in space at each point in learning the content and moving to a new state with each learned concept. ALEKS reassesses the student periodically by providing mixed questions and adjusting the student's knowledge based on their responses to ensure retention of the learned topic. Therefore, help students to master the given topic/content. With AI in ALEKS, students are almost always successful in learning a topic as ALEKS offers the complexity of questions based on prerequisite knowledge. ALEKS offers free-response questions (just like pen and paper responses) and avoids multiple-choice questions. After a break, the system will automatically return to previous assignments when students log in.

1.2.5 Research Agenda

Considering the exposed background and research gap, this research evaluated the effectiveness of ITSs, particularly ALEKS, on the mathematics achievement of 8th-grade students. This research study compared the results of pretest and posttest between teacher-led instructions versus ALEKS-led instructions from the two consecutive years. In the first year (2019-2020), teachers used only McGraw's curriculum "Reveal," and in the second year (2020-2021), teachers implemented ALEKS as a supplemental tool in a mathematics support class for 50 minutes every other day for a year to provide supportive instruction to the struggling underachieving students

along with McGraw's curriculum "Reveal." This research study has also compared the pretest and posttest of ALEKS to evaluate whether the use of ALEKS shows significant improvement in mathematics achievement based on the math standards and class periods in one year period.

1.2.6 Research Questions

The following research questions guided this scientific investigation: RQ1) Does the use of ALEKS show improvement in students' mathematics achievement than traditional teacher-led instructions, as measured by pretests and posttests? RQ2) Does the use of ALEKS show improvement in mathematics achievement based on the mathematics standards in one year period? RQ3) Does the use of ALEKS show improvement in mathematics achievement based on class periods?

1.3 Method

This research study used a quasi-experimental design and investigated mathematics achievement (ITS-led versus teacher-led). ALEKS was chosen for this research study as it was adopted recently by the school district. Moreover, ALEKS's curriculum is aligned with state standards and has shown a positive association between the assessment performance and the state test scores. This research study was conducted in a Rural South Georgia School District on approximately n=158 8th-grade students. 62-68% of the students in this district belong to the economically disadvantaged population, with approximately 12% of students proficient in mathematics (Public School Review, 2019). The teacher used only McGraw's curriculum "Reveal"to provide teacher-led instructions during the first year. In the second year, ALEKS-led instruction, ALEKS was used as a supplemental tool for 50 minutes every other day for a year in the presence of a teacher. Students took a pretest to generate a baseline about what students know and a posttest toward the end of the year. The data were compared based on pretest and posttest between teacher-led instructions and ALEKS-led instructions to improve students' mathematics achievement (see Figure 1.1).

1.3.1 Research Variables

This research study defines mathematics achievement as the difference between pretest and posttest outcomes on the ALEKS assessment. The Independent Variable (IV) was the use of ALEKS (i.e., ALEKS users as the treatment group, and non-users as the control group), and the dependent variables (DVs) were mathematics achievement, mathematics standards, and class periods. The DV, mathematics achievement, is defined as students' attainment of new mathematical skills that can be measured by their performance on the sample items from a standardized test.

1.4 Results

To address RQ1, 8th- grade mathematics data comprising pretests and posttests from two consecutive years were compared. The results indicated that the students showed more improvement in mathematics achievement in Teacher-led instructions than ALEKS-led instructions.

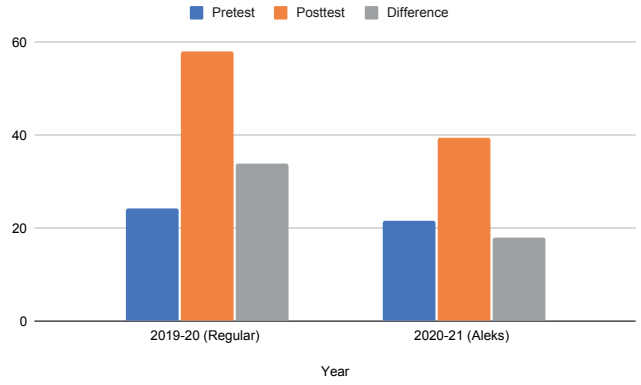


Figure 1.1 Comparison between teacher-led instructions versus ALEKS-led instructions

A similar trend was observed when data from the past five years of End of Grade (EOG) state assessments with no use of ALEKS, compared with data from a one-year EOG state assessment using ALEKS (see Figure 1.2). According to the Achievement Level Descriptors (ALDs), there are four achievement levels for EOG assessment: Beginning Learner, Developing Learner, Proficient Learner, and Distinguished Learner. Students who fall under the "Remediate learning" category are beginning learners. "Monitor learning" refers to students who fall under the developing learner category, and "Accelerate learning" refers to students under the proficient and distinguished learner category. Figure 1.2 indicates a negative trend in mathematics achievement over the years. The number of students in the Accelerate learning category declines, whereas the number of students in the remediating category rises. Even with the use of ALEKS, this trend continued. The possible decline in mathematics achievement over the years, especially from 2018, was a change in leadership. The principal of Mitchell County High School changed, and at the beginning of 2021, the school had appointed two different superintendents.

To address RQ2, Does the use of ALEKS show significant improvement in mathematics achievement based on the mathematics standards in one year period? Pretest (initial knowledge check) and posttest (latest knowledge check) from ALEKS were compared. Students took a pretest at the beginning of the year, and the posttest was taken towards the end of the year. In the ALEKS, mathematics domains for 8th-grade mathematics are divided into eleven standards: Whole Numbers and Integers; Fractions; Decimals; Ratios, Proportions, and Measurement; Percents; Equa-

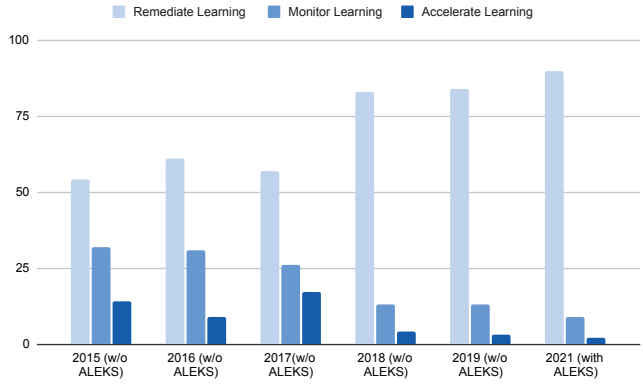


Figure 1.2 Comparison between End of Grade with and without ALEKS-led instructions

tions and Inequalities; Graphs, Functions, and Sequences; Exponents, Polynomials, and Radicals; Lines, Angles, and Polygons; Transformations; Perimeter, area, and volume; and Data Analysis and Probability. The data indicated that ALEKS seem to show overall greater mathematics achievement in Decimals, followed by Whole Numbers and Integers. Students showed similar gains in fractions, Equations, and Inequalities (see Figure 1.3). The possible explanation could be that ITSs are based on mastery learning. Students can only move to a different topic if they have indicated 80% mastery. Students used ALEKS only on alternate days, so they could not complete all eleven standards.

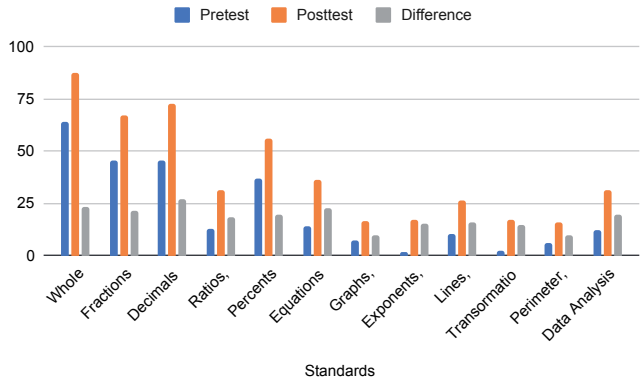


Figure 1.3 ALEKS-led improvement on mathematics standards

To address RQ3, ALEKS data were generated by class period. The number of students in these class periods are as follows: First period–14 students, second period–14 students, third period–19 students, fourth period–13 students, fifth period–9 students, sixth period–12 students, seventh period–11 students, and eighth period–8

students. Figure 4 indicated that students in the fourth and eighth periods showed greater mathematics achievement than in any class (see Figure 1.4), which could be attributed to the fact that students in these classes were grouped based on their ability level.

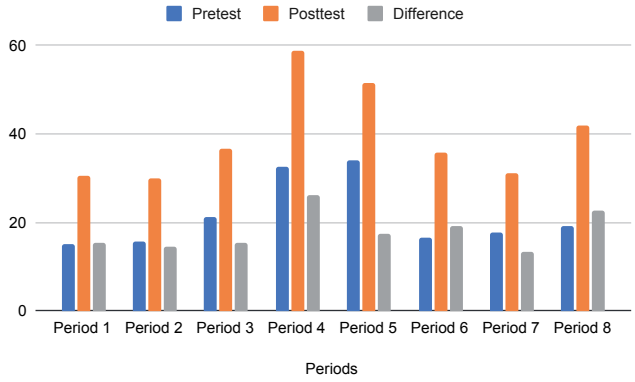


Figure 1.4 ALEKS-led improvement in mathematics achievement based on class period

1.5 Discussion

RQ1 investigated whether ALEKS improves students' mathematics achievement than traditional teacher-led instructions, as measured by pretests and posttests. The results indicate higher gains in mathematics achievement in teacher-led instructions than ALEKS-led instructions. Several possible explanations may shed light on this reverse trend.

One possible explanation is that Intelligent and adaptive tutoring systems are designed in a specific manner. Once students take a pretest (initial knowledge check), the ITSs generate an automatic learning path based on students' current knowledge state. Most of the students in this school system are underachieving students who are 3-4 grades behind. Therefore, when these students take the initial assessment, the ITSs, such as ALEKS, assign them elementary lessons; for example, students in the 8th-grade at the Mitchell County high school do not know their multiplication tables. Therefore, they may spend more time doing simple 2nd-grade multiplication problems or making errors. As a result, ITSs assume that students need to learn multiplications; hence, a lot of time is invested in learning basic prerequisite skills, and students are not able to learn grade-level skills by using ITSs in a year. Moreover, it isn't easy to obtain at least 3-4 grade level gains in a year, even using ITSs. ITSs can be proven helpful if students start using them at an early age, so the achievement gap is not widening, and at the same time, it can assist in reducing the achievement gap.

Another possible explanation for this reverse trend could be that ALEKS was in the implementation stage, and teachers were learning how to use ALEKS in the classroom. Moreover, teachers were using ALEKS as per the administrations' guidelines. ITSs, such as ALEKS, can be used in two ways. One way is the teacher allows students to follow a learning path generated based on initial assessments, which may comprise learning prerequisite skills. Another way is that teachers in the mathematics support class can collaborate with a regular mathematics teacher and assign grade-level content based on their weaknesses. Students who have mastered the skills, ITSs can navigate them to learn another grade-level topic. ITSs will improve their basic or prerequisite skills in the first scenario, but it may not necessarily translate into mathematics achievement at the grade level.

Furthermore, it could be possible that due to COVID-19, teachers were lenient in the grading process. These students missed classes in their 7th-grade due to complete school closure for the COVID-19 pandemic and got promoted to 8th-grade without taking state-level examinations and school exams. This learning loss is also contributing to overall relatively small mathematics achievement. Moreover, during the COVID-19 pandemic, keeping students safe and maintaining social distancing for in-person learning, the school system divided the class in half and called them on alternate days. As a result, students could receive ALEKS-led instruction for only half a year. Therefore, inadequate time could be another reason ALEKS-led instructions did not show equal or greater mathematics achievements than teacher-led instructions. However, it is worth noting that students in the ALEKS-led instruction were more independent and required less attention from the teacher. This research study may need to be replicated as the ALEKS was in the first-year implementation stage, and teachers were learning how to use it. Moreover, we should not neglect that effective teachers with a repertoire of evidence-based pedagogical practices may equate to ITSs-led instructions. The use of ALEKS has indicated greater achievement in the Decimals, followed by Fractions and Equation and Inequalities.

For RQ2, this research study investigated the use of ALEKS to show improvement in mathematics achievement based on the mathematics standards in one year period. Findings from the data analyses suggest that students showed overall improvement in all eleven standards as follows: Decimals (27); Whole Numbers and Integers (24); Fractions (22); Equations and Inequalities (22); Percents (19); Perimeter, Area and Volume(19); Ratios, Proportions, and Measurements (18); Lines, Angles and Polygons (16); Transformations (15); Exponents, Polynomials, and Radicals (15); Graphs, Functions, and Sequences (10); and Perimeter, Area and Volume(10). The numbers in the brackets indicate the overall improvement in the mathematics achievements, calculated by the overall difference between pretest and posttest using ALEKS. The pretest is an initial knowledge check administered at the beginning of the year, and the posttest is the latest knowledge check administered toward the end of the year. Based on the mathematics achievement, Figure 1.3 shows that students improved overall in the first six standards.

The following reasons can be attributed to this trend: ITSs, such as ALEKS, based on mastery learning, and prerequisite skills must be met before students move to the next level after learning the content with 80% accuracy. The students could use ALEKS only on alternate days for a year, so they could not complete all the standards. Figure 1.3 indicates that most students could not finish all the standards, followed by Equations and Inequalities. A slight mathematics improvement in these standards may be due to the knowledge/ prerequisite skills they acquired by mastering the content on ALEKS, which helped them eliminate incorrect answers, increasing the probability of showing some gains compared to the pretest. Also, the graph indicates more prerequisite knowledge on initial mathematics standards in both pretest and posttest, and then it declines. The possible explanation is that the initial standards are comparatively easier, and students may have learned prerequisite skills for these standards in the previous grades.

In RQ3, this research study investigated whether the use of ALEKS shows improvement in mathematics achievement based on class periods. The students attended these classes on alternate days and received ALEKS-led instructions. The overall improvement in mathematics achievement is as follows: first period–16, second period–15, third period–16, fourth period–26, fifth period–18, sixth period–19, seventh period–13, and eighth period–23. These numbers were calculated by finding an overall difference between pretest and posttest for each class period. The results indicate that fourth and eighth-period students exhibited more improvement in mathematics achievement.

The students in these classes were grouped based on their ability level. High-achieving students with good work ethics were grouped. The second-period students had a higher concentration of students with special needs. Therefore, they did not show overall greater mathematics achievement due to their cognitive deficits stemming from their disabilities. Students in other class periods exhibited relatively small improvement in mathematics achievement. They were less focused on academics and paid more attention to irrelevant things, such as socialization, to look better and fit in among their peers. Students were dealing with psychological and social-emotional issues that stemmed from social isolation and having a family member, friends, or relatives suffering from illness due to COVID-19.

This study adds to the literature that ITSs may not always show gains compared to traditional teaching methods, as they seem to promise. Moreover, it may take at least a few years for students to exhibit improvement in mathematics achievement. Also, teachers should use the ITSs as they see the best fit rather than using them at the administration's discretion. Technological tools can support teaching and learning processes; however, effective pedagogical practices can ultimately make a difference. The results of this research study should be interpreted with caution, given that ALEKS was in the first-year implementation stage, and teachers were getting familiar with how to use ALEKS. Also, the small sample size and the impact of COVID may affect the outcome of this study. Future studies should include larger populations and ensure that the school system uses ALEKS for at least a few years,

and that teachers are adequately trained to use ALEKS. Continued research on the effectiveness of ITSs is critical to support teaching and learning processes.

1.6 Conclusions

This quasi-experimental research study investigated the impact of ITSs on the mathematics achievements of underachieving students, which could provide a possible solution for the underachieving rural population. Based on state assessment data, only 12% of the 8th-grade students were proficient in mathematics. The research study analyses provide insights into the use of mathematics ITS to improve mathematics achievement. Although several studies have suggested that ITSs enhance mathematics achievements in students than teacher-led instructions (Brasiel et al., 2016; Craig et al., 2013; Fine et al., 2009; Hu et al., 2013; Sullins et al., 2014), the findings from the research study indicated the opposite. It indicated that ALEKS-led instructions do not show higher mathematics achievement in underachieving students than teacher-led instructions. The data analyses revealed that students indicated more improvement in math standards that were relatively easier, as they had some prerequisites knowledge. Also, Figure 1.3 indicated that students showed more improvement in the first six mathematics standards, as most of the students could only master them and could not move beyond those standards due to mastery learning and limited time. When comparing ALEKS data by class period, the results indicated that students in the fourth and eighth periods exhibited more improvement as they were grouped based on their ability level.

Technological tools with AI have become ubiquitous and reach more consumers than ever before. Educational institutions are increasingly using ITSs to support teaching and learning processes. This research study indicated that students showed greater mathematics achievement in teacher-led instruction than ALEKS-led instructions. This research study highlights that integrating technology to improve mathematics achievement in underachieving student populations may not always be the only solution advertised by intelligent educational software companies. This educational software is expensive and comes with a yearly subscription that can add up over the years. Therefore, stakeholders need to make careful decisions to invest in ITSs. Also, stakeholders need to invest in strategies to hire and retain effective teachers.

Chapter 2

Measuring Efficacy of ALEKS

This quasi-experimental research study examines whether the use of Assessment and LEarning in Knowledge Spaces (ALEKS), an ITS, shows a statistically significant improvement in students' mathematics achievement than traditional teacher-led instruction. This non-randomized research study measured the efficacy of ALEKS on underachieving students' mathematics achievement among 158 (60 in the teacher-led group and 98 in the ALEKS-led group) 8th-grade students. A pretest and posttest were employed between teacher-led instructions versus ALEKS-led instructions from two consecutive years. During the first year, only McGraw's curriculum "Reveal" was used with no use of ALEKS. In the second year, the school implemented ALEKS as a supplemental tool in a mathematics support class for fifty minutes every other day for a year to provide instruction to struggling students along with McGraw's curriculum "Reveal." We also compare the results of five years of End of Grade (EOG) without ALEKS with one-year EOG with the use of ALEKS. Data were analyzed using paired t-test and analysis of covariance (ANOVA) to evaluate the efficacy of ALEKS on students' mathematics achievement. We find that the results of ALEKS-led and teacher-led instructions are highly statistically significant. The results show that teacher-led instructions are more effective because of higher test scores and lower variance for teacher-led instructions.

This chapter is based on:

Khazanchi, R., Di Mitri, D., & Drachsler, H. (2023). Measuring Efficacy of ALEKS as a Supportive Instructional Tool in K-12 Math Classroom with Underachieving Students. *Journal of Computers in Mathematics and Science Teaching*, *42*(2), 155-176. doi:10.70725/204333qjmwhs

2.1 Introduction

Traditional teacher-led instruction/human tutoring has long been rooted in the history of education. Human tutoring is very effective with one-on-one support; however, it requires much interaction, feedback, and support (Graesser et al., 2011; VanLehn et al., 2007). Educational researchers and scientists have been finding ways to automate teaching and learning processes, giving rise to Intelligent Tutoring Systems (ITSs) (Craig, 2018). ITSs are web-based tutoring systems that employ artificial intelligence (AI) and machine learning to accurately evaluate students' skill levels and respond with individualized, targeted teaching according to learning principles. ITSs are increasingly used in K-12 classrooms and higher education. Millions of students use ITSs or some type of assessment that uses AI to assess and instruct students in K-12 classrooms. The Assessment and Learning in Knowledge Spaces (ALEKS) is a web-based adaptive, intelligent tutoring system designed to deliver mathematics instruction and ongoing assessments to assess students' current knowledge.

The ALEKS was developed in 1997 and was commercially available in 1999 in the United States. Later in 2013, ALEKS merged with McGraw Hill, leading to the wide use of ALEKS in K-12 classrooms and higher education. ALEKS uses a curriculum-based approach and is aligned with state standards. Therefore, ALEKS is capable of providing an entire grade-level mathematics curriculum in an individualized manner (McGraw Hill Education, 2022). Over two decades, ALEKS has acquired a large amount of data from student interactions, further providing insights into implementing Knowledge Space Theory (KST) effectively. Numerous studies have been conducted to identify the relationship between the use of ALEKS and students' performance on standardized testing or success in a course, for instance, in mathematics (Craig et al., 2011; Hagerty et al., 2010; Huang et al., 2016), in chemistry (Hu et al., 2007), and in college statistics (Craig et al., 2011). The result of the present study differs as it focuses on measuring the efficacy of ALEKS as a supportive instructional tool for underachieving 8th graders in a rural South Georgia School System. In this research study, the efficacy of ALEKS was measured by a) comparing the pretest/posttest from Teacher-led instructions versus ALEKS-led instructions, b) comparing data from the past five years of state assessments without the use of ALEKS with one year of state assessment with the use of ALEKS.

Poor mathematical achievement is an issue of great concern, widening as students transition from elementary to middle and high school. Causes for poor mathematical achievement include lower socioeconomic status, mathematics anxiety, poor executive functions, and working memory, large teacher-to-student ratio, and inefficacious and traditional teaching pedagogical practices (Moradi & Amiripour, 2017; Meece et al., 1990; Olsen & Huang, 2021; Pantoja et al., 2020). Children from high-poverty families/neighborhoods show a decline in mathematical ability (Pearman, 2019). Data from mathematical benchmarks at the national and international levels indicate that many students cannot understand and apply mathematical concepts (The Nation's Report Card | NAEP, n.d.). Numerous studies suggest that computer-

assisted instruction in mathematics has a positive influence on student learning compared with teacher-led or conventional teaching methods (Kulik, 2003; Morgan & Ritter, 2002; VanLehn, 2011), including underachieving students (Burns et al., 2010; Chappell et al., 2015; Outhwaite et al., 2017; Rutherford et al., 2014).

Underachievement in mathematics refers to a situation where students perform below their potential in mathematics, resulting in a significant disparity between a student's cognitive abilities, mathematical aptitude, or prior achievements, and their actual performance in mathematics courses. This discrepancy manifests as consistently lower grades, test scores, or academic outcomes than what their abilities suggest they can achieve (Reis & McCoach, 2000; Smith, 2003). Several factors can contribute to this underutilization of a student's mathematical potential, including motivational issues, ineffective study habits, negative attitudes toward mathematics, or a lack of appropriate support and resources. It is important to note that underachievement in mathematics can be attributed to external factors such as low socioeconomic status and experienced discrimination. A research study by Eamon (2005) has established a direct correlation between parents' income and mathematical achievement, highlighting the influence of socioeconomic factors on underachievement.

Intelligent Tutoring Systems (ITSs) are based on step-based granularity, thus supporting students' thinking processes during problem-solving and modeling complex pedagogical strategies as human tutors/teachers (VanLehn, 2011). Research studies have shown statistically significant improvement in student learning with the use of ITSs, such as ALEKS, SQL-Tutor, Cognitive Tutor, ASSISTments, and Andes Physics Tutoring (Craig et al., 2013; Heffernan & Heffernan, 2014; Koedinger et al., 2010; Mitrovic, 2003; Pane et al., 2014; Toner, 2011).

The body of research on the impact of ALEKS on students' mathematics achievement is limited. Most of these research studies have been conducted in post-secondary education. Some studies carried out in the K-12 classrooms have shown mixed results related to students' mathematics achievements. Therefore, among the reviewed ITSs, we focus on ALEKS due to its unique features, such as accurately diagnosing each student's knowledge state, providing analytics to track students' progress, and providing actionable instructional data that teachers can use to support student learning. In 2021, ALEKS was implemented as a supplemental tool in mathematics support classes to increase mathematics achievement for underachieving students in a rural school in the United States for the first time. Thus, ALEKS was chosen for this research study. ALEKS was used in combination with McGraw's curriculum in mathematics. AI enables ALEKS to determine what students already know and what they are ready to learn next. ALEKS then adapts the instructions and creates a learning path based on what a student is ready to learn. ALEKS has progress checks/periodical assessments to ensure mastery learning (Fang et al., 2019).

The use of ALEKS in teaching mathematics in K-12 classrooms is very scarce. Some research studies have examined the effectiveness of ALEKS on students' learning compared to teacher-led instructions (Brasiel et al., 2016; Conati, 2009; Graesser

et al., 2018; Lippert et al., 2020; Morgan & Ritter, 2002; O'Shea, 1979). Many research studies have been conducted in higher education examining ALEKS's effectiveness on student learning (Boyce & O'Halloran, 2020; Fine et al., 2009; Hagerty & Smith, 2005; Mojarad et al., 2018; Reddy & Harper, 2013; Serhan, 2017). In the last five years, no study has been conducted on ALEKS usage and students' mathematics achievement in underachieving students in K-12 classrooms. This research study will help public schools to adopt and implement ITSs to enhance teaching and learning, and add to the knowledge of ITS's role in improving students' mathematics achievement.

2.2 Background

2.2.1 Skills Gap in Mathematics Education

Mathematical skills are necessary for academic and economic success and critical for several employments in this digital era (Lipnevich et al., 2011; Meece et al., 1990; Soares et al., 2018). Trends in International Mathematics and Science Study (TIMSS) indicated that US 8th-graders ranked 11th in TIMSS mathematics score among 46 countries, with an average score of 515, whereas 8th-graders from Singapore scored an average of 615 (National Center for Education Statistics, 2019). These results are not significantly different from TIMSS conducted in 2015. Moreover, TIMSS results revealed a relatively large gap between top and bottom-performing students among 8th-graders. The top-performing students are performing better; however, the performance is simultaneously declining for bottom performers, resulting in no significant change from 2015 to 2019.

2.2.2 Intelligent Tutoring Systems

Intelligent Tutoring Systems (ITSs) provide personalized instructions and feedback by adapting to students' needs and creating a learning path based on what students are ready to learn and may improve their mathematics performance (Craig et al., 2013; Huang et al., 2016; Pane et al., 2014). ITSs draw on AI that provides interactive instructions to students and step-based feedback in real-time, thus being able to tutor as effectively as humans (Alshawwa et al., 2019; Johnson et al., 2009). Examples of ITSs include Alef Education, Assessment and LEarning Knowledge Spaces (ALEKS), Alta, Bjyu, Century, Dreambox, iReading, Smart Sparrow, and Toppr. ITSs can customize and pace learning based on a student's specific needs, interests, and educational goals. ITSs provide real-time feedback, enhance student engagement, develop a skill set, and allow students to progress faster (Mohammed & Nell'Watson, 2019). By the end of the next decade, AI will profoundly impact deeper self-learning and be capable of assisting and coaching (Holmes et al., 2019).

ITS combines domain knowledge and pedagogical practices to engage students in complex learning processes and meet their comprehensive needs (Self, 1998). The student model of ITSs analyzes what students know, gauges their motivation, and

uses it to enhance various student outcomes (Carbonell, 1970). ITSs can recognize and respond to emotions, talk in natural language, model complex teachers, use pedagogical strategies, and adapt and scaffold learning (Bouyias & Demetriadis, 2012; Graesser et al., 2018; Lippert et al., 2020). ITSs can improve themselves from the feedback they receive from students' responses, learning how to teach, studying what worked, and maximizing students' learning. (Beck et al., 2000; Beck, 1997; O'Shea, 1979). Research studies have shown positive outcomes of student learning, including ALEKS (Craig et al., 2013), Cognitive Tutor (Pane et al., 2014), ASSISTments (Koedinger et al., 2010), and SQL-Tutor (Mitrovic, 2003).

2.2.3 Learning Theories underpinning the ITSs

ITSs provide real-time feedback based on students' responses. Step-based hints are generated if students face difficulty in solving a problem. Students may need considerable effort to understand these hints (Merrill et al., 1992; Wittwer & Renkl, 2008). ALEKS is based on the theoretical framework of KST. KST determines a student's knowledge state accurately in a particular subject domain. For example, Algebra 1 has 50,000 knowledge states. ALEKS accurately assesses students' current knowledge and presents them with the topics they are ready to learn. Therefore, students experience less frustration and boredom. ALEKS claims that learning occurs at a rapid rate as students take ownership of their learning. Students' growth is visible in the pie chart, which represents their progress towards mastery learning.

Programmed Instructions by Skinner (1954) formed the basis of computer-assisted instruction (CAI). Computer-assisted programs are based on behavioral principles as they change the behavior of the learners. Computer-assisted programs, such as ITS, distinguish desired behavior and prepare events so students will experience success, thus reinforcing learning. ITS breaks down the task into smaller steps and provides immediate corrective feedback based on the student's responses.

2.2.4 ALEKS ITS

ALEKS is a web-based ITS that uses KST for students' assessments and learning based on a combinatorial and probabilistic model (Cosyn et al., 2021; Doble et al., 2019; Falmagne et al., 1990). KST represents a particular domain as a knowledge map that consists of many knowledge states (KS). With inbuilt AI, KST can predict the current knowledge state of students and what a student is ready to learn next. ALEKS utilizes a diagnostic assessment to determine the student's initial knowledge state. The diagnostic assessment includes free-response problems and avoids multiple-choice questions. Students can choose to work on any given topic based on their readiness to learn. ALEKS generates topics that students are ready to learn, presented in the individualized pie chart and their learning progress (Xie et al., 2017). A solved example is presented when students request an explanation of the current problem, and a similar new problem is generated for the student to solve.

When students first log in to ALEKS, it provides a brief tutorial to guide them on utilizing answer input tools, followed by the ALEKS Assessment (pretest), which consists of approximately 20-30 questions to determine initial knowledge. The ALEKS-generated assessments are unique to each student as it chooses the next question based on previous questions' responses. ALEKS summarizes what the student has mastered under each knowledge category in a pie chart and generates a list of problems that the student is ready to work on based on their knowledge states. Students can choose to work on the topic of their preference, and once they master the topic/problem type, it is added to their knowledge state, and a new set of problems is presented that they are ready to learn.

In 8th-grade mathematics, the learning concepts or subject matter are divided into 475 topics. In this scenario, the student is somewhere in space at each point in learning the mathematics topics/concepts and moving to a new state with each learned topic/concept. ALEKS periodically reassesses students' knowledge by providing mixed questions and adjusting their knowledge to ensure retention of the learned topic. ALEKS does not provide scores for mastery learning; instead, it focuses on where the student is in terms of knowledge and what they need to learn. With the integration of AI, students are almost always successful in learning a topic, as ALEKS provides the complexity of questions based on prerequisite knowledge. ALEKS has a comprehensive message center for students to assist them with two-way communication. Moreover, the ALEKS curriculum is aligned with the standard-based course content.

2.2.5 Previous Research using ALEKS

Several research studies conducted on ALEKS have shown to reduce the academic achievement gap when implemented in an after-school setting (Craig et al., 2013; Hu et al., 2013; Huang et al., 2016), higher retention of mathematics concepts (Wilder & Berry, 2016), high mathematics achievement scores (Brasiel et al., 2016; Sullins et al., 2014), increase mathematics learning and engagement (Wang et al., 2018), and reduced remediation (Fine et al., 2009). ALEKS has shown a greater effect size when implemented for the short term (Craig et al., 2011; Fang et al., 2019; Steenbergen-Hu & Cooper, 2013). Pai et al. (2021) compared Chinese mathematical dialogue-based ITS with the traditional teaching of 134 fifth-grade students. The results showed that students' performance was comparable between ITS and teacher-led instructions. ITSs have shown effect sizes comparable (VanLehn, 2011), small to moderate (Kulik & Fletcher, 2016), and moderate to large as compared to teacher-led instructions and computer-based instructions (Fang et al., 2019; Ma et al., 2014).

ALEKS was implemented to teach the fundamentals of mathematics in Calculus I class at the University of North Colorado (UNCO). Students completed 30 hours of course modules using ALEKS, mostly outside of their classrooms. Although the use of ALEKS helped students to learn pre-requisite skills for Calculus 1; however, students mentioned that the current use of ALEKS was overwhelming and suggested a

better synchronization between prerequisite learning modules courses, and Calculus I content (Han-cock et al., 2021). In some studies, the use of ALEKS on student learning outcomes was similar to traditional teacher-led instructions, and no significant difference was found in mathematics achievement (Craig et al., 2013; Fang et al., 2019; Pai et al., 2021; Wilder & Berry, 2016; Xu et al., 2009).

The existing literature review revealed mixed results on the effectiveness of ALEKS on students' mathematics achievement in K-12 classrooms. It is worth noting that there is a limited number of recent studies focused on the use of ALEKS on underachieving students' mathematics achievement. This research study aims to bridge this research gap. The findings from this research study shed light on the impact of ALEKS on underachieving students' mathematics achievement and implementing ITSs effectively in K-12 classrooms. Finally, this research would provide insight to stakeholders on how to implement ITSs effectively to enhance teaching and learning.

2.2.6 Research Aims

This descriptive research study aims to investigate whether the use of ALEKS shows a statistically significant improvement in students' mathematics achievement than traditional teacher-led instruction of 8th-grade students.

Research Questions

The following research questions guided this scientific investigation:

RQ1. Does the use of ALEKS show a statistically significant improvement in students' mathematics achievement than traditional teacher-led instructions, as measured by pretests and posttests?

RQ2. Does the use of ALEKS show statistically significant improvement in students' mathematics achievement based on the mathematics standards in one year?

Null Hypotheses

H01: There is no statistically significant difference between ALEKS-led and teacher-led instructions on students' mathematics achievement, as measured by pretests and posttests.

H02: There is no statistically significant difference in students' mathematics achievement with the use of ALEKS-led instructions based on the mathematics standards in one year.

2.3 Method

This research used a non-randomized quasi-experimental study that used a treatment group and a control group to investigate mathematics achievement between ALEKS-led versus teacher-led instructions. Data from the teacher-led instructions

were collected from the academic year of 2019- 2020, and ALEKS-led instruction was collected from 2020-2021. Pretests and posttests were administered to the treatment and control groups to evaluate statistically significant improvement in students' mathematics achievement.

The research protocol conformed to the ethical guidelines of the Research Ethics Committee (cETO) designated by the Open University of the Netherlands. Permission from the Institutional Review Board (IRB) was not needed per the email conversation, as the research was conducted through the Open University of the Netherlands. The school superintendent, principal, and teacher gave permission prior to the research. Ethical considerations and guidelines about the participants' privacy were carefully considered throughout the research process.

ALEKS's curriculum is aligned with state standards and has shown a positive association between assessment performance and state test scores (Craig et al., 2013). This research study was conducted in a rural school district in South Georgia. It involved a total of n=158 8th-grade students, with 60 students in the teacher-led group and 98 students in the ALEKS-led group. Within the school district, a significant population of students, ranging from 62-68%, come from economically disadvantaged backgrounds. Additionally, only 12% of students are proficient in mathematics (Public School Review, 2019), which is considerably lower than the statewide average of 35%. Students used ALEKS as a supplement instruction in their mathematics resource class for 50 minutes every other day for a year in the presence of a teacher. During the 2019-2020 academic year, the teacher used only McGraw's curriculum "Reveal" to provide teachers-led instructions during the first year, and in the 2020-2021 academic year, ALEKS was implemented.

Students took a pretest to generate a baseline about what students know (initial knowledge check) and a posttest (final knowledge check) at the end of the year. The pretest and posttest data between teacher-led and ALEKS-led instructions were used to determine statistically significant improvement in students' mathematics achievement. The results of five years of End of Grade (EOG) state assessment without using ALEKS were compared with one-year EOG state assessment using ALEKS. Descriptive statistics were used to analyze the results. A paired t-test and ANOVA were used to examine the statistically significant improvement in students' mathematics achievement based on pretests and posttests, mathematics standards in one year.

2.3.1 Research Variables

For this research study, the Independent Variable (IV) was the use of ALEKS (i.e., ALEKS users as a treatment group and non-users as a control group), and the dependent variables (DVs) were mathematics achievement and mathematics state standards. The DV, mathematics achievement, is defined as students' attainment of new mathematical skills that can be measured by their performance on the sample items from a standardized test. This research study defines mathematics achievement as

the difference between pretest and posttest outcomes on the ALEKS assessment.

2.3.2 Results

To address RQ1, 8th-grade mathematics data comprising pretests and posttests from two consecutive years were compared. A two-tailed paired sample t-test was conducted to identify whether the use of ALEKS showed statistically significant improvement in students' mathematics achievement than traditional teacher-led instructions. The results revealed a highly statistically significant improvement in students' mathematics achievement with the ALEKS-led instructions and teacher-led instructions. For ALEKS-led instructions, pretest *(M =21.5, SD = 20.80)* and posttest *(M=39.58, SD = 24.89*); p-value = 1.14663E-07 and for traditional teacher-led instructions, pretest *(M=24.15, SD= 11.69)* and posttest (*M=58.12, SD= 9.13*); p-value = 1.48199E-37. The results indicated that teacher-led instructions were more effective than ALEKS-led instructions because of higher test scores and lower variance for teacher-led instructions. Therefore, H01 is rejected, and it can be concluded that teacher-led instructions were more effective than ALEKS-led instructions.

In addition, a one-way ANOVA was conducted to evaluate the efficacy of ALEKS on students' mathematics achievement. The results indicated a highly statistically significant improvement in students' mathematics achievement with both ALEKS-led instructions and teacher-led instructions. The results indicate a low average (17.63 and 35.27) and high variance (279.05 and 435.81) for ALEKS-led instruction. Students performed better with teacher-led instructions, as indicated by a higher average (24.05 and 57.88) and low variance (138.32 and 81.35). Thus, H01 is rejected, and it can be concluded that teacher-led instructions were more effective than ALEKS-led instructions.

The students who received the teacher-led instructions performed better on the End of Grade (EOG) standardized state assessment. The results of five years of EOG standardized state assessment data (2015 to 2019) with no use of ALEKS compared with 2021 EOG standardized state assessment data with the use of ALEKS (see Figure 2.1). As per the Achievement Level Descriptors (ALDs), there are four achievement levels for EOG assessment: Beginning Learner, Developing Learner, Proficient Learner, and Distinguished Learner. Beginning learners fall under the category of "Remediate learning." "Monitor learning" means students are in the developing learner category, and "Accelerate learning" refers to students falling under the proficient and distinguished learner category (see Figure 2.1). A negative trend has been observed in students' mathematics achievement over the years. The number of students in the remediating category rises, whereas the number in the accelerating category declines; even with the use of ALEKS, this trend continued further. This decline in mathematics achievement over the years could be due to a change in leadership in 2018. The principal of Mitchell County High School was changed in 2018, and at the beginning of 2021, the school appointed two different superintendents.

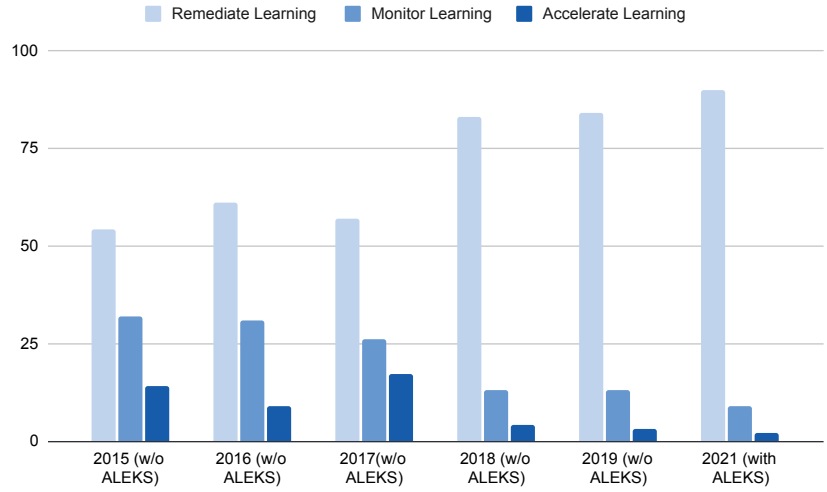


Figure 2.1 Comparison between End of Grade with and without ALEKS-led instructions

To address RQ2, Does the use of ALEKS show significant improvement in mathematics achievement based on the mathematics standards in a year period? Data from ALEKS were compared. At the beginning of the year, students took a pretest (Initial Knowledge Check) and a posttest (final knowledge check) towards the end of the year. A t-test and ANOVA were used as descriptive analysis tools to determine if the use of ALEKS significantly improved mathematics achievement based on mathematics standards. There are five mathematics domains in ALEKS for 8th-grade mathematics, which are divided into eleven standards: Whole Numbers and Integers; Fractions; Decimals; Ratios, Proportions, and Measurement; Percents; Equations and Inequalities; Graphs, Functions, and Sequences; Exponents, Polynomials, and Radicals; Lines, Angles, and Polygons; Transformations; Perimeter, area, and volume; and Data Analysis and Probability. The difference in mean scores (posttest-pretest) indicated that ALEKS showed significant mathematics achievement in all mathematics standards. Therefore, H0 is rejected, and it can be concluded that using ALEKS significantly improved all mathematics standards. However, the gains in mathematics standards varied. Based on mean scores, students showed the highest gain in Decimal mathematics standard (M=27.13); followed by Whole Numbers and Integers (M=23.5); Equations and Inequalities (M=22.38); Fractions (M=21.63); Percents (M=19.36); Data Analysis and Probability (M=19.25); Ratios, Proportions, and Measurements (M=18.13); Lines, Angles, and Polygons (M=15.75); Exponents, Polynomials, and Radicals (M=15.25); Transformations (M=14.88); Perimeter, area, and volume (9.75); Graphs, Functions, and Sequences (M=9.5) as shown in Table 5 (see Table 5). A possible explanation could be that ITSs are based on mastery learning. Students can only move to a different topic if they have indicated 80% mastery. Students used ALEKS only on alternate days, so they could

not complete all eleven standards.

2.3.3 Discussion

For RQ1, this research study aimed to investigate whether the use of ALEKS shows statistically significant improvement in students' mathematics achievement than traditional teacher-led instructions, as measured by pretests and posttests. The results indicate highly statistically significant gains in mathematics achievement in both teacher-led and ALEKS-led instructions; however, students in the teacher-led instructions performed better than in ALEKS-led instructions. This finding is closely parallel to the result of a meta-analysis study reported by Fang et al. (2019) and Ma et al. (2014). Several possible explanations may shed light on this trend.

One possible explanation is that ITSs generate an automatic learning path based on students' current knowledge after a diagnostic assessment (initial knowledge check). Most of the students at this school were underachieving students who were 3-4 grades behind, and ALEKS assigned them lessons based on basic computational skills. For example, students in the 8th grade at the Mitchell County High School who struggle with multiplication may spend more time doing simple multiplication problems for making errors. As a result, ITSs assume that students need to learn multiplication; hence, a lot of time is invested in learning basic prerequisite skills, and students do not have the opportunity to learn grade-level skills by using ITSs in a year. Moreover, obtaining at least 3-4 grade level gains in a year is difficult, even using ITSs. ITSs may support mathematics learning if students begin using them at the elementary school level, which may prevent the widening of the achievement gap in mathematics.

Another possible explanation for this trend could be that the teachers received training and got familiar with using ALEKS in the classroom as ALEKS was implemented for the first time. Moreover, Teachers used ALEKS as per the guidelines provided by the administrators. In general, ALEKS can be utilized in two ways. One way is the teacher allows students to follow an individualized learning path generated based on initial assessments, which may comprise learning prerequisite skills. Another way is that the teacher in the mathematics support class coordinates with another teacher from a regular mathematics class and assigns grade-level content based on students' weaknesses. As students master the mathematical topic/concepts, ITSs can navigate them to learn another grade-level topic. ITSs may improve students' basic or prerequisite skills in the first scenario, but it may not necessarily translate into mathematics achievement at the grade level.

Furthermore, the COVID-19 pandemic had an impact on the grading process. Teachers were asked to consider the social and emotional aspects of the pandemic when it came to grading. Additionally, these students missed classes in their 7th grade due to the complete school closure for the COVID-19 pandemic and got promoted to 8th grade without taking state-level examinations and school exams. This learning loss is also contributing to the overall relatively small mathematics achievement.

Moreover, during the COVID-19 pandemic, the school system divided the class into two groups and called them on alternate days to keep students safe and maintain social distancing for in-person learning. As a result, students could receive ALEKS-led instruction for only half a year. Therefore, inadequate time could be another reason ALEKS-led instructions did not show equal or greater mathematics achievement than teacher-led instructions. However, it is worth noting that students in the ALEKS-led instruction were more independent and required less attention from the teacher.

ALEKS has indicated greater achievement in the Decimals, followed by Fractions, and Equations and Inequalities. This research study may need to be replicated as the ALEKS was implemented for the first time, and teachers were learning how to use it. Moreover, we should not neglect that effective teachers with a repertoire of evidence-based pedagogical practices may equate to ITS-led instructions.

For RQ2, this research study investigated the use of ALEKS to show statistically significant improvement in students' mathematics achievement based on the mathematics standards in one year. The pretest is an initial knowledge check administered at the beginning of the year, and the post-test is the latest knowledge check administered toward the end of the year. Based on the descriptive data analyses, students showed overall statistically significant improvement in all eleven standards based on the difference in mean scores between the posttest and pretest. However, the mathematics gain differs by standards.

ALEKS was accessible only on alternate days for a year; therefore, students could not complete all the standards. The following reasons can be attributed to this trend: ALEKS is based on mastery learning, which means students must learn the content with 80% accuracy before moving to the next topic. A small improvement in some of these mathematics standards may be attributed to the knowledge/prerequisite skills they acquired by mastering the content on ALEKS. Also, high mean scores indicate that students have more prerequisite knowledge with certain mathematics standards. The possible explanation is that these standards are comparatively easier, and students may have learned prerequisite skills for these standards in the previous grades.

Several secondary and postsecondary institutions are implementing ITSs across the United States to enhance students' mathematics achievements and to reduce the mathematics achievement gap in struggling students. These mathematics ITSs provide adaptive and individualized instructions to students to improve mathematics achievement. ITSs are based on behavioral principles and can prepare learning events, so students experience success and reinforce learning. The present study could not employ randomized trials as participants were 8th graders, and the school system did not want to deprive students of using ALEKS. Therefore, data were collected from all 8th-grade students, and the results were compared with the teacher-led instructions from the previous year.

The results from this study should be interpreted with caution as the ALEKS was

implemented for the first time, and teachers were getting familiar with using ALEKS in the classroom. Also, the impact of COVID-19 and the small sample size may affect the outcome of this study. Future studies should include a larger sample size and a randomized trial to measure the efficacy of ALEKS on students' mathematics achievement of underachieving students. The results may differ when ALEKS is implemented for at least a few years. Continued research on the effectiveness of ITSs is critical to support the teaching and learning process.

2.4 Conclusions

This quasi-experimental research study is the first one that measured the efficacy of ALEKS as a supplemental tool for 8th graders in mathematics classrooms in rural South Georgia. Descriptive analysis, such as t-test and ANOVA, were used to determine statistically significant improvement in the mathematics achievement of underachieving students. Findings from this research study indicate that instructional practices in ALEKS that include mastery learning of mathematical concepts/topics, focusing on learning prerequisite skills, and increased retention of learned concepts can significantly improve students' mathematics achievement in underachieving students.

This research study finds that both ALEKS-led and teacher-led instructions have shown statistically significant improvement in students' mathematics achievement of underachieving students. Students performed better in the teacher-led instructions as compared to the ALEKS-led instructions. However, the student using ALEKS seeks less teacher assistance. This research study could provide a possible solution for the underachieving rural population and help reduce the mathematics achievement gap.

Educational institutions are increasingly using ITSs to support teaching and learning processes. Mathematics ITSs can provide adaptive and personalized learning. ITSs can provide support with the teaching and learning processes efficiently. The ITSs have the potential to replace traditional teaching methods in K-12 classrooms. The findings from this research study provide insight into the use of ITSs in K-12 classrooms. This study adds to the literature that ITSs significantly improve students' mathematics achievements in underachieving students. These findings also align with the research studies conducted in the K-12 classrooms, which have shown a positive and statistically significant achievement on mathematics state standardized assessments (Brasiel et al., 2016; Sullins et al., 2014). This study can provide insight to stakeholders on integrating ITSs to improve mathematics achievement in underachieving student populations at risk for failure.

Part II

Exploring AIED: Adaptive Learning Systems

Chapter 3

Effect of AI-Based Systems on Mathematics Achievement

This chapter is based on:

Khazanchi, R., Di Mitri, D., & Drachsler, H. (2025). The Effect of AI-Based Systems on Mathematics Achievement in Rural Context: A Quantitative Study. *Journal of Computer Assisted Learning*, 41(1), e13098. doi:10.1111/jcal.13098

3.1 Abstract

Background: Despite educational advances, poor mathematics achievement persists among K-12 students, particularly in rural areas with limited resources and skilled teachers. Artificial Intelligence (AI) based systems have increasingly been adopted to support the diverse learning needs of students and have been shown to enhance mathematics achievement through personalized learning experiences by adapting to student's needs. Existing studies have documented the positive impact of AI-based systems on mathematics achievement. However, there is a lack of research that has studied AI-based systems on students' mathematics achievement and engagement in rural settings. The present study addresses the existing literature gap by focusing on the AI-based Edmentum Exact Path, analyzing its effectiveness in enhancing mathematics achievement and engagement among 8th-grade students in rural schools in the Southern United States. By examining both cognitive and affective engagement, along with students' mathematics achievement, this research explores the role of AI-based systems in student learning.

Objective: This study aims to explore the effectiveness of Edmentum Exact Path, an AI-based system, in improving 8th-grade students' mathematics achievement and affective and cognitive engagement in the Southern United States.

Methods: This study utilized a quasi-experimental design involving 78 students from socioeconomically disadvantaged backgrounds, comparing those receiving supplemental Edmentum Exact Path-led instruction and traditional teacher-led methods to a control group receiving only the teacher-led instructions. Mathematics achievement was measured through pretests and posttests, while student engagement was assessed using the 5-point Student Engagement Instrument (SEI). Statistical analysis was performed using *t*-tests and ANOVA.

Results and Conclusions: The findings revealed statistically significant improvements in mathematics achievement for both the experimental and control groups. However, the group using teacher-led instruction showed a statistically significant improvement in affective engagement, while no statistically significant differences were observed in cognitive engagement between groups.

Implications: The findings suggest that integrating AI-based systems like Edmentum Exact Path may enhance affective engagement in mathematics among students from rural areas. However, the impact on cognitive engagement remains unclear, indicating a need for further research. These results support the potential for integrating AI-based systems to enhance mathematics achievement in rural settings.

Summary

- What is currently known about this topic?
  - AI-based systems have a positive impact on students' mathematics achievement.
  - AI-based learning is comparable to traditional teaching.

  - AI-based system enhances students' engagement.

- What does this paper add?
  - This study makes a valuable contribution to the existing body of research by examining the effectiveness of Edmentum Exact Path as a supplementary tool for enhancing students' mathematics achievement from socioeconomically disadvantaged backgrounds.
  - This study provides insights into the potential use of AI-based systems to bridge the achievement gap and support mathematics learning in rural contexts.
  - This study highlights the positive impact of traditional teacher-led instruction on students' affective engagement.
- The implications for practice/or policy
  - The findings are essential for educators and policymakers interested in enhancing mathematics achievement in students from socioeconomically disadvantaged backgrounds.
  - The current study incorporated Edmentum Exact path as a supplemental tool to support mathematics learning of students from socioeconomically disadvantaged backgrounds. The findings from this study provide insights into the synergy between AI-based systems and effective pedagogical practices for enhancing students' mathematics achievement.

3.2 Introduction

In the United States, teachers have persistently encountered challenges in enhancing mathematics achievement, particularly in rural areas. Many students find mathematics to be abstract, challenging to understand, and monotonous (Grootenboer and Marshman 2016; Murray 2011). Students from socioeconomically disadvantaged backgrounds and minorities are at particular risk for poor mathematics performance (Hanushek and Rivkin 2006; Singh 2015; Reeves 2012). A study by McCoy (2005) revealed that students from lower socioeconomic statuses and minority groups tend to struggle more with mathematics, emphasizing the need for AI-based systems in rural areas to provide personalized learning experiences and support. Indicators of socioeconomically disadvantaged status in the United States include the percentage of students eligible for free or reduced-price lunch (Clayton 2011; Harwell and LeBeau 2010). Socioeconomically disadvantaged students are raised in poverty, have limited access to resources, and tend to have lower grades and scores on achievement tests (Cooper and Crosnoe 2007; Duncan and Magnuson 2011; Reardon 2018; Sirin 2005). A significant issue contributing to these challenges is the lack of engagement in meaningful curricular activities, affecting at least two-thirds of high school students nationwide (Brown 2008; Sedlak 1986).

Student engagement refers to active participation in the learning process, where students invest effort and are deeply involved in tasks, encompassing behavioral, emotional, and cognitive dimensions essential for enhancing learning outcomes (Axelson and Flick 2010; El-Sabagh 2021; Fredricks, Blumenfeld, and Paris 2004; Kuh 2009; Alrakhawi, Jamiat, and Abu-Naser 2023; Mohammed and Watson 2019; Jasin et al. 2023; Song, Shin, and Shin 2024; VanLehn 2011; Xie et al. 2019). Engagement plays a pivotal role in the learning process, as Fung, Tan, and Chen (2018) demonstrated that students actively engaged in math learning activities tend to achieve greater academic success.

Students often experience fluctuations in their engagement levels when introduced to a new mathematics concept, leading to decreased interest and participation (Martin et al. 2015). Many students struggle with low self-confidence and a negative attitude toward mathematics, which worsens with repeated failures. Affective engagement pertains to students' emotions, attitudes, perceptions, and interests in the learning process (Fredricks, Blumenfeld, and Paris 2004). Cognitive engagement pertains to students' perseverance in academic tasks and utilizing cognitive strategies in the learning process (Fine, Duggan, and Braddy 2009). Students with higher levels of cognitive engagement have demonstrated positive gains in mathematics achievement (Maamin et al. 2021). Traditionally, teachers have employed various effective teaching strategies to promote student engagement (Han 2021).

Traditional teaching methods often pose challenges in engaging all students effectively and providing immediate feedback (Han 2021; Hyun, Ediger, and Lee 2017). Additionally, school districts encounter difficulties recruiting and retaining highly qualified teachers due to low salaries, isolation, limited access to professional development, and a less diversified student population (Ingersoll and Tran 2023; Monk 2007; Shikalepo 2020). AI-based systems address these issues by providing access to high-quality educational content and allowing students to control their learning pace through online platforms. They also offer insights for targeted interventions (Khosravi, Sadiq, and Gasevic 2020; Molenaar and Knoop-van Campen 2018). AI-based systems like Edmentum Exact path and teacher-led instructions differ significantly in their approaches to personalized education (Jasin et al. 2023; VanLehn 2011). Edmentum Exact Path uses artificial intelligence to create individualized learning pathways, adapting in real-time based on performance data to provide immediate feedback and scalability (Edmentum 2023a, 2023b). Teacher-led instruction relies on teachers' adaptability and intuition to modify strategies, offer emotional support, and engage students through interactive activities.

Empirical evidence has documented the positive impact of AI-based systems on students' mathematics achievement and attitudes (Feng, Huang, and Collins 2023; Ma et al. 2014; Nye et al. 2018; Pane et al. 2014; Steenbergen-Hu and Cooper 2013; Wang et al. 2023c). Integrating AI-based instructions with effective pedagogical approaches can maximize learning outcomes through personalized feedback and enhanced engagement (Craig et al. 2013; Huang et al. 2016; Pane et al. 2014). Most empirical studies on the impact of AI-based systems in education have been

conducted with higher education students, while significantly fewer studies have focused on high school students (Wang et al. 2023b; Xie et al. 2019). This research aims to explore the effectiveness of the Edmentum Exact Path on students' mathematics achievement, affective engagement, and cognitive engagement in 8th-grade students from three different school districts in the Southern United States. Despite existing evidence supporting the efficacy of AI-based systems in enhancing mathematics achievement (Clẽment et al. 2024; Feng, Huang, and Collins 2023; Hillmayr et al. 2020; Nagashima et al. 2022; Rodrigues et al. 2023), there is a scarcity of empirical studies examining the impact of Edmentum Exact Path as a supplemental tool to enhance student engagement and mathematics achievement in K-12 schools, particularly in rural context. This study aims to fill this gap by exploring the impact of Edmentum Exact Path on the engagement and mathematics achievement of students from socioeconomically disadvantaged backgrounds in the Southern United States.

The main research questions read as follows:

RQ1. *How does mathematics achievement, as measured by pre-tests and post-tests, differ between students receiving instruction from Edmentum Exact Path and those receiving traditional teacher-led instructions?*

RQ2. *In what ways does affective engagement, as assessed using the SEI, vary between students instructed through Edmentum Exact Path compared to those experiencing traditional teacher-led instructions?*

RQ3. *What are the differences in cognitive engagement, as measured by the SEI, between students taught with Edmentum Exact Path and those who receive traditional teacher-led instructions?*

3.3 Background and Theoretical Framework

3.3.1 AI-Based Learning Systems

AI-based systems are digital platforms that leverage artificial intelligence (AI) to provide personalized learning experiences by dynamically adapting learning content to students' abilities (Aleven et al. 2016; Appleton, Christenson, and Furlong 2008; D'Mello and Graesser 2023; Fredricks, Blumenfeld, and Paris 2004; Fung, Tan, and Chen 2018; Khosravi, Sadiq, and Gasevic 2020). These systems identify knowledge gaps and create individualized learning paths, enabling students to progress at their own pace, bridging the learning divide, and accelerating their learning (Terzieva, Ivanova, and Todorova 2022). Moreover, AI-based systems provide real-time assessments and feedback and assist teachers in monitoring students' progress, highlighting their strengths and weaknesses (Metje, Frank, and Croft 2007; Pliakos et al. 2019; Xie et al. 2019). Personalized feedback and automated grading are prominent features of AI-based systems, empowering teachers to allocate more time to assist students (Craig et al. 2013; Feng, Huang, and Collins 2023; Pliakos et al.

2019).

Empirical evidence indicates that technology use in mathematics has positively impacted student learning (Craig et al. 2013; Huang et al. 2016; Pane et al. 2014). Several studies have reported the positive impact of AI-based systems in improving examination scores and test performance (Alrakhawi, Jamiat, and Abu-Naser 2023; Clẽment et al. 2024; Ma et al. 2014; Niño Rojas et al. 2024; Steenbergen-Hu and Cooper 2013; VanLehn 2011), as well as significantly enhancing math learning (Clẽment et al. 2024; Hillmayr et al. 2020; Kulik and Fletcher 2016; Ma et al. 2014; Nagashima et al. 2022; Rodrigues et al. 2023). AI-based systems have been shown to enhance mathematics achievement compared to traditional teacher-led Instructions (Craig et al. 2013; Fine, Duggan, and Braddy 2009; Hu et al. 2013; Ma et al. 2014; Wang et al. 2023a). A study by Ma et al. (2014) found no difference between learning from AI-based systems and learning from individualized human tutoring or small-group instruction. Few research studies demonstrated that AI-based systems are comparable to teacher-led instructions (Leddo and Garg 2021; Nye et al. 2018; Olney et al. 2012; VanLehn 2011).

In the United States, several AI-based systems, such as iReady (Curriculum Associates), MATHia (Carnegie Learning), Edmentum Exact Path, Cognitive Tutor Algebra I (Carnegie LEarning), and Assessment and LEarning in Knowledge Spaces (ALEKS) are commonly employed to enhance mathematics achievement in among K-12 students (Almoubayyed et al. 2023; Fang et al. 2019; Nitkin, Ready, and Bowers 2022; Urbina and Polly 2017). Emerging evidence suggests that AI-based systems can foster students learning (Pane et al. 2014; Phillips et al. 2020; VanLehn 2011; Xie et al. 2019) by providing personalized instructions. In K-12 classrooms, these systems have positively impacted mathematics performance (Beal et al. 2010; Faber, Luyten, and Visscher 2017; Koedinger, McLaughlin, and Heffernan 2010; Molenaar and Knoop-van Campen 2018). VanLehn's (2011) study on the effectiveness of several tutoring approaches, human tutoring, Intelligent Tutoring System (ITS), and scenarios without tutoring, revealed that ITS can be just as effective as human tutors in educational contexts. A large-scale study evaluated the effectiveness of Cognitive Tutor Algebra I in middle and high schools, revealing a significant improvement in students' mathematics performance in high school settings (Pane et al. 2014). Research studies have suggested that the impact of ALEKS on students' learning is comparable to that of traditional teaching methods (Beal et al. 2010; Craig et al. 2013; Hu et al. 2013).

This research focuses explicitly on Edmentum Exact Path, an AI-based system, due to its unique features, including adaptive diagnostic assessments and targeted learning paths that provide personalized learning experiences at the students' own pace. Edmentum Exact Path equips teachers with actionable instructional data to inform classroom instruction and is designed for K-12 classrooms (McLeod 2017). Its recent implementation in a rural school in the southern United States prompted the need for research on the effectiveness of Edmentum Exact Path in improving students' mathematics achievement. Furthermore, there is a shortage of studies exam-

ining the efficacy of the Edmentum Exact path, particularly for socioeconomically disadvantaged students in mathematics.

A study was conducted to estimate the effectiveness of Edmentum's Exact Path on students' reading achievement in kindergarten through 3rd grade, which yielded significant improvement in reading achievements for students who completed at least eight exact path lessons of the Exact Path Diagnostic Assessment compared to those who did not complete the lessons (Randel 2018). Furthermore, McLeod (2017), a researcher at Edmentum, conducted a correlation study involving a large sample size ($n = 6577$) from several kindergartens to 6th-grade schools across the United States. Results from this study indicated a statistically significant correlation between the Edmentum's learning path and student achievement in mathematics, reading, and English Language and Arts. This research aims to contribute to the existing knowledge gap by investigating the impact of Edmentum Exact Path as a supplemental tool for improving the mathematics achievement of socioeconomically disadvantaged students.

3.3.2 Edmentum Exact Path

Edmentum Exact Path is an AI-based system that utilizes an adaptive algorithm to assess students' present level and deliver individualized instruction, immediate feedback, and real-time adjustments to their progress (Edmentum 2023a, 2023b). It is available to K-12 mathematics, reading, and language arts students. The system comprises a diagnostic assessment, progress checks, individualized instruction, skill practice, and supplementary resources. Employing a formative assessment approach, Edmentum Exact Path continuously adjusts students' instruction and monitors their progress (see Figure 3.1). Assessments are conducted periodically, typically three times a year in fall, winter, and summer, resulting in an individualized placement within the Exact Path learning progression. Students undergo a diagnostic assessment at the onset of the academic year, yielding a diagnostic score called the Learning Path Entry Grade (LPEG).

The teacher dashboard of Edmentum Exact Path provides a comprehensive overview of students' current activities, knowledge map, and class results. The Knowledge map illustrates the sequence of skills students must acquire within a specific domain. The Knowledge map (see Figure 3.2) visually represents the progression of skills that students need to learn for a particular domain.

Students retake the diagnostic assessment in the winter to reflect on their learning growth. Based on these updated diagnostic scores, their learning placements within the Edmentum Exact path are adjusted, potentially including lessons they did not previously pass.

The Edmentum Exact Path learning progression aligns with the state standards and spans from Kindergarten (KG) to high school. The number of lessons and skills in mathematics typically ranges from 20 to 30 per grade level. Lessons are assigned in groups of three or four, each targeting specific skills. Progress checks in the form

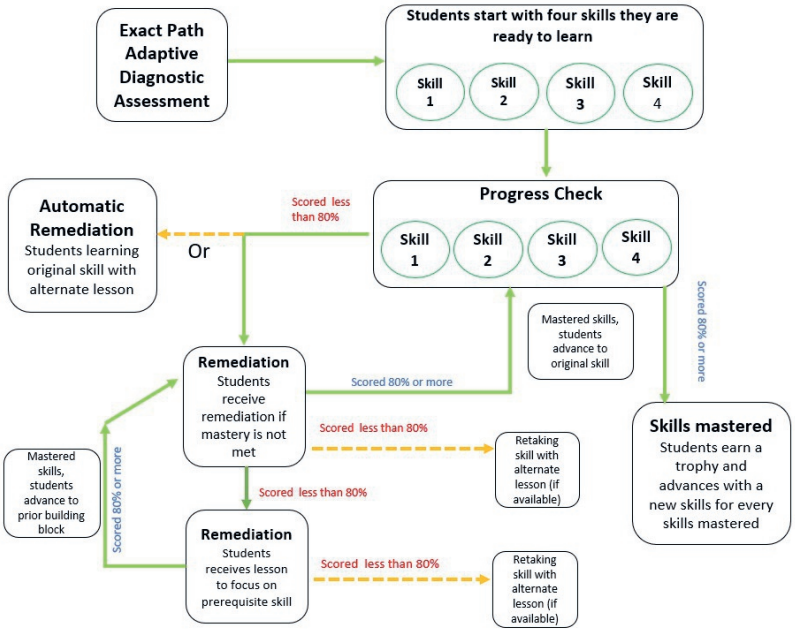


Figure 3.1 Edmentum Exact Path knowledge map.

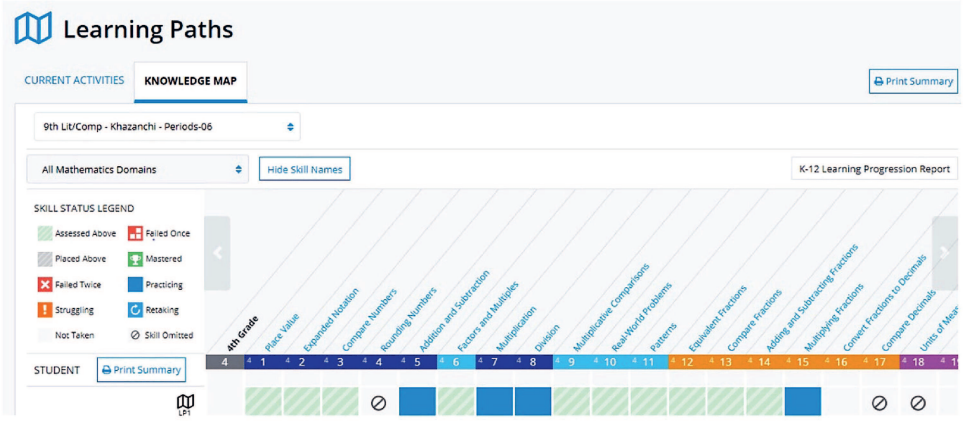


Figure 3.2 Edmentum Exact Path learning progression. Source: Adapted from https:// edmentum.com

of short quizzes follow each lesson to gauge student's understanding. Students not passing the progress checks are assigned additional tasks to address the necessary skills. Once students achieve 80% mastery of the progress checks, they can advance to a new set of lessons and progress through the skills and concepts outlined in the learning progression (McLeod 2017; Randel 2018).

3.3.3 Theoretical Framework

This research study utilized two theoretical frameworks: the Stein and Levine (2013) and the D'Mello and Graesser (2012). The Stein and Levine (2013) model integrates an individual's affective states or emotions with learning processes, establishing a connection between their goals and emotions.

This approach adopts a goal-oriented, problem-solving method, aligning with theories emphasizing the hedonic principle in emotions (Stein and Levine 1999). It posits that individuals prefer pleasant emotional states, such as happiness, while avoiding unpleasant emotional states, such as sadness. According to this model, when individuals learn new content, it assimilates into their existing schemas. Emotional experiences often arise when interacting and making sense of information. Learning something new creates a discrepancy with the existing schemas, leading to autonomic nervous system arousal (ANS). In conjunction with the cognitive appraisal of the situation, the ANS arousal results in an emotional response (Stein and Levine 2013). Therefore, this theoretical model predicts that learning will likely occur during an emotional response. When students solve problems using Edmentum Exact Path, they are more likely to engage with and comprehend the content if they experience positive emotions. Positive affective states are directly linked to learning processes, suggesting that when students are positively engaged, they are likely to perform better on assessments (Li, Gow, and Zhou 2020).

On the other hand, the model of Affective Dynamics (D'Mello and Graesser 2012) emphasizes the impact of cognitive disequilibrium on deep learning. Cognitive disequilibrium occurs when individuals encounter obstacles to their learning goals, such as misconceptions, contradictions, or interruptions (D'Mello and Graesser 2012). The critical component of cognitive disequilibrium is the affective state of confusion (D'Mello and Graesser 2014), which, if left unresolved, can lead to frustration, boredom, and disengagement. However, when the individuals can resolve their confusion, they return to equilibrium and continue to engage with their learning goals (D'Mello and Graesser 2012; D'Mello et al. 2014). For instance, when using Edmentum Exact Path, students may experience confusion or frustration upon encountering a challenging problem, a state known as cognitive disequilibrium. However, they can utilize the built-in hints provided by Edmentum Exact Path to resolve these difficulties. Successfully solving the problem helps students return to cognitive equilibrium, allowing them to remain engaged with the task (D'Mello and Graesser 2012). This comprehensive approach allows for a deeper understanding of the complex interplay between learners' affective states, cognitive challenges, and overall learning outcomes. It highlights the potential for adaptive learning tech-

nologies to enhance student engagement's affective and cognitive aspects, thereby improving mathematics achievements.

3.4 Methodology

3.4.1 Study Design and Tool Selection

This research study employed a quasi-experimental design to investigate the effectiveness of the Edmentum Exact Path on students' mathematics achievement, affective engagement, and cognitive engagement. A quasi-experimental design is particularly suited for educational research where random assignment may not be feasible (Gopalan, Rosinger, and Ahn 2020). This design allows for comparison between groups and assessing the intervention's impact while acknowledging potential limitations in controlling all variables (Rogers and Revesz 2019). Edmentum Exact Path was chosen for this study due to its recent adoption by the school district and its alignment with the Georgia Standards of Excellence (GSE) mathematics curriculum (Edmentum 2023a, 2023b). This ensures consistency with existing educational standards, enhancing the study's ecological validity.

3.4.2 Participant Selection and Ethical Considerations

The study targeted students in rural areas, a demographic often underrepresented in educational research. The non-random selection was ethically guided to ensure no student was denied access to potentially beneficial resources (Kumar 2018). This approach underscores the importance of ethical considerations in educational research, particularly when interventions could significantly impact student learning. Parental consent was obtained for each participating student.

3.4.3 Sample Size and Group Composition

The sample size was determined through a statistical power analysis to ensure that the study had enough participants to detect the effects of the intervention reliably. Based on statistical power analysis, a sample size of 50 students per group was determined to be necessary. Despite efforts to achieve the sample size recommended by the power analysis, participation was restricted to students who returned the consent forms. In total, 78 consent forms were returned, with 43 students in the experimental group, 15 in control group 1, and 20 in control group 2. The experimental and control group 1 comprised solely economically disadvantaged students, while control group 2 included 56% economically disadvantaged students. Incorporating exclusively economically disdvantaged groups and a mixed-economic status group allows the study to examine the intervention's effectiveness across different socioeconomic backgrounds, adding depth to the analysis.

In 2022, according to data from the Georgia Department of Education (GaDOE 2022a, 2022b), 31% of students in Georgia achieved at or above the National As-

sessment of Educational Progress (NAEP) Proficient level in mathematics. The proficiency levels varied significantly across different school districts: 8% of students in School District 1 and 4% in School District 2 demonstrated math proficiency, markedly below the state average. In contrast, School District 3 exhibited slightly above-average math proficiency, with 33.8% of its students performing at or above the proficient level (see Table 3.1).

TABLE 3.1 | Student demographics: Gender, ethnicity, economically disadvantaged, and math proficiency.

Characteristics	**District 1** (Experimental)	**District 2** (Control Group 1)	**District 3** (Control Group 2)
Gender			
Male	54%	56%	53%
Female	46%	44%	47%
Ethnicity			
Caucasian	6.83%	24.26%	71.48%
Minority (incl. African American)	93.17%	74.5%	28.52%
African American	84.96%	56.72%	16.11%
Economically Disadvantaged	100%	100%	56%
Math Proficiency	8%	4%	33.8%

Note. Demographic data are from GaDOE (2022a, 2022b).

3.4.4 Study Duration and Instructional Methods

The study spanned 5 weeks, with daily sessions of 50 min each. Teachers utilized the 8th-grade McGraw-Hill math curriculum "Reveal" and incorporated Edmentum Exact Path as a supplemental tool for the experimental group. The experimental and control groups received teacher-led instruction, but the experimental group also had Edmentum Exact Path-led instruction in their mathematics support class for the same duration. In the mathematics support class, students worked at their own pace on personalized learning paths created by Edmentum Exact Path based on diagnostic assessments conducted at the beginning of the school year. Lessons in these paths were grouped into sets of three or four, targeting the students' specific achievement levels. After completing each lesson, students took a short quiz. Upon finishing a set of lessons, they took a progress check. Students who passed the progress check with at least 80% accuracy received a new set of lessons. Those who did not pass were assigned additional lessons to develop the necessary skills.

The teacher dashboard provided a color-coded, interactive view of each student's progress, indicating whether students were struggling, had failed, mastered, or omitted lessons. Teachers could offer one-on-one help to struggling students or

assign additional activities, such as extra lessons or short videos, to help them understand the concepts. Edmentum Exact Path awarded badges and trophies for each skill mastered to motivate students. Integrating Edmentum Exact Path into the existing curriculum could provide insights into how AI-based educational tools can be effectively incorporated into standard teaching practices.

3.4.5 Assessment Development and Administration

Both experimental and control groups completed the pretest before the instructional intervention and took the same test as the posttest upon completion of the unit. The administration of the pretest/posttest was carried out under the supervision of the teachers, who were provided with the necessary materials by the researcher before the onset of the study. Although all students participated in the pretest/posttest, data collection was restricted to those who consented to participate in the research study. All students completed the pretest and posttest within the 60-min testing window.

3.4.6 Student Engagement Measurement

SEI is a brief 35-item self-reporting survey that measures students' cognitive and affective engagement in the school (Appleton, Christenson, and Furlong 2008) and is used to measure student engagement. The SEI is a 5-point Likert scale varying from strongly agree, agree, disagree, to strongly disagree. The low scores indicate a high level of student engagement. The reliability of this scale in terms of internal consistency ranged from 0.76–0.88, and the test–retest interrater was 0.60–0.62. The criterion-related validity reported positive correlations between engagement and academic performance indicators.

3.4.7 Data Analyses

This quasi-experimental study incorporates a range of descriptive and inferential statistics to examine the effects of Edmentum Exact Path-led versus teacher-led instructions on student engagement. The statistical analyses employed include the independent sample *t*- test and ANOVA, which were utilized to identify the statistical significance of mean differences between the Edmentum Exact Path-led and teacher-led groups. The SEI survey was administered to assess student engagement.

3.5 Results

To address RQ1, pretest and posttest data from 8th-grade math were compared. A two-tailed paired sample *t*-test was conducted to evaluate the differences in mathematics achievement between students receiving instruction from Edmentum Exact Path and those receiving traditional teacher-led instruction. The experimental group using Edmentum Exact Path showed a mean increase from 30.76 (SD =

14.74) on the pretest to 36.05 (SD = 16.80) on the posttest, with a statistically significant improvement. A paired-sample *t*-test revealed a significant improvement in scores, $p = 0.03$ (one-tailed), $p = 0.05$ (two-tailed). Control Group 1, receiving traditional instruction, exhibited a mean increase from 27.21 (SD = 10.03) to 38.93 (SD = 21.57), with a one-tailed p value of 0.04 and a two-tailed p value of 0.09, indicating marginal improvement. Control Group 2, also receiving traditional instruction, showed a substantial mean increase from 34.00 (SD = 13.47) to 48.53 (SD = 21.21), with highly significant *t*- test results, $p = 0.002$ (one-tailed), $p = 0.004$ (two-tailed) (see Table 3.2).

TABLE 3.2 | Paired two-sample *t*-test for means indicating students' performance in the experimental and control groups.

	Experimental Group		**Control Group 1**		**Control Group 2**	
	Pretest	**Posttest**	**Pretest**	**Posttest**	**Pretest**	**Posttest**
Mean	30.76	36.05	27.21	38.93	34.00	48.53
SD	14.74	16.80	10.03	21.57	13.47	21.21
Variance	222.58	288.24	100.18	328.53	179.78	408.49
Observations (n)	42	42	14	14	19	19
Pearson Correlation	0.42		–0.35		0.41	
t Statistic	–1.99		–1.86		–3.30	
p (one-tail)	.03		.04		.002	
p (two-tail)	.05		.09		.004	

These findings suggest that while Edmentum Exact Path led to significant gains in mathematics achievement, traditional instruction, particularly in Control Group 2, resulted in more substantial improvements. It is essential to note that both the experimental group and Control Group 1 comprised 100% economically disadvantaged students, with below-average math proficiency rates of 8% and 4%, respectively. In contrast, Control Group 2 included only 56% of economically disadvantaged students, with a math proficiency rate of 33.8% (see Table 3.1), which is slightly higher than the state average of 31%.

Based on the findings, it can be concluded that AI-based systems, such as Edmentum Exact Path, have the potential to enhance mathematics achievement in students from socioeconomically disadvantaged backgrounds with lower mathematics proficiency. This improvement is likely because the AI-based system creates individual learning paths based on students' current knowledge. Students from these socioeconomic backgrounds often lack basic math skills, and AI-based systems can fill these gaps. Since AI-based systems provide meaningful personalized learning experiences (Harry 2023; Terzieva, Ivanova, and Todorova 2022), they are particularly beneficial in rural areas where access to highly qualified teachers is often limited (García and Weiss 2020; Ingersoll and Tran 2023; Lazarev et al. 2017; Monk 2007; Shikalepo 2020). Schools can better support student learning and help close

achievement gaps by supplementing traditional instruction with AI-based tools.

Additionally, a one-way ANOVA (Analysis of Variance) was conducted to compare the effectiveness of Edmentum Exact Path-led instruction versus teacher-led instruction on students' mathematics achievement. The F value is 0.65, with a p value of 0.52 and an F critical value of 3.12 (see Table 3.3). Since the F value is lower than the F critical value and the p value is greater than 0.05, we conclude that there is no statistically significant difference between the groups in terms of their means. While the t-tests suggest improvements in mathematics achievement, the ANOVA results indicate no significant differences between the groups.

TABLE 3.3 | ANOVA: Single factor indicating student performance in the experimental and control groups.

Summary

Groups	Count	Sum	Average	Variance
Experimental group	43	1323	30.77	217.28
Control group 1	15	419	27.90	100.78
Control group 2	20	665	33.25	181.57

ANOVA

Source of variation	SS	df	MS	F	p	F critical
Between groups	243.09	2	121.55	0.65	0.52	3.12
Within groups	13986.35	75	186.48			
Total	14229.44	77				

It is important to acknowledge that the small sample size might have influenced the results, and the presence of confounding variables such as prior academic achievement, motivation and interest, socioeconomic status, classroom environment, and other factors could have impacted the outcome of this study. The outcome of this study could have been different if random assignments had been employed among the students. This study could not be randomized because it would be unethical to prevent students from accessing Edmentum Exact Path or potentially missing out on the positive outcomes it could offer. The school administration preferred not to restrict student access to the program for ethical reasons. These findings show that Edmentum Exact path-led and traditional teacher-led instructions significantly improved students' mathematics achievement; however, no significant difference was observed between the two instructional approaches. To generalize the findings of this research study, it is imperative to conduct further research with large sample sizes while considering confounding variables. This will provide more conclusive insights into the effectiveness of the Edmentum Exact Path compared to teacher-led instructions. Additional research is warranted to gain a broader understanding

of the impact of the Edmentum Exact Path as a supplemental tool for enhancing mathematics achievements among students from socioeconomically disadvantaged backgrounds. This will help extend the applicability of the current study's findings.

To ensure the validity of this study, we conducted an ANOVA analysis on the pretest scores across the three groups to confirm initial equivalence in math proficiency. The F value of 0.65 is much lower than the critical F value of 3.12. Additionally, the p value of 0.53 is significantly higher than the commonly used significance level threshold of 0.05 (see Table 3.4). This indicates that there is no statistically significant difference in pretest scores between the experimental group and the two control groups.

The SEI survey, which measures overall student engagement, was administered at the end of the posttest to address Research Questions 2 and 3.

TABLE 3.4 | ANOVA: Single factor for pre-test scores among experimental and control groups.

Summary

Groups	Count	Sum	Average	Variance
Experimental group	43	1325	30.81	215.68
Control group 1	15	419	27.93	100.78
Control group 2	20	665	33.25	181.57

ANOVA

Source of variation	SS	*df*	MS	*F*	*p*	*F* critical
Between groups	242.77	2	121.38	0.65	0.53	3.12
Within groups	13919.20	75	185.59			
Total	14161.96	77				

The SEI survey comprises two categories, affective and cognitive engagement, each with three variables. Affective engagement includes Teacher-Student Relationships (TSR), Peer Support at School (PSS), and Family Support for Learning (FSL). For cognitive engagements, the three variables are Control and Relevance of Schoolwork (CRSW), Future Aspirations and Goals (FG), and Intrinsic Motivation (IM). The average affective engagement was calculated using the values of TSR, PSS, and FSL. Similarly, the average cognitive engagement was calculated from CRSW, FG, and IM values.

For affective engagement (RQ2), the means are as follows: experimental group has a mean of 3.23, control group 1 has a mean of 3.69, and control group 2 has a mean of 3.76 (see Table 3.5). While the mean scores for affective engagement were higher in the control groups than in the experimental groups, it is important to note that it is only one aspect of overall instructional effectiveness. The slight differences in mean scores do not conclusively support the superiority of one instructional method over the other. Additionally, the small sample size and a lack of presurvey could contribute to these findings.

TABLE 3.5 | Average means: Affective and cognitive engagement across groups.

	Affective engagement	**Cognitive engagement**
Experimental group	3.23	3.66
Control group 1	3.69	3.75
Control group 2	3.76	3.62

A one-way ANOVA was conducted to determine if there was a statistically significant variation in affective engagement (RQ2). The ANOVA results showed a significant difference in affective engagement between the groups, with an F value of 8.67 and a p value of 0.0004, below the conventional threshold of 0.05 (F critical value = 3.11) (see Table 3.6). These findings indicate that traditional teacher-led instruction results in higher affective engagement compared to Edmentum Exact Path.

TABLE 3.6 | ANOVA: Single factor for affective engagement scores among experimental and control groups.

Summary

Groups	Count	Sum	Average	Variance
Experimental group	43	139	3.23	0.24
Control group 1	15	55.4	3.69	0.23
Control group 2	20	75.2	3.76	0.39

ANOVA

Source of variation	SS	*df*	MS	*F*	*p*	*F* critical
Between groups	4.84	2	2.42	8.67	0.0004	3.11
Within groups	20.93	75	0.28			
Total	25.77	77				

These results suggest that traditional teacher-led instruction positively impacts students' affective engagement, possibly due to emotional connections that students form with teachers. Future research should consider a larger sample size and a pre-survey to capture baseline engagement levels before the intervention.

To address RQ3, the average means were calculated, the average scores were as follows: experimental group ($M = 3.67$), control group 1 ($M = 3.75$), and control group 2 ($M = 3.62$) (see Table 3.7). A one-way ANOVA was conducted to determine if there was a statistically significant variation in cognitive engagement. The results indicated no significant difference between the groups, with an F value of 0.29 and a p value of 0.74, above the threshold of 0.05 (F critical value = 3.11) (see Table 3.7). This suggests that both AI-based and traditional teacher-led instruction have similar effects on cognitive engagement.

TABLE 3.7 | ANOVA: Single factor for cognitive engagement scores among experimental and control groups.

Summary

Groups	Count	Sum	Average	Variance
Experimental group	43	157.8	3.67	0.13
Control group 1	15	56.3	3.75	0.46
Control group 2	20	72.4	3.62	0.39

ANOVA

Source of variation	SS	*df*	MS	*F*	*p*	*F* critical
Between groups	0.15	2	0.08	0.29	0.74	3.11
Within groups	19.34	75	0.26			
Total	25.77	77				

These findings suggest that while Edmentum Exact Path is comparable to traditional instruction in promoting cognitive engagement, it may not be as effective in fostering affective engagement. These insights can guide educators and policymakers in

integrating AI-based learning tools into educational settings, recognizing the need for a balanced approach that supports both the affective and cognitive aspects of student engagement. Further research and analysis of additional variables are needed to gain a deeper understanding of the factors influencing cognitive engagement in the instructional setting.

3.6 Discussion

The integration of AI-based systems in education promises adaptive and personalized learning (D'Mello and Graesser 2023; Nagashima et al. 2022; Pane et al. 2014; Phillips et al. 2020; Rodrigues et al. 2023; Terzieva, Ivanova, and Todorova 2022; VanLehn 2011; Xie et al. 2019). However, there is a gap in research on the impact of AI-based systems on students' mathematics achievement and engagement in rural settings. While existing studies have documented the positive effects of AI-based systems on mathematics achievement (Ma et al. 2014; Pane et al. 2014; Nye et al. 2018; Steenbergen-Hu and Cooper 2013; Wang et al. 2023c), there is a lack of research focusing on their effectiveness in rural areas where resources and skilled teachers are limited. To address this gap, the current study examined the effectiveness of Edmentum's Exact Path, an AI-based system, on students' mathematics achievement and engagement, particularly among students from socioeconomically disadvantaged backgrounds. Using paired *t*-tests and ANOVA, this study analyzed differences in mathematics achievement and engagement between an experimental group using Edmentum Exact Path, designed to enhance students' learning experiences (McLeod 2017; Wang et al. 2023b), and two control groups receiving traditional teacher-led instruction, with data collected through pre-tests, post-tests, and SEI measures of affective and cognitive engagement.

This research study found mixed results, with *t*-tests indicating that the experimental group using Edmentum Exact Path improved significantly in mathematics achievement compared to Control Group 1, suggesting AI-based systems can enhance performance. However, Control Group 2, with slightly higher math proficiency and fewer socioeconomically disadvantaged students showed significant improvement with teacher-led instruction. ANOVA results revealed no statistically significant differences in mean scores between the groups, indicating that while individual improvements were noted, there was no definitive advantage for any instructional method overall. The significant improvement observed in Control Group 2 could be attributed to their baseline math proficiency being above the state average, and the presence of fewer socioeconomically disadvantaged students. These factors are supported by research indicating a strong correlation between academic achievement and socioeconomic status (Haveman and Wolfe 1995; Martin et al. 2012; Reeves 2012; Sirin 2005; Vadivel et al. 2023).

The mixed results from this study can be explained using the framework of the Affective Dynamics Model (D'Mello and Graesser 2012). AI-based systems like Edmentum Exact Path support mathematics learning by resolving cognitive disequilib-

rium encountered during challenging problems. The built-in feedback of Edmentum Exact Path provides hints to solve these problems, helping students return to cognitive equilibrium and remain engaged in the learning process (D'Mello and Graesser 2012; D'Mello et al. 2014). The Stein and Levine Model further support these findings. According to Stein and Levine (2013), setting specific learning goals can influence students' emotional engagement, as achieving these goals is tied to their emotional states. In traditional teacher-led settings, teachers can help students set and achieve personalized learning goals, providing the emotional support and encouragement needed to foster both cognitive and affective engagement. Therefore, the presence of a supportive teacher who can address both the cognitive and emotional needs of students might explain why traditional instruction shows higher levels of affective engagement compared to AI-based systems.

This research contributes to the literature by directly reporting the effects of AI-based systems on the math learning of students from socioeconomically disadvantaged populations. This study's findings align with the results from several research studies, indicating that AI-based systems positively affect mathematics achievement in disadvantaged populations from rural areas (Feng, Huang, and Collins 2023; Huang et al. 2016). Since AI-based systems are comparable to teacher-led instruction, they can be used as a supplemental tool to provide personalized learning experiences (Terzieva, Ivanova, and Todorova 2022). This personalized instruction is particularly valuable for socioeconomically disadvantaged students who lack basic mathematical skills and may need additional support. AI-based systems can support teachers by freeing up their time and allowing them to provide one-on-one help to struggling students. Moreover, schools in rural areas often struggle to find highly qualified teachers (García and Weiss 2020; Ingersoll and Tran 2023; Lazarev et al. 2017; Monk 2007; Shikalepo 2020), which can negatively influence students' mathematics achievement. AI-based systems have the potential to supplement instruction by providing high-quality, personalized education (Harry 2023; Terzieva, Ivanova, and Todorova 2022).

Notably, the field study employed Edmentum Exact Path as a supplemental tool to support student learning during school hours. VanLehn (2011) identified limitations in studies comparing AI-based systems to human tutoring, noting that the small number of experiments and partial replacements of activities like homework made it difficult to attribute learning gains solely to AI-based systems. By exclusively using Edmentum Exact Path for instruction, the current study addresses these issues, allowing for the direct attribution of positive changes to the AI-based system.

A meta-analysis by Ma et al. (2014) compared AI-based systems to non-AI learning environments and revealed that AI-based system use was associated with higher achievement compared to teacher-led, large-group instruction ($g = 0.42$), non-AI computer-based instruction ($g = 0.57$), and textbooks or workbooks ($g = 0.35$). There were no significant differences between learning from AI-based systems and individualized human tutoring ($g = 0.11$) or small-group instruction ($g = 0.05$). Positive effect sizes were consistent across various uses of AI-based systems, educa-

tional levels, subject domains, and regardless of feedback or modeling of student misconceptions. These findings are directly relevant to the present study, suggesting that Edmentum Exact Path can significantly enhance student achievement in the current educational context.

Clément et al. (2024) conducted a field study comparing a learning progress-based (LP-based) automatic curriculum generation system with a hand-designed curriculum, both with and without self-choice. The findings suggested that LP-based personalization improves learning performance while producing a positive and motivating learning experience. These results align with the present research using Edmentum Exact Path, an AI-based system, to support student learning. Both studies highlight the effectiveness of personalized AI-based systems in enhancing student outcomes.

Huang et al. (2016) conducted a study on 6th-grade students from economically disadvantaged backgrounds to investigate performance gaps in mathematics education and the role of Intelligent Tutoring Systems (ITS) in reducing these gaps in an after-school setting. The findings suggested that ITS particularly benefits disadvantaged individuals and groups. These results align with the present research, which uses Edmentum Exact Path, an AI-based system, to support student learning. Craig et al. (2013) evaluated the efficacy of ALEKS, an AI-based system for mathematics instruction in an after-school setting. They found no significant differences in mathematics performance between the ALEKS-led instruction and teacher-led instruction groups. Pane et al. (2014) reported mixed results from their study evaluating the efficacy of Cognitive Tutor Algebra, with no statistically significant differences in algebra proficiency in the first year, but statistically significant results in the second year for high school students.

The findings of this research study that evaluated the effectiveness of AI-based systems suggested that they can facilitate student learning. This research study contributes to the existing literature (Craig et al. 2013; Fang et al. 2019; Feng, Huang, and Collins 2023; Hu et al. 2013; Pane et al. 2014; Phillips et al. 2020; Xie et al. 2019) by demonstrating the effectiveness of AI-based systems in improving mathematics achievement in socioeconomically disadvantaged students from rural areas. However, our conclusions should be interpreted with caution, and further research is needed to validate these findings in different contexts and with other AI-based instructional tools.

A more pronounced distinction emerged in affective engagement, where ANOVA results indicated a significant variance among the groups. Students who received traditional teacher-led instruction exhibited higher levels of affective engagement than those using the AI-based system. This finding aligns with similar studies indicating that AI-based systems lack emotional awareness and empathy (Kort, Reilly, and Picard 2001; Lin, Wu, and Hsueh 2014; Malekzadeh, Salim, and Mustafa 2014). This finding raises critical questions about the AI-based system's capacity to emotionally engage students, which is a vital component of the learning process (Reyes et al. 2012). These results suggest that while AI-based tools like Edmentum Exact Path

can be effective in certain aspects of learning, they might not fully address all learning facets, particularly affective engagement, and suggest that human interaction plays a significant role in emotional engagement. However, it is important to consider that the higher levels of affective engagement in teacher-led instruction could be due to pre-existing higher engagement levels and the small size of the control groups. Additionally, the absence of a pre-survey to establish baseline engagement levels further limits the strength of our conclusions.

In contrast, cognitive engagement showed no significant differences across the instructional methods, indicating that AI-based systems like Edmentum Exact Path are comparable to traditional methods in fostering cognitive engagement among students. However, the lack of significant cognitive engagement suggests that neither teacher-led nor AI-led instruction clearly fosters cognitive engagement and might even decrease it. The absence of a pre-survey to establish baseline engagement levels makes it difficult to draw convincing conclusions.

While AI-based systems effectively support cognitive engagement by addressing cognitive disequilibrium, they may not significantly impact affective engagement due to a lack of emotional awareness and empathy. Human interaction, characterized by empathy and emotional awareness, is a critical component of traditional teacher-led instruction (Reyes et al. 2012). Consequently, traditional teacher-led instruction may have a more significant impact on the affective components of learning.

While the study did not find a statistically significant difference in cognitive engagement between teacher-led instruction and Edmentum Exact path-led instruction, it is worth noting that previous research has demonstrated mixed results in this regard. Further examination into the impact of AI-based systems on cognitive engagement, considering variables such as instructional design, student characteristics, and learning outcomes, would contribute to a deeper understanding of their effectiveness.

In contemporary K-12 classroom settings, AI-based systems have gained prominence for their ability to provide tailored instruction to suit individual students' specific needs, backgrounds, and experiences. This research highlights the practical significance of AI-based systems, such as Edmentum Exact Path, in improving mathematics achievement and enhancing student engagement of socioeconomically disadvantaged students in rural areas. It is worth noting that teacher-led instruction may be equally effective. These findings have important implications for educators and policymakers seeking to enhance mathematics achievement from socioeconomically disadvantaged backgrounds. The practical implications of this study suggest that AI-based systems, like Edmentum Exact Path, can serve as valuable tools to support mathematics learning, particularly for socioeconomically disadvantaged students from socioeconomically disadvantaged backgrounds. Implementing AI-based systems in schools, especially in rural areas where access to highly qualified teachers may be limited (Garcéa and Weiss 2020; Ingersoll and Tran 2023; Lazarev et al. 2017; Monk 2007; Shikalepo 2020), can provide additional instructional support and personalized learning experiences. Furthermore, AI-based systems can serve

as supplemental tools in school and home settings. AI-based systems can provide credit opportunities for struggling students in after-school or summer school settings.

This research study adds to the growing body of literature on AI-based systems in education and their impact on student achievement and engagement. While the findings indicate the positive effect of Edmentum Exact Path on mathematics achievement, further research is needed to explore the broader implications, effectiveness, and potential limitations of AI-based systems in diverse educational contexts. By leveraging the strengths of AI-based systems and recognizing the unique contributions of teachers, educational stakeholders can make informed decisions about integrating these technologies to support teaching and improve student learning outcomes.

3.7 Limitations and Future Directions

This research study demonstrates the effectiveness of AI-based systems in improving the mathematics achievement of socioeconomically disadvantaged students. The experimental design allowed for rigorous control over variables, enhancing the internal validity of the findings. By conducting the study in a naturalistic setting, it was possible to capture the real-world impact of AI-based systems on students' learning outcomes. In contrast, field studies often face challenges with confounding variables such as prior academic achievement, personal interest, teaching styles, teacher quality, peer influence, and other external factors that can impact mathematics achievement.

However, several limitations should be acknowledged. A small sample size and the lack of a pre-survey are notable constraints that may impact the study's rigor and the generalizability of the findings. Despite efforts to achieve the sample size recommended by the power analysis, participation was restricted to students who returned the consent forms. Future study designs could be improved by considering a larger and more diverse sample size to enhance the generalizability of findings across different demographics and educational settings. Additionally, utilizing a pre-survey to capture the mean scores of the class before the intervention would strengthen the conclusions on the impact of AI-based systems in improving mathematics achievement and engagement. The metric of affective engagement alone is not sufficient to declare teacher-led instruction more effective than AI-based instruction. Higher levels of affective engagement in teacher-led instruction could be due to pre-existing higher engagement levels and the small size of the control groups, which may impact the conclusiveness of our findings. The lack of significant differences in cognitive engagement suggests that neither instructional methods clearly fosters cognitive engagement and might even decrease it. The absence of a pre-survey to establish baseline engagement levels further limits the strength of our conclusions. The variability in baseline math proficiency and socioeconomic status among the groups complicates direct comparisons and interpretations.

The COVID-19 pandemic imposed unique challenges that significantly affected our research as data were collected during the 2021-22 school year. School closures in rural Georgia led many parents to transition their children to homeschooling or remote learning, resulting in a reduced sample size (Lee et al. 2021). Moreover, some students were absent during certain phases of the study due to COVID-19 infections in their families, further reducing the number of participants available and limiting data collection. These disruptions likely influenced the engagement and performance data in our study. Future research should use the same sample population, as students previously unavailable due to the pandemic may now be accessible, allowing for a more comprehensive understanding of student engagement and achievement.

Future research should address these limitations by incorporating larger, more diverse samples and employing random assignments to increase validity and reliability. Including a pre-survey to capture the mean engagement scores of the class before the intervention would provide a clearer understanding of the impact of AI-based systems on student engagement. Incorporating qualitative data, such as student interviews or classroom observations, would also provide richer insights into students' experiences and perceptions of different instructional approaches.

Conducting similar studies with AI-based systems, such as Edmentum Exact Path, can provide broader insights into their effectiveness in improving mathematics achievement. Furthermore, examining the integration of AI-based instruction with traditional methods will be crucial for optimizing educational outcomes. Investigating the long-term effects of AI-based systems on academic performance, retention rates, and career trajectories would offer a more comprehensive understanding of their impact on student success. While this study examines student outcomes, it does not explore teachers' perspectives on implementing AI-based systems in the classroom. Understanding teachers' experiences, challenges, and perceptions could inform strategies for effectively integrating technology into instructional practices. Future research should include qualitative methods to capture these perspectives and provide a holistic view of the implementation process.

Many confounding variables can impact this study's results, including prior academic achievement and motivation. Future research on the effects of Edmentum AI on the mathematics achievement of students from South Georgia should delve deeper into these variables. Specifically, factors such as teacher effectiveness, socioeconomic status, parental involvement, access to technology, learning environment, student engagement, attendance, and health and well-being (Konstantopoulos 2009; Reeves 2012; Reardon 2018; Roorda et al. 2011; Singh 2015) should be considered. Examining these variables will provide a more comprehensive understanding of the influences on student learning and engagement, thereby validating the findings and informing strategies for effectively integrating AI-based systems in diverse educational contexts.

3.8 Conclusion

This study explored the effectiveness of AI-based systems, specifically Edmentum Exact Path, in enhancing mathematics achievement and engagement among students from socioeconomically disadvantaged backgrounds in rural areas. The findings indicate that AI-based systems can significantly improve mathematics achievement in these populations. AI-based systems, comparable to teacher-led instruction, can be used as a supplemental tool to provide personalized learning experiences. This personalized instruction is particularly valuable for economically disadvantaged students who lack basic mathematics skills and may need additional support.

AI-based systems support teachers by freeing up their time (Harry 2023), allowing them to provide one-on-one help to struggling students. This is especially crucial in rural areas, where schools often struggle to find highly qualified teachers (Garcéa and Weiss 2020; Ingersoll and Tran 2023; Lazarev et al. 2017; Monk 2007; Shikalepo 2020), negatively impacting students' mathematics achievement. High-poverty and high-minority schools in the United States had four times more uncertified teachers compared to low-minority schools (Sutcher, Darling-Hammond, and Carver-Thomas 2016).

AI-based systems have the potential to supplement instruction by providing high-quality, personalized education, adapting to individual students' needs, and supporting both traditional and remote classroom environments (D'Mello and Graesser 2023; Ma et al. 2014; Phillips et al. 2020). The transformative influence of emerging educational technologies is causing a paradigm shift in the teaching and learning processes. AI-based systems continuously evolve and can maximize learning based on individual students' knowledge, preferences, and readiness levels (D'Mello and Graesser 2023; Wang et al. 2023a). Teachers play a pivotal role in enhancing the effectiveness of students' learning by harmoniously integrating these AI-based systems with effective pedagogical approaches (Kinshuk et al. 2016; Wang, Liu, and Tu 2021). While higher levels of affective engagement were observed in teacher-led instruction, each instructional method has unique strengths.

Due to limitations such as the small sample size, lack of pre-survey data, and variability in baseline math proficiency and socioeconomic status, these results should be interpreted with caution. Despite these limitations, this study makes a valuable contribution to the existing body of research by examining the effectiveness of Edmentum Exact Path as a supplementary tool for enhancing students' mathematics achievement and supporting teaching and learning processes. The significance of this study lies in the limited availability of research on Edmentum Exact Path, making it one of the pioneering studies in this area.

Previous studies have shown a positive association between AI-based systems and students' academic achievement and test scores (Alrakhawi, Jamiat, and Abu-Naser 2023; Appleton, Christenson, and Furlong 2008; Pane et al. 2014; Schacter 1999; Xie et al. 2019). However, it is important to acknowledge that the effectiveness of AI-based systems also depends on teachers and their implementation of pedagogical

practices in K-12 classrooms. Additionally, Miller, Votruba-Drzal, and Setodji (2013) highlighted the association between mathematics achievement and school location, with rural area schools exhibiting lower overall achievement compared to urban areas (Dronkers and Robert 2008).

Focusing on socioeconomically disadvantaged students, this research provides insights into the potential use of AI-based systems to bridge the achievement gap and support students' mathematics learning. Integrating AI-based systems like Edmentum Exact Path shows promise in addressing these challenges and enhancing socioeconomically disadvantaged students' mathematics achievement. While this study sheds light on the effectiveness of Edmentum Exact Path as a supplemental tool, further research is needed to explore its broader implications, effectiveness, and potential limitations.

Future research could investigate the impact of different AI-based systems, compare their efficacy with Edmentum Exact Path, and consider additional factors such as instructional design, student characteristics, and learning outcomes. By leveraging the strengths of AI-based systems, educators and policymakers can make informed decisions to integrate these emerging technologies effectively, ultimately enhancing student learning outcomes in mathematics and beyond.

Author Contributions

Rashmi Khazanchi: conceptualization, methodology, investigation, writing-review and editing, validation, writing-original draft, formal analysis. **Daniele Di Mitri:** supervision, writing-review and editing, validation. **Hendrik Drachsler:** supervision, validation, writing-review, and editing.

Conflicts of Interest

The authors declare that they have no conflicts of interest related to this research, including financial interests, employment, affiliations, or personal relationships that could influence the results or interpretation of the work presented in this manuscript.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Part III

Systematic Literature Review

Chapter 4

Impact of Artificial Intelligence-Based Systems on Mathematics Achievement: A Systematic Review

ABSTRACT

Purpose: The integration of artificial intelligence (AI) in education is gaining momentum, with recent breakthroughs in AI technology enabling the development of advanced AI-based learning systems. These intelligent adaptive learning systems are increasingly integrated into K-12 educational settings due to their ability to adapt academic content to meet individual student needs, offering a more personalized and effective learning experience. Several studies have explored the use of AI-based systems in both K-12 and higher education. This systematic literature review aims to investigate the types of AI-based systems used in mathematics education, the educational level at which they are implemented, the variation of its implementation based on socioeconomic status, and their impact on mathematics achievement in K-12 classrooms. This systematic literature review followed the guidelines of the Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) framework.

Methods: A literature review was conducted using six major databases: ACM Digital Library, ERIC (EBSCO), JSTOR, Wiley, ScienceDirect (Elsevier), and SpringerLink, in alignment with the PRISMA phases: identification, screening, eligibility, and inclusion. Peer-reviewed research articles between 2008 and 2023 were selected, focusing on three key research questions (RQs) related to AI-based Intelligent tutoring systems and their impact on mathematics achievement in K-12 classrooms. Excluded non-peer-reviewed articles such as books, news articles, magazines, posters, and non-English articles in other languages. Of the 1945 papers retrieved from six digital databases from 2008 to October 2023, 225 papers were short-listed based on title and abstract scanning. A total of 42 papers are finally included after applying our exclusion and inclusion criteria.

Results: A systematic literature review on AI-based systems found varying effect sizes and outcomes across elementary, middle, and high school levels. Most studies reported a positive impact on mathematics achievement, with effect sizes (Cohen's

d) ranging from significant (1.46) to very small (0.098). AI-based systems, including intelligent tutoring systems and adaptive learning systems, were primarily used as supplemental tools to enhance engagement, personalize learning, and support remediation. The finding highlights the potential of AI-based systems to narrow achievement gaps among students from diverse socioeconomic backgrounds and to improve mathematics learning, particularly for low-achieving students.

Discussion: The systematic review discusses the various AI-based systems used in mathematics education and their impact on mathematics achievement across different K-12 education levels. The study will examine whether AI-based systems will help reduce achievement gaps between students from low socioeconomic backgrounds, with the description of key features such as personalized learning, real-time feedback, and adapting to individual student needs.

Key Words: AI-based systems, artificial intelligence, intelligent tutoring systems, K-12 education, mathematics education, PRISMA, systematic literature review

4.1 Introduction

Artificial Intelligence in Education (AIED), from its inception in 1950 to the present, has evolved tremendously due to big data sets, development in computing power, and advanced algorithms (Duan et al., 2019). With the rapid advancement of technology, AI-based educational systems have evolved (Murtaza et al., 2022). They can adapt both content and assessments according to the learner's comprehension and knowledge level (Ercikan & McCaffrey, 2022). Among these AI-based learning systems are Intelligent tutoring systems (ITS), adaptive learning systems (ALS), and recommender systems (Kabudi et al., 2021). ITS is designed to deliver personalized instruction by adjusting the content presented based on the student's current knowledge in a particular domain and by providing support and feedback needed to learn and progress through the material (Clément et al., 2024; D'Mello & Graesser, 2023). These systems are built on a structured architecture comprising four modules: the student model, domain model, pedagogical model, and user interface model. By integrating these modules with cognitive theories, and AI, ITS can provide customized learning experiences (Kulik & Fletchers, 2016; Ma et al., 2014). ITS uses AI to simulate human tutoring, provide personalized feedback, and create learning paths based on the student's context (Hasanov et al., 2019; Nguyen et al., 2024). By analyzing student responses, ITS provide targeted feedback and select problems that align with the students' behavior and progress.

ALS use AI, machine learning, and item response theories to provide personalized learning by adjusting content, pace, and instruction to match individual students' needs and current knowledge (Wang et al., 2023). ALS make instructional decisions based on three modules: domain model, student model, and task model (Lee & Park., 2008). These systems adjust the sequence, difficulty, and timing of tasks while incorporating students' preferences to optimize the learning outcome. (Pliakos et al., 2019; Xie et al., 2019). By utilizing real-time data, ALS analyzes student performance and enables personalized instruction to enhance student engagement and learning (D'Mello & Graesser, 2023; Terzieva et al., 2022). ALS continuously monitors student interaction and progress, providing real-time feedback, targeted interventions, and tailored support (Gligorea et al., 2023; Kabudi et al., 2021). On the other hand, Recommender systems use machine learning and information retrieval techniques to suggest potentially helpful resources aligned with the user's interests (Syed et al., 2017).

In traditional teacher-led instruction, lessons are presented to the entire class, making it difficult to provide immediate feedback and personalized support to all students (González, 2018; Han, 2021). This one-size-fits-all approach can lead to disengagement (Kettlewell et al., 2012) and gaps in understanding, particularly in subjects like mathematics and science, where some students may require additional support. Adaptive learning systems offer a solution by using data-driven algorithms to personalize instruction in real-time. These systems leverage artificial intelligence and data analytics to continuously assess student performance, provide immediate feedback, and tailor learning pathways to meet individual needs (Gligorea et al.,

2023; Kabudi et al., 2021; Xie et al., 2019). By offering targeted support, adaptive learning enhances student engagement and ensures that those who need extra assistance receive the guidance necessary for academic success. AI-based systems have great potential to enhance teaching and learning because they are scalable, making it possible to support larger student bodies where one-on-one tutoring may not be feasible (Robinson et al., 2024). They can also bridge the achievement gap in rural areas, particularly where students are from socioeconomically disadvantaged backgrounds, and lack access to highly qualified teachers, especially in critical subjects like mathematics (Garcia & Weiss., 2020; Shikalepo., 2020). Research shows that AI-based systems are effective when used as a supplemental tool to improve mathematics learning among students from socioeconomically disadvantaged backgrounds (Khazanchi et al., 2025; Kretzschmar & Seitz, 2024; Yue et al; 2018).

The literature review of meta-analytic and systematic studies indicates that AI-based systems have shown mixed effects on mathematics achievement, with outcomes ranging from negative to positive. These differences highlight the need for a deeper investigation into the factors impacting the efficacy of AI-based systems in mathematics education. This SLR aims to explore the types of AI-based systems used in mathematics, the educational levels at which they are implemented, their impact on student performance, and their potential role in reducing achievement gaps across different socioeconomic backgrounds. To address these gaps, this study focuses on the following research questions:

RQ1. What types of AI-based systems are used in mathematics and at what education level?

RQ2. What is the impact of AI-based systems on students' mathematics performance in K-12 classrooms?

RQ3. Do AI-based systems reduce the achievement gap in mathematics from low socioeconomic backgrounds and what specific features contribute to this effect?

4.2 Background

4.2.1 AI-Based Systems

AI-based systems are increasingly being used in educational settings to improve student learning (Zhai et al., 2021). AI-based systems help to generate new content, make predictions of future events, and customized suggestions based on user needs (Olari & Romeike, 2024). Traditional teacher-led instructions have certain limitations, such as limited opportunities to provide personalized feedback and individual support (Altun, 2023). Conversely, numerous research studies have shown the benefits of individualized instruction. One-to-one human tutoring can improve learning performance by up to two standard deviations (Bloom, 1984; VanLehn, 2011). For decades, researchers have explored scalable methods to replicate the benefits of one-on-one tutoring, which has contributed to the development of AI-based sys-

tems. In recent years, AI-based systems have emerged as a valuable tool to support student-centered learning. By utilizing advanced machine learning algorithms and trained on large datasets, these AI-based systems can deliver real-time, personalized instructions to large groups of learners (Clément et al., 2024; Murtaza et al., 2023; Wang et al., 2023). While early intelligent tutoring systems (ITS) aimed at mimicking human tutors, recent adaptive learning systems have evolved substantially. Today's AI-based systems can dynamically adjust educational content based on a student's current knowledge, abilities, and learning needs by using predictive machine learning models, helping to close learning gaps and create tailored learning pathways (D'Mello & Graesser, 2023; Pliakos et al., 2019; Xie et al., 2019; Terzieva et al., 2022). These systems provide real-time assessments and feedback, allowing teachers to track student progress and identify areas that need attention (Pliakos et al., 2019; Xie et al., 2019). Providing immediate feedback helps students correct their errors in real time and clear up any misconceptions or misunderstandings behind those errors (Aleven et al., 2016). AI-based systems analyze student responses and generate immediate, specific feedback that enhances learning by adapting to each student's level of understanding (VanLehn., 2011). This feedback is often more detailed than what is typically provided by teachers in traditional classrooms, which can lead to improved conceptual understanding of the content (Somers et al., 2021). Dashboards embedded in AI-based systems provide insights into student performance and highlight patterns that inform instructional decisions (Aleven et al., 2022).

AI-based systems are most effective when used to supplement rather than replace traditional classroom instruction (Hillmayr et al., 2020; Kulik & Fletcher, 2016; Lewine et al., 2019; Young et al., 2018; Wang et al., 2023). Their success is influenced by factors such as grade level (Young et al., 2018), adherence to implementation guidelines (Lewine et al., 2019), and teacher training (Bernard et al., 2019; Firat & Firat, 2020; Hillmayr et al., 2020; Kabudi et al., 2021). The duration and structure of implementation also significantly affect the impact of AI-based systems. Short-term interventions that typically last one to six months with weekly sessions of 30 to 75 minutes have demonstrated greater effectiveness compared to longer implementations (Hillmayr et al., 2020; Kulik & Fletcher, 2016; Lewin et al., 2019; Steenbergen-Hu & Cooper, 2013; Ran et al., 2021). These AI-based systems also tend to yield stronger results on locally developed assessments than on standardized tests, suggesting that alignment with specific instructional contexts enhances their overall effectiveness (Kulik & Fletcher, 2016).

4.2.2 AI-Based Systems in K-12 Classrooms

AI-based systems are increasingly being adopted in K-12 settings. These emerging technological tools are transforming teaching practices, the role of teachers, and how students engage with learning. These AI-based systems assist teachers with providing differentiated instructions and feedback in writing and problem-solving in areas such as mathematics (Murphy, 2019). AI-based systems are designed to promote

mastery learning, allowing students to progress only after achieving a specified level of understanding. These systems adapt instructional content to align with each student's current knowledge level (Murphy, 2019). They also conduct frequent assessments, continuously monitor student progress, and provide automated feedback to support learning (Ma et al., 2014; VahnLehn, 2011). In the United States, numerous AI-based systems have been adopted in K-12 classrooms, including ALEKS, ASSISTments, AutoTutor, Cognitive Tutor, Edmentum, Khan academy, iReady, MATHia, Maths-Whizz, Dreambox Learning, and Woot Math (Bush, 2021; Craig et al., 2013; Dutta et al., 2024; Fancsali et al., 2023; Feng et al., 2023; Graesser, 2016; Grant et al., 2023; Mavrikis et al., 2022; Pane et al., 2014; Khazanchi et al., 2025; Ulum, 2023).

In K-12 educational settings, the effectiveness of AI-based systems is influenced by factors such as instructional role, teacher involvement, and classroom integration strategies (Bernard et al., 2019; Hillmayr et al., 2020). Teacher guidance plays a critical role in enhancing the impact of AI-based systems. Bernard et al. (2019) compared the effectiveness of adaptive, student-centered instruction with traditional teacher-centered approaches in K-12 education. Their findings indicated moderate improvements under adaptive and individualized conditions. The teacher's role in mentoring and guiding students appeared promising, while adaptability and flexibility had no significant impact. Interestingly, self-paced learning had a negative effect when implemented in a student-centered approach. Similarly, Kabudi et al. (2021) and Firat and Firat (2020) found that ITS and ALS significantly improved mathematics achievement when paired with strong teacher involvement. Firat and Firat (2020) noted that Web 3.0 tools, such as 3D visual environment, produced medium to large effect sizes in math learning when integrated thoughtfully into instruction. Li and Ma (2010) demonstrated the positive impact of computer technology (CT) on K-12 math learning, particularly among elementary and special education students. Grade level also emerged as a moderating factor in Young et al. (2018), where higher effectiveness was observed in younger learners.

4.2.3 AI-Based Systems in Mathematics

AI-based systems have demonstrated a positive impact on mathematics performance by enhancing problem-solving skills (del Olmo–Muñoz, 2022; Harskamp & Suhre, 2006), fostering critical thinking, enhancing conceptual understanding, and increasing overall achievement (Jia et al., 2024). These AI-based systems are increasingly integrated into K-12 classrooms to improve learning outcomes, particularly in basic mathematics instruction (Mohamed et al., 2022). Emerging research continues to validate these findings. Several meta-analyses have reported consistent positive impacts on mathematics achievement, showcasing the effectiveness of ITS and ALS (Firat & Firat, 2020; Kabudi et al., 2021; Kulik & Fletcher, 2016; Lewine et al., 2019; Li & Ma, 2010; Steenbergen-Hu & Cooper, 2013; Young et al., 2018).

Fang et al. (2019) conducted a meta-analysis of 24 studies to assess the effectiveness of ALEKS in secondary and post-secondary education. The analysis revealed

that ALEKS demonstrated a small but positive advantage over traditional classroom instruction. In a meta-analysis of 34 studies, Steenbergen-Hu and Cooper (2013) found that ITS had a modest overall effect on K-12 students' mathematics learning. Similarly, bin Mohamed et al. (2022) and Wardat et al. (2024) emphasized the potential of AI-based instruction to significantly improve mathematics achievement. However, the effectiveness of these tools largely depends on thoughtful integration and appropriate teacher support. Escueta et al. (2020) and Ran et al. (2021) noted that adaptive and collaborative learning tools, particularly those used for problem-solving, are more beneficial than general or assessment-only applications. Collaborative environments were associated with higher learning gains (Ran et al., 2021). Hillmayr et al. (2020) reviewed 92 studies and concluded that AI-based systems, particularly ITS and simulations, improved student achievement in mathematics and science. Large-scale studies by Major et al. (2021) and Wang et al. (2023) also confirmed the effectiveness of adaptive learning and ITS tools across diverse student populations. Chen et al. (2022) noted that educational robots and ITS remain among the most effective AI applications for mathematics achievement.

4.3 Data and Methods

4.3.1 Data Collection and Selection

This study used PRISMA guidelines to conduct an SLR of peer-reviewed journal articles from 2008 to 2023, addressing three key research questions. An SLR is a systematic approach to collecting, evaluating, and synthesizing findings from multiple studies on a specific topic, providing an overview of the research domain (Pati & Lorusso, 2018). The PRISMA framework ensured methodological rigor and quality in analyzing the collected articles. PRISMA is a standardized, peer-reviewed methodology that includes a checklist and flowchart to guide authors in conducting systematic reviews and meta-analyses (Conde et al., 2020; Moher et al., 2015). The four PRISMA phases-identification, screening, eligibility, and inclusion were applied to systematically analyze the impact of AI-based systems on mathematics achievement.

4.3.2 Information Sources and Search Strategy

To ensure a comprehensive review of relevant literature, studies were sourced from six major electronic databases: a) ERIC (EBSCO), (b) JSTOR (c) ScienceDirect, (d) SpringerLink, (e)Wiley, and (f) ACM Digital Library. These databases were specifically chosen for their established reputation and wide selection of research articles relevant to education and artificial intelligence. Each database offers unique strengths that align with the research focus on AI-based systems in mathematics education. The search was limited to full-text, peer-reviewed journal articles in English. A combination of broad and specific search terms was used to maximize relevant findings. Key terms included "Intelligent Tutoring Systems," "AI Tutors,"

"Intelligent Tutors," "ntelligent Learning Environment," "Mathematics Performance," "Math Learning," and "Mathematics Achievement." The search strings were formulated as:

("Intelligent Tutoring Systems" OR "AI Tutors" OR "Intelligent Tutors" OR "Intelligent Learning Environment") AND ("Mathematics Performance" OR "Math Learning" OR "Mathematics Achievement" OR "Mathematics").

4.3.3 Inclusion and Exclusion Criteria

The selection process was based on predefined inclusion and exclusion criteria. Studies were chosen for their relevance to three research questions examining AI-based intelligent tutoring systems and their impact on K-12 mathematics achievement. Non-peer-reviewed materials such as books, news articles, magazines, posters, and studies in languages other than English were excluded.

Inclusion criteria:

1. Empirical studies have investigated the effectiveness of ITS in improving learning outcomes in mathematics (standardized test scores, course grades, or retention rate).
2. Studies published or reported from January 2008 to September 30, 2023, must be available in English.
3. Studies have used a randomized controlled trial/experimental/quasi-experimental design/predictive correlational design to compare the use of an ITS with a control condition with traditional classroom instruction.
4. Studies focused on students in K-12 classrooms, including high achievers, low achievers, and remedial students.
5. Studies that have been published in peer-reviewed journals or conference proceedings.
6. Studies that have reported quantitative data on learning outcomes (e.g., test scores, grades, retention rates).

Exclusion criteria:

1. Empirical studies have not investigated the effectiveness of ITS in improving learning outcomes in mathematics (standardized test scores, course grades, or retention rate).
2. Studies not published or reported from January 2013 to March 30, 2023, must be available in English.
3. Studies that have not used a randomized controlled trial/experimental/quasi-experimental design/predictive correlational design to compare the use of an ITS with a control condition with traditional classroom instruction.

4. Studies have not focused on students in K-12 classrooms, including high achievers, low achievers, and remedial students.
5. Studies that have not been published in peer-reviewed journals or conference proceedings.
6. Studies that have reported quantitative data on learning outcomes (e.g., test scores, grades, retention rates).

4.3.4 Data Preprocessing

The initial search query identified 4,789 articles. After filtering peer-reviewed and full-text research articles, 1,964 remained. After removing duplicates, 1,945 papers remained, from which 225 were shortlisted based on title and abstract screening. Applying the inclusion and exclusion criteria further narrowed the selection to 42 studies for the final analysis. The study selection process is illustrated in Figure 4.1. Upon searching with the specified string in the electronic databases, the following results were obtained:

a) ERIC (EBSCO): The initial search identified 393 papers. After applying filters for peer-reviewed articles and full-text availability, the number was reduced to 162 papers. Sorting through abstracts and titles narrowed down to 19 papers, which was further reduced to 10 based on the inclusion and exclusion criteria.

b) JSTOR: The search initially yielded 281 papers. After applying the filters for peer-reviewed and full-text articles, this number was narrowed to 59 papers. Sorting by abstract and title further reduced the list to 13 papers, which was then limited to four after applying the inclusion and exclusion criteria.

c) ScienceDirect: The initial search returned 750 papers. After applying filters for peer-reviewed and full-text availability, the result was narrowed to 557 papers. Through abstract and title sorting, the list was reduced to 48 papers, which was further refined to nine after applying the inclusion and exclusion criteria.

d) SpringerLink: The search initially returned 2,855 papers. After filtering peer-reviewed and full-text articles, this was reduced to 642 papers. Sorting by abstracts and titles narrowed this to 57 papers, which was then further reduced to 14 after applying the inclusion and exclusion criteria.

e) Wiley: The search produced 157 papers initially. After filtering for peer-reviewed and full-text availability, the result was narrowed to 133 papers. Sorting by abstracts and titles brought this number down to 16 papers, which was further limited to three based on the inclusion and exclusion criteria.

f) ACM Digital Library: The initial search identified 353 papers. After applying filters for peer-reviewed and full-text articles, this was narrowed to 236 papers. Abstract and title sorting reduced this number to 20 papers, which was then narrowed to two after applying the inclusion and exclusion criteria. A total of 42 papers were included in the final data analysis for this systematic review.

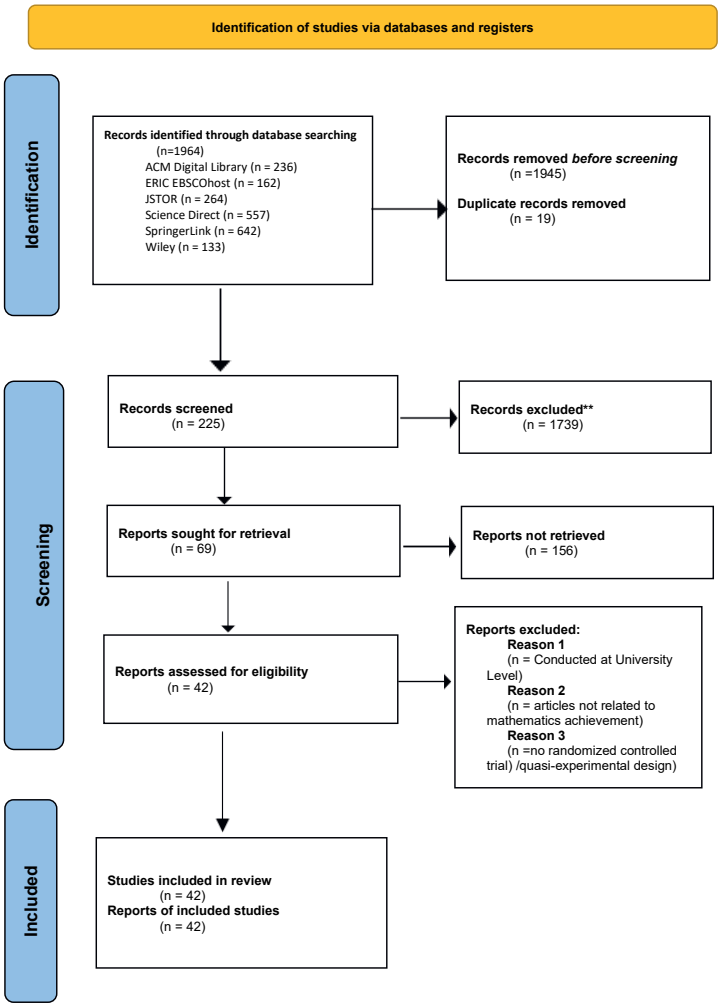


Figure 4.1 PRISMA flow chart of the study

4.3.5 Data Classification and Analysis

Following the systematic review methodology outlined by Tranfield et al. (2003), the analysis of selected studies involved a structured and rigorous content analysis

process in such a way that it is highly resourceful, systematic, and independent. This approach, as articulated by White and Marsh (2006), enabled the systematic interpretation of textual data through the classification and coding of key themes. To facilitate data extraction and synthesis, a structured classification framework was employed, guiding the analysis of 42 eligible studies (see Appendix 1). Each of the 42 identified articles was read and analyzed by the authors following a systematic and consistent procedure. A coding scheme was then developed, aligned with the study's core research questions:

- What types of AI-based systems are used in mathematics education?
- How do AI-based systems vary across different education levels?
- What is the impact of AI-based systems on students' mathematics performance?
- How do AI-based systems contribute to reducing the mathematics achievement gap among students from low socioeconomic backgrounds?
- What specific features of AI-based systems support students from disadvantaged socioeconomic contexts?

The selected articles were analyzed with the goal of identifying patterns across various dimensions such as country of origin, type of AI-based systems employed, education level, and outcomes related to mathematics learning. A classification framework was designed and segmented into two parts: general descriptive elements and content-specific analytical features. The general descriptive section included key bibliographic and contextual information such as the year of publication, country of study, education level, and journal of publication.

The second part of the framework focused on analyzing the content and implementation of AI-based systems. Data was extracted and organized in a spreadsheet that included 16 variables, such as the type of AI-based learning system (e.g., ALS, ITS), instructional role (primary or supplementary), study design, sample size, duration of the intervention, and reported mathematics outcomes. Other variables captured included key system features such as feedback mechanisms and adaptivity, the reported impact on the mathematics achievement gap for students from low socioeconomic backgrounds, and study limitations. Effect sizes (Cohen's d) were calculated when not explicitly provided. The resulting dataset was filtered using spreadsheet to identify patterns and trends relevant to the research questions, allowing for a nuanced synthesis of the role and effectiveness of AI-based systems in mathematics education.

4.4 Results

AI-based systems, including ITS and ALS, have been utilized in various countries to enhance mathematics education, either as supplemental tools or primary instruc-

tional methods. Out of 42 studies (see Figure 4.2), 25 (59%) were conducted in the USA, showcasing the use of several AI-based systems such as Assessment and Learning in Knowledge Spaces (ALEKS), Cognitive Tutor Algebra 1 (CTA1), ASSISTments, Helping At-risk students Learn Fractions (HALF), Math Nation intelligent virtual learning environment (IVLE), MathSpring, and Decimal Point, which provide personalized instruction and assessment. Some studies also reported the use of adaptive learning games like Lynnette, DragonBox, Woot Math Adaptive Learning (WMAL), and Math Whizz (see Appendix 1).

In Germany, three studies implemented eFit, Peer Education Diagnostic and Learning Environment (PEDALE), and interactive eBooks with adaptive scaffolding, while one study conducted in both Germany and the USA examined CTA1. In France, one study used ITS algorithms such as ZPDES and RiaRiT. Four studies from Taiwan explored Model-Tracing Intelligent Tutor (MIT) system and dialogue-based tutors, Affective and Cognitive factors-based Adaptive Learning System (ACALS), as well as Adaptive concept-effect relationship (CER)-based mathematics games. Brazil implemented OLM-based ITS and Personal Affective Tutor to Math (PAT2Math), while India used AmritaITS to support mathematics learning. Several other countries were each represented by a single study: Turkey (Turkish abbreviation of Adaptive and INtelligent WEBbased MAThematics teaching-learning system [UZWEBMAT]), Egypt (Adaptive Personalized Platform for an Effective and Advanced Learning [APPEAL]), Austria (Bettermarks), and Spain (Hypergraph Intelligent Tutoring System [HINTS]). These findings indicate that the use of AI in education is a global phenomenon, with AI-based tutoring and adaptive learning technologies being employed to support mathematics learning worldwide.

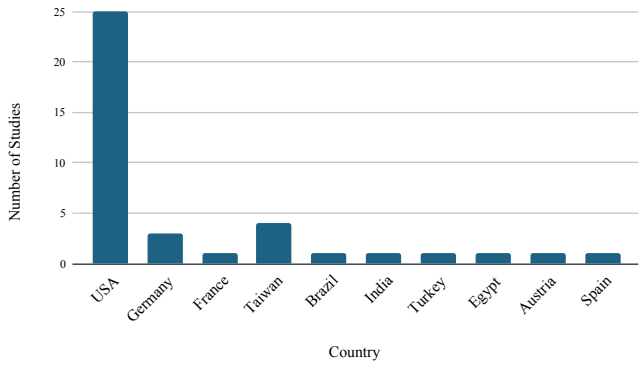


Figure 4.2 Number of studies using AI-based systems in mathematics by country

The diverse range of AI-based systems used in mathematics education, as highlighted in the studies, provides a comprehensive overview of the types and levels at which these technologies are implemented. From primary to higher education, systems like ALEKS, CTA1, and ASSISTments are implemented to provide adaptive

and personalized instruction. Adaptive learning games and interactive eBooks are also utilized across various educational levels to enhance engagement and learning outcomes.

RQ1. What types of AI-based systems are used in mathematics and at what education level?

To answer RQ1, data was filtered in Excel according to elementary, middle, and high school levels, including multiple education level categories. Among the 42 studies analyzed, middle schools emerged as the most common setting for AI integration, with 14 studies (33.3%) focusing on this level. Elementary schools accounted for 13 studies (31%), while seven studies (16.7%) focused on high schools. Eight studies (19%) spanned multiple education levels, such as elementary, middle, and high school or a combination of all three (see Figure 4.3, Appendix 1)

At the elementary school level, various ITS and ALS have been implemented to enhance mathematics learning. Of the 13 studies analyzed, eight utilized ITS, including HALF-ITS, MIT, Fractions ITS, Amrital-TS, Math Whizz, ALEKS, HINTS, ZPDES, and RiaRiT. Three studies focused on ALS, including ACALS, APPEAL, and WMAL. Some studies explored alternative AI-based approaches, such as digital learning games and interactive eBooks with adaptive scaffolding.

At the middle school level, ITS has been more widely used than ALS to support students' mathematics learning. Commonly used ITS platforms include CTA1, MATHia, Algebra Nation, and Bettermarks. Other frequently used ITS tools in middle school include Lynnette, eFit, ASSISTments, ALEKS, PAT2Math, and Model Tracing Tutor. ALS implementations included Decimal Point, a digital learning game with open learner model (OLM) and open enjoyment model (OEM), and DragonBox, an educational game designed to develop algebraic thinking. Interactive eBooks with adaptive scaffolds and feedback were also used to enhance student learning.

At the high school level, both ITS and ALS have been employed to support mathematics education. Among the 7 studies analyzed, the identified ITS platforms include ALEKS, CTA1, Succeed in Math! (SCIM), and a combination of ALEKS and CTA1. The ALS platforms identified for high school mathematics education include UZWEBMAT and PEDALE.

Across various school levels, ITS and ALS have been integrated to support student learning. At the elementary and middle school level, EPGY, an ALS, was utilized. At the middle and high school levels, AI-based systems such as MathSpring, Algebra Nation (AN), IVLE, and CTA1were implemented. OLM-based ITS and Bettermarks were used across all three education levels, to support students learning in mathematics.

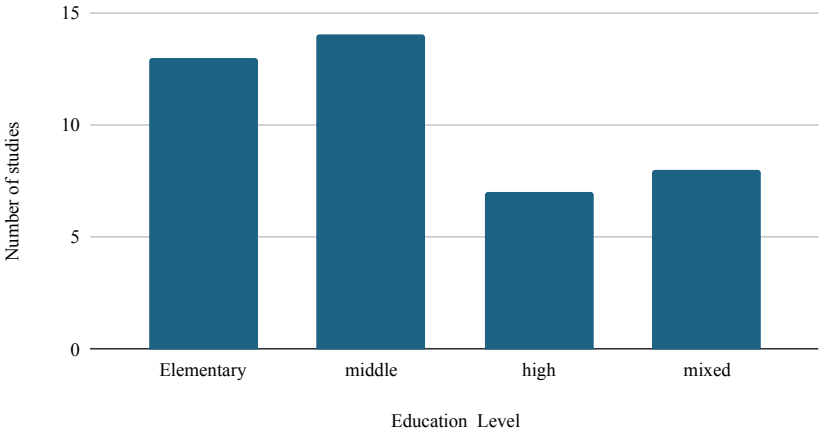


Figure 4.3 Distribution of AI-based systems by education level

RQ2. What is the impact of AI-based systems on students' mathematics performance in K-12 classrooms?

To address RQ 2, research studies were analyzed to identify the Impact of AI-based systems on students' mathematics performance in K-12 classrooms. The findings indicate a generally positive impact, ranging from significant to small improvements across elementary, middle, and high school levels. These findings should be interpreted with caution, as the potential publication bias may favor studies reporting positive outcomes. The term *impact* refers to the measurable and reported effects of AI-based systems on students' mathematics learning outcomes in K–12 settings. This includes improved academic performance (e.g., test scores, concept mastery), increased engagement and motivation, greater learning gains, reduced anxiety, improved attitudes toward mathematics, and greater self-efficacy. Mathematics improvement was coded into four levels based on mathematics performance and effect sizes: significant improvement, moderate improvement, small improvement, and no improvement. Among the 42 studies examined, seven studies reported significant improvement (effect size greater than 0.8), 15 studies showed moderate improvement (effect size between 0.5 and 0.8), 17 studies indicated small or non-significant improvement (effect size between 0 and 0.5), and three studies found no improvement (see Figure 4.4). In terms of implementation, 29 studies utilized AI-based systems as supplemental learning tools, while 13 studies integrated them as primary instructional tools. The effectiveness of these systems varied across different education levels, demonstrating their potential to enhance mathematics learning in K-12 classrooms (see Appendix 1).

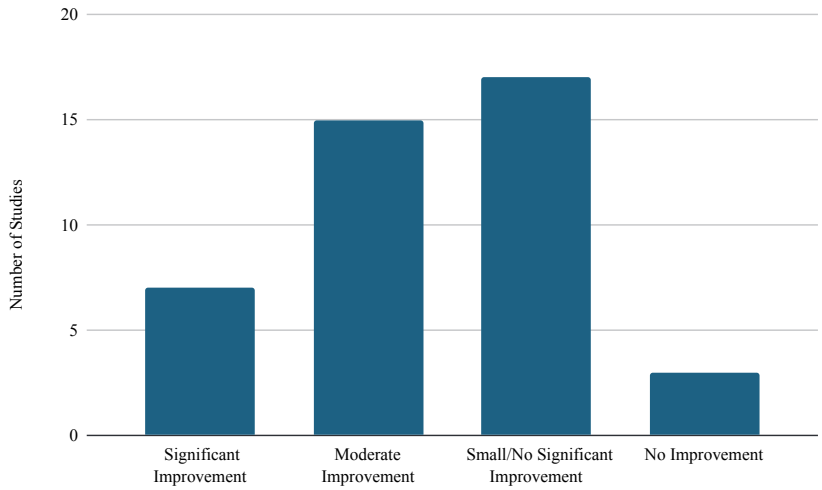


Figure 4.4 Impact of AI-based systems on mathematics performance in K-12 classrooms

At the elementary level, research suggests that AI-based systems, when used as supplementary tools, enhance mathematics achievement, with improvements ranging from significant to small. Among the 13 studies analyzed (see Table 1), 11 implemented AI-based instruction as a supplemental tool, while two studies used it as the primary instructional method. Of these, four studies reported significant improvement, five showed moderate improvement, and four indicated small or no significant improvement.

Significant improvements in performance, engagement, and retention scores were observed. For instance, Hwang et al. (2020) found that the ACALS-ALS system significantly improved achievement and reduced anxiety among elementary students, with an effect size of 0.5. Similarly, Sayed et al. (2023) reported that the APPEAL-ALS system led to more effective learning, reduced time, and improved grades, with a notable effect size of 0.9. On the other hand, Clement et al. (2015) observed significant improvements in math skills using ITS algorithms like ZPDES and RiaRiT, though the effect size was smaller at 0.12. Studies like Mendiburo et al. (2014) and Chu et al. (2021) also highlighted the benefits of AI systems such as HALF-ITS and CER-based Mathematics Games, with effect sizes of 0.82 and 0.66, respectively. Additionally, Lee et al. (2020) demonstrated that an intelligent agent system integrated with robotic edutainment significantly improved performance in mathematical concepts for remedial students, with an impressive effect size of 1.28. However, some studies, like Haridas et al. (2020), showed only modest improvements, with an effect size of 0.019. Overall, the impact of AI-based systems on mathematics performance varies, with some systems showing substantial benefits while others yield more modest gains.

Table 4.1 Impact of AI-based systems on mathematics performance at the elementary level

Study	Types of ITS/ALS	Instructional Role	Impact on Math Performance	Effect Size
Hwang et al., 2020	ACALS - ALS	Supplementary	Moderate	0.5
Sayed et al., 2023	APPEAL - ALS	Supplementary	Significant	0.9
Clément et al., 2015	ITS algorithms: ZPDES & RaiRiT	Supplementary	Small	0.12
Mendiburo et al., 2014	HALF - ITS	Supplementary	Significant	0.82
Chu et al., 2021	CER-based Mathematics Game	Supplementary	Moderate	0.66
Chu et al., 2014	MIT - ITS	Primary	Small	0.41
Lee et al., 2020	Intelligent agent system integrated with robotic edutainment and humanized co-learning	Supplementary	Significant	1.28
Olsen et al., 2017	Fractions ITS	Primary	Significant	1.46
Haridas et al., 2020	AmritaITS - ITS	Supplementary	No significant improvement	0.019
Bush, 2021	WMAL - ALS	Supplementary	Moderate	0.6
Clark & Whetstone, 2014	Math Whizz - ITS	Supplementary	Moderate	0.5
Huang et al., 2013	ALEKS - ITS	Supplementary	Small	0.48
del Olmo-Muñoz et al., 2022	HINTS - ITS	Supplementary	Moderate	0.58

At the middle school level, 14 studies explored the use of AI-based systems in education. Among these, eight utilized AI-based learning systems as a supplemental tool, while six integrated them as the primary mode of instruction. The effectiveness of AI-based systems in middle school mathematics largely depends on factors such as engagement levels and system design. Research indicates that adaptive and personalized learning environments can lead to improvements in mathematics performance. Out of 14 studies, one reported significant improvement, four showed moderate improvements, and eight demonstrated small or no significant improvement. One study showed no effect at all. For example, Hou et al. (2022) and Zheng et al. (2019) found no substantial differences in learning outcomes, with effect sizes of 0.21 and 0.11, respectively. These results suggest that while students interacted with the AI systems, their academic performance did not significantly improve.

In contrast, Graff et al. (2008) reported significant improvements, with effect sizes of 1.17 and 0.54, respectively. These studies highlight the effectiveness of AI systems such as eFit-ITS and ASSISTments-ITS in boosting arithmetic and homework performance. Similarly, Fang et al. (2017), Kelly et al. (2014), and Waalkens et al. (2013) found moderate improvements, with effect sizes of 0.52 and 0.58, respectively, demonstrating that systems like Lynnette-ITS and ITS for Linear Algebraic Equations can foster both learning gains and engagement. However, other studies, such as Kessler et al. (2015), reported no significant overall gains, with an effect size of -0.04. This suggests that the effectiveness of AI-based systems can vary

widely depending on the context and how they are implemented.

Table 4.2 Impact of AI-based systems on mathematics performance at the middle school level

Study	Types of ITS/ALS	Instructional Role	Impact on Math Performance	Effect Size
Hou et al., 2022	Decimal Point	Primary	Small	0.21
Zheng et al., 2019	CTA 1 - ITS	Supplementary	Small	0.11
Waalkens et al., 2013	ITS for Linear Algebraic Equations	Supplementary	Moderate	0.54
Long & Aleven, 2017	Lynnette - ITS; DragonBox - ALS (Educational Game)	Primary	Small	0.39
Graff et al., 2008	eFit - ITS	Supplementary	Significant	1.17
Kelly et al., 2014	ASSISTments - ITS	Supplementary	Moderate	0.54
Fang et al., 2017	ALEKS - ITS	Primary	Moderate	0.52
Fancsali & Ritter, 2014	MATHia	Supplementary	Small	0.2
Reinhold et al., 2020	eBook with interactive adaptive scaffolds and feedback	Primary	Small	0.32
Jaques et al., 2013	PAT2Math - ITS	Supplementary	Moderate	0.58
Craig et al., 2013	ALEKS - ITS	Primary	Small	0.18
Nagashima et al., 2021	ITS with anticipatory diagrammatic self-explanation	Supplementary	Small	0.1
Shih et al., 2022	Dialogue-based Mathematics - ITS	Supplementary	Small	0.15
Kessler et al., 2015	MIT	Primary	No significant improvement	0.04

At the high school level, seven studies examined the use of AI-based systems in mathematics instruction, with mixed results. Three of these studies implemented AI-based learning systems as a supplemental tool, while four used them as the primary mode of instruction. One study did not report effect size, but the remaining studies showed varying levels of impact on mathematics achievement: two reported significant effects, two reported moderate effects, and two showed small or no significant effects.

Özyurt et al. (2014) found that the adaptive learning system UZWEBMAT-ALS significantly improved mathematics performance, with males outperforming females. Similarly, Mills (2021) observed that engagement time and mastery ratio predicted better final grades and PSAT scores when using the ALEKS-ITS. However, some studies, such as Phillips et al. (2020), found no significant effects on algebra exam scores, citing inconsistent implementation and low adherence to recommended usage levels as contributing factors. Despite these challenges, personalized learning tools like CTA1-ITS and ALEKS were found to enhance student engagement and understanding, with some studies reporting a high effect sizes, such as a Cohen's d of 0.95 for ALEKS and Carnegie (Mills, 2021; Sabo et al., 2013).

Table 4.3 Impact of AI-based systems on mathematics performance at the high school level

Study	Types of ITS/ALS	Instructional Role	Impact on Math Performance	Effect Size
Özyurt et al., 2014	UZWEBMAT - ALS	Supplementary	Moderate	0.59
Mills, 2021	ALEKS - ITS	Primary	Significant	0.95
Phillips et al., 2020	ALEKS - ITS	Supplementary	Small	0.2
Konert et al., 2012	PEDALE - ALS	Primary	Results indicated improved learning outcomes	Not reported
Walkington & Bernacki, 2019	CTA1 - ITS	Primary	Moderate	0.56
Sabo et al., 2013	ALEKS - ITS & CTA1 - ITS	Primary	Significant	0.95
McDonough & Tra, 2017	SCIM - ITS	Supplementary	No significant improvement	0.098

In the mixed group, which included studies spanning elementary and middle school, middle and high school, and all three levels combined, a total of eight studies were identified. Of these, seven implemented AI-based systems as supplementary tools, while only one study used an AI-based system as the primary mode of instruction. The effectiveness of these interventions varied, with two studies reporting moderate effects on mathematics learning, five studies showing small or no significant impact, and one study finding no effect on students' mathematics achievement.

Arroyo et al. (2014) found that MathSpring-ALS, used as a supplementary tool, improved learning, engagement, and retention among middle and high school students, with an effect size of 0.35. Similarly, Spitzer and Moeller (2020) reported that Bettermarks-ITS significantly enhanced student performance during school closures due to its adaptive learning paths and immediate feedback, yielding an effect size of 0.45. Suppes et al. (2014) observed positive learning gains with EPGY-ALS, particularly for students with lower pretest scores, with an effect size of 0.62.

Some studies showed more mixed results. Leite et al. (2019) found that Algebra Nation (AN) had varying effects, where higher usage correlated with better end-of-course (EOC) scores, but the lack of a control group left room for external factors to influence the outcomes (effect size = 0.19). Rocha et al. (2024) conducted a randomized controlled trial using an OLM-based ITS but found no significant differences in self-regulation or performance, with an effect size of 0.4. Similarly, Chakraborty et al. (2021) reported that moderate engagement with Math Nation IVLE led to improved EOC scores, whereas low engagement showed no benefit, resulting in an overall negative effect size of -0.07.

In contrast, some studies demonstrated stronger positive outcomes. Salden et al. (2010) found that CTA1-ITS, utilizing adaptive fading, significantly improved students' problem-solving skills in both immediate and delayed post-tests, with an effect size of 0.59. Sales and Pane (2019) also reported a moderate positive effect (effect size = 0.22) on post-test scores for high school students, particularly those who had been frequently promoted.

RQ3. Do AI-based systems reduce the achievement gap in mathematics from low socioeconomic backgrounds and what specific features contribute to this effect?

To address RQ3, we analyzed studies to explore the correlation between AI-based systems and their potential to reduce the achievement gap in mathematics among students from different socioeconomic backgrounds. Among the 42 studies reviewed, 12 explicitly mentioned low socioeconomic status (SES), two focused on high SES, five reported mixed SES, and 23 did not provide SES data (see Appendix 1). Within the 12 studies (see Table 4.4, Figure 4.5) that highlighted low SES, three indicated a significant impact on mathematics learning. The eFit study showed that the treatment group experienced significant improvements in arithmetic, with an effect size of 1.17. Similarly, a study implementing ALEKS as a primary instructional tool reported an effect size of 0.95, whereas Half-ITS with an effect size of 0.82, indicating enhanced engagement.

Table 4.4 Effect sizes of AI-based systems on mathematics performance (Low SES)

Authors (APA)	Types of ITS/ALS	Instructional Role	Impact on Math Performance	Effect Size	SES
Arroyo et al., 2014	MathSpring - ALS	Supplementary	Small	0.35	Low
Mills, 2021	ALEKS - ITS	Primary	Significant	0.95	Low
Leite et al., 2019	Algebra Nation - ALS	Supplementary	Small	0.19	Low
Mendiburo et al., 2014	HALF - ITS	Supplementary	Significant	0.82	Low
Graff et al., 2008	eFit - ITS	Supplementary	Significant	1.17	Low
Phillips et al., 2020	ALEKS - ITS	Supplementary	Small	0.2	Low
Suppes et al., 2014	EPGY - ALS	Supplementary	Moderate	0.62	Low
Haridas et al., 2020	AmritaITS - ITS	Supplementary	No significant improvement	0.019	Low
Salden et al., 2010	CTA1 - ITS	Primary	Moderate	0.59	Low
Craig et al., 2013	ALEKS - ITS	Primary	Small	0.18	Low
Huang et al., 2013	ALEKS - ITS	Supplementary	Small	0.48	Low
McDonough & Tra, 2017	SCIM - ITS	Supplementary	No significant improvement	0.098	Low

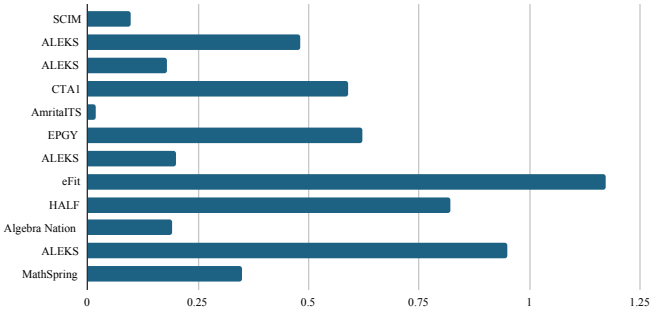


Figure 4.5 Effect sizes of AI-based systems on mathematics performance (Low SES)

Moderate effects on mathematics learning were observed in AI-based systems such

as ALS-EPGY (0.62), which had a positive impact on learning, particularly for students with lower pretest scores. CTA1 (0.59) also demonstrated significant improvement, utilizing adaptive fading techniques to enhance problem-solving skills.

Other studies reported smaller learning gains. MathSpring (0.35) showed improvements in performance, engagement, and retention. Algebra Nation (0.19) found that higher usage correlated with better End-of-Course (EOC) scores, with practice questions having the strongest impact. Half ITS (0.14) contributed to learning gains by improving classroom learning environments and providing targeted support. ALEKS, when used as a primary instructional tool, achieved an effect size of 0.18, proving as effective as teacher-led instruction while reducing the need for teacher assistance. As a supplementary tool, ALEKS showed effect sizes of 0.20 and 0.48, helping to close achievement gaps between African American and White students.

Other studies, such as Amiratal ITS (0.019) and SCIM (0.098), reported small gains. SCIM, which was implemented in high schools over a year, contributed to increased proficiency, particularly among minority students. Several AI-based systems, including ALS and ITS, have demonstrated their ability to support students from diverse socioeconomic backgrounds. These systems offer personalized learning experiences through real-time feedback, tailored instruction, and individualized learning pathways. By adapting to students' needs, AI-based tools may contribute to improved engagement and academic performance, particularly for students who lack access to high-quality instruction outside the classroom.

4.5 Discussion

In this SLR, we examined the types of AI-based systems used in mathematics education, the educational levels at which they are implemented, and the impact of these systems on students' mathematics performance in K-12 classrooms. In addition, we investigated whether AI-based systems help reduce the achievement gap in mathematics in students from low socioeconomic backgrounds and identified the specific features that contribute to this effect (Appendix 1).

4.5.1 Types of AI-Based Systems in Mathematics and Education Level

The findings of this SLR indicate that AI-based systems, including ITS and ALS, are widely used in K-12 education across various countries, and implemented as either primary or supplementary instructional tools to enhance mathematics performance. Most studies on AI integration were in K-12 classroom and focused on elementary and middle school students. This focus is largely due to the challenges students face during these years and the persistent need to improve their mathematics achievement. The findings support the need to integrate AI-based systems to address these learning gaps. Efforts in the U.S. and other countries to close the math achieve-

ment gap align with the increasing use of AI-based interventions to improve math learning (Bjorklund-Yong & Plasman, 2020).

The findings reveal that fewer studies have examined the role of AI-based systems in high school settings, even though high school students continue to struggle with math proficiency and exhibit poor learning outcomes. Trends in International Mathematics and Science Study (TIMSS) and National Assessment of Educational Progress (NAEP) shows that U.S. students consistently lag behind as compared to other countries (Mainali, 2025). Despite fewer number of studies, emerging evidence suggests that AI-based tutoring systems can positively impact high school students' math skills (Özyurt et al.,2014; Yi et al., 2024). These results are promising, yet the lack of comprehensive data makes it difficult to draw definitive conclusions or compare the effectiveness of AI-based systems across various education levels. This suggests the necessity for further research to determine how these AI-based technologies can be effectively implemented in high school settings.

At the elementary level, eight out of 13 studies focused on ITS. These ITS systems personalized the instruction based on real-time student performance, provided diagnostic assessments, placed students at appropriate skill levels, and adapted instructional content as students progressed. These AI-based systems provided instant and step-by-step guidance, helping students develop foundational math skills such as number sense, fractions, and arithmetic. Three studies focused on ALS to enhance math learning, by adjusting difficulty levels, pacing, and providing instructions based on students' performance. Further research is needed to compare the impact of ALS and ITS on mathematics achievement and determine which systems are more effective for elementary and middle school students.

The findings also show a similar trend in middle schools, where ITS is more commonly implemented than ALS to improve math skills. ITS platforms such as CTA1, MATHia, Algebra Nation, and Bettermarks offer real-time feedback, step-by-step guidance, and automated scaffolding, thus helping students to understand more complex mathematical concepts in algebra and geometry.

At the high school level, fewer AI-based systems are utilized, and the results have been mixed in terms of mathematics achievement. Among the seven studies, five implemented ITS and two used ALS. Six studies reported positive impact on mathematics achievement. Systems like UZWEBMAT and ALEKS showed significant gains in student performance when used consistently and aligned with students' learning needs. Özyurt et al. (2014) found that UZWEBMAT significantly improved mathematics achievement, with male students outperforming female peers. Mills (2021) found that interaction patterns, such as time on task and mastery ratio, were strong predictors of performance gains and standardized test outcomes when using ALEKS, aligning with previous literature emphasizing the benefits of adaptive feedback, learner control, and personalized pathways in improving learning outcomes for high school students, who are generally more capable of independent learning.

However, not all implementations demonstrated significant benefits. Phillips et al. (2020) found no improvement in algebra scores, attributing the lack of results to inconsistent use and deviations from recommended usage. These findings highlight the importance of fidelity in implementation, along with teacher training and adequate infrastructure. The effectiveness of AI-based systems is not solely dependent on their design but also on how well they are integrated into classroom and supported by teachers.

Despite these challenges, the findings suggest that when implemented with fidelity, AI-based systems can enhance student engagement and understanding of content. Future research should continue to explore contextual factors such as teacher readiness, usage patterns, and demographic variables to better understand and maximize the impact of AI-based systems in K-12 classrooms.

4.5.2 Impact of AI-Based Systems on Students' Mathematics Performance

As AI-based systems continue to evolve, they offer increasing potential to deliver adaptive and personalized instruction. This SLR examined the impact of such systems on mathematics achievement and found mixed but generally positive outcomes. While some studies reported significant gains, others observed small or moderate gains, with the overall trend indicating a moderate positive effect on student mathematics achievement.

These findings align Kabudi et al. (2021), whose reviewed 147 studies reported significant improvements in student performance when AI-based systems such as ITS and ALS were used alongside teacher support. However, their review also indicated that many of these AI-based systems are still in early developmental stages and not widely implemented in authentic classroom settings. Similarly, Mohamed et al. (2022) conducted a systematic review of AI in mathematics education, confirming that AI-assisted teaching is highly effective for basic mathematics instruction. Their findings reinforced AI's role in enhancing critical thinking, problem-solving skills, and overall mathematics achievement.

Further evidence of the significant improvement of adaptive technologies is provided by Major et al. (2021), who investigated the impact of technology-supported adaptive and personalized learning among 53,029 students aged 6-15 in low- and middle-income countries and found statistically significant positive effect in learning outcomes, particularly with adaptive learning approaches that adjusted to students' skill levels.

It is worth noting that students using AI-based systems outperformed their peers in control groups, demonstrating statistically significant improvements in post-test scores, standardized assessments, and long-term knowledge retention. These findings support previous research suggesting that AI-enhanced instruction can improve learning efficiency and accelerate mastery (Clément et al., 2024; D'Mello & Graesser, 2023; Harry, 2023; Khazanchi et al., 2025).

Despite these promising results, the evidence across studies remains variable. While several studies reported either moderate improvement or limited/no significant effect, indicating that the benefits of AI-based instruction are not universally consistent. Only a small number of studies, seven in total showed significant improvement, suggesting that while AI systems can be effective, their success may depend on factors such as implementation quality, student demographics, or instructional context. These findings highlight the need for further research to determine the conditions under which AI-based learning tools are most effective and how they can be refined to support broader educational outcomes.

AI-based systems, such as ALEKS, have been shown to increase engagement, improve topic mastery, and support retention, particularly for those who struggle in mathematics (Mills, 2021). Research suggests that when used as a supplementary tool, ALEKS enhances student engagement by creating personalized learning pathways and provides targeted feedback and support, thereby increasing its effectiveness. These findings are consistent with previous studies (Craig et al., 2013; Khazanchi et al., 2023; Sun et al., 2021) and align with the SLR by Wang et al. (2023), which analyzed 40 studies conducted between 2011 to 2022. Wang et al.(2023) and Hillmayr et al. (2020) found that ITS were most effective when used as a supplemental tool rather than a replacement for traditional instruction, with adaptive and personalized approaches leading to moderate improvements in student outcome.

This SLR indicated a moderate positive effect of AI-based systems on mathematics achievement, which aligns with previous research by Hillmayr et al. (2020) and Bernard et al. (2019). Hillmayr et al. (2020) reviewed 92 studies and concluded that AI-based systems, particularly ITS and simulations, contributed to improved student performance in mathematics and science. They emphasized the importance of teacher training and student support in maximizing the benefits of digital tools. Bernard et al. (2019) compared the effectiveness of adaptive, student-centered instruction with traditional teacher-centered approaches in K-12 education. Their findings indicated moderate improvements under adaptive and individualized conditions, with an average effect size of $g = 0.44$. The teacher's role in mentoring and guiding students appeared promising, while adaptability and flexibility had no significant impact. Interestingly, self-paced learning had a negative effect when implemented in a student-centered approach.

Ran et al. (2021), in a meta-analysis of 77 studies, reported a small but statistically significant positive effect on student achievement. The study findings indicated that technology was most effective when it supported collaborative problem-solving activities, rather than being used only for monitoring or assessment without additional instructional support. Short-term use of technology showed greater impact compared to prolonged use without proper integration into teaching practices.

In addition to improving performance, AI-based systems have been shown to reduced math anxiety and improved comprehension (Abd Algani, 2024; Hwang et al., 2020). These systems are effective in identifying and correcting misconceptions,

providing guided support that helps students understand mathematical concepts. Their interactive and adaptive features engage learners, address individual needs, and contribute to improved overall outcomes in mathematics. This aligns with findings from several studies. Arroyo et al. (2014) examined the impact of Wayang Post (now MathSpring), and found that it significantly improved math performance, standardized test scores, and student engagement, especially among female and low-achieving students. Similarly, Chu et al. (2021) studied the effect of adaptive game-based learning systems that used concept-effect relationships to personalize instruction. The findings suggest that these systems significantly improved elementary students' mathematics achievement, self-efficacy, and learning attitudes. Long and Aleven (2017) compared the educational game DragonBox with the intelligent tutoring system Lynnette; while students reported greater enjoyment with DragonBox, those using Lynnette achieved higher gains in equation-solving skills. Another advantage of AI-based systems is their ability to accurately identify students at risk of failing final exams. Haridas et al. (2020) found that AmritaITS could effectively predict both formative and summative assessment scores, enabling early intervention for students who may struggle. Students require significantly less teacher assistance when completing daily assignments, highlighting AI's role in promoting independent learning. This is supported by Craig et al. (2013), who found that students in the ALEKS condition required significantly less assistance from teachers, particularly in after-school classrooms required significantly less assistance in mathematics from teachers to complete their daily work.

These systems contributed to improved problem-solving skills and an increased use of formal algebraic strategies; however, no significant differences were observed in conceptual and procedural knowledge gains (Nagashima et al., 2021). However, other studies reported minimal or no improvements in mathematics achievement. For example, Phillips et al. (2020) reported no significant improvements in algebra exam scores, which they attributed to inconsistent implementation and low adherence to recommended usage. Similarly, Chakraborty et al. (2021) reported that moderate engagement with Math Nation IVLE improved EOC scores. In contrast, low engagement showed no benefit, resulting in a negative effect size of -0.07. Similarly, research by del OlmoMuñoz et al. (2022), Hou et al. (2022), and Zheng et al. (2019) revealed wide variation in outcomes, with no substantial differences between experimental and control groups. This inconsistency suggests that while AI-based systems can enhance learning, their effectiveness depends on factors such as implementation, student demographics, and study design. For example, AI-based systems like ALEKS may lead to positive outcomes in post-secondary settings where students tend to be more self-directed. However, their impact may be limited among younger or less independent students if not accompanied by adequate teacher support (Fang et al., 2019). AI-based systems are more effective in classrooms where teachers receive proper training on how to integrate the technology into their teaching practices and show a strong commitment to using it consistently and accurately (Ran et al., 2021). Koedinger and Anderson (1993) compared the outcomes of a teacher with experience using ITS to those of two teachers who were new to ITS

instruction. Their findings showed that students taught by experienced teachers showed significant improvement in performance, while those taught by less experienced teachers had a negative impact on performance. This suggests that teacher familiarity with ITS is a key factor in its successful implementation.

Similarly, Pane et al. (2013) found that during the first year of using Cognitive Tutor, there was no significant effect on student test scores. However, in the second year, when teachers had more experience with the system, there was a small but statistically significant improvement in student outcomes. The type of control group used in research studies is another important factor that influences the effectiveness of AI-based systems. According to Kulik and Fletcher (2013), studies that used conventional control groups, where students received traditional instruction, reported a median effect size of 0.66. In contrast, studies that used nonconventional control groups, in which instruction included materials derived from ITS interactions, reported a lower median effect size of 0.28. AI-based systems can replicate certain aspects of human tutoring, and when used as a supplemental tool with teacher instruction, they enhance the learning process by allowing teachers to focus more on providing individualized attention to students (del OlmoMuñoz et al., 2022; Mandal & Naskar, 2021).

4.5.3 Achievement Gap in Mathematics of Students from Low Socioeconomic Backgrounds

This SLR examined whether AI-based systems help reduce the mathematics achievement gap among students from low SES backgrounds and identify key features that contribute to their effectiveness. The findings provide insight into the impact of AI-based systems on learning outcomes for low SES students. Although the effectiveness varied across studies, evidence suggests that these systems have the potential to enhance mathematics learning and to close achievement gaps. The findings of this study are consistent with prior research suggesting that AI-based tools can improve mathematics outcomes for underserved populations. Several AI-based systems, including ALEKS, MathSpring, and eFit, were associated with improved mathematics performance among students from low SES populations. The study by Mills (2021) found that students using the ALEKS intelligent tutoring system showed significant gains in mathematics achievement. Similarly, Graff et al. (2008) reported positive learning outcomes with the implementation of eFit in secondary school mathematics classrooms, suggesting that AI tools can play a meaningful role in supporting students from low SES backgrounds.

This study aligns with existing literature depicting the importance of adaptive features, such as personalized feedback, mastery-based progression, and individualized learning paths, in supporting students from low SES backgrounds. Arroyo et al. (2014) found that the integration of adaptive features in MathSpring provides personalized instruction, which can increase student engagement and foster sustained effort in learning. The findings of this study are also in agreement with Leite et al. (2019), who found that the integration of interactive and scaffolded

content in Algebra Nation was associated with better learning outcomes for struggling students, including those from low SES backgrounds. The findings of this study are also consistent with prior research showing that AI-based systems incorporating problem-solving strategies and immediate feedback can positively influence student learning. AI-based systems such as EPGY and CTA1 demonstrated moderate improvements in mathematics performance, which could be attributed to adaptive feedback and problem-solving strategies supporting students in mathematics (Salden et al., 2010; Suppes et al., 2014).

The findings of this study also align with prior research indicating that not all AI-based systems consistently lead to significant improvements in student learning outcomes. While some studies reported minimal gains, such as the limited effects observed with SCIM-ITS (McDonough & Tra, 2017) and AmritaITS (Haridas et al., 2020).

These findings suggest that while AI-based systems have the potential to narrow the achievement gap and enhance mathematics achievement for students from low SES backgrounds, their effectiveness depends on various factors such as implementation, student engagement, teacher training, and system adaptability. The ability of AI-based tools to provide personalized instruction, real-time feedback, and tailored learning pathways can promote equity in education. However, their impact remains inconsistent, highlighting the need for further research to explore optimal implementation strategies that maximize their benefits for all students.

4.6 Conclusions

This SLR analyzed 42 studies published between 2008 and 2023 to examine the impact of AI-based systems on mathematics achievement in K–12 education. The findings indicate that the impact of these systems on mathematics achievement varies, with outcomes ranging from small or no improvement to significant improvements in students' math performance. Overall, AI-based systems demonstrated a moderate positive impact on mathematics learning, particularly when used as supplementary tools. These studies revealed that experimental groups consistently outperformed control groups in post-test scores, standardized test performance, and long-term retention in mathematics.

AI-based systems deliver adaptive and personalized instruction tailored to students' individual needs, prior knowledge, and learning readiness. By generating customized learning pathways and providing real-time feedback, these systems help sustain student engagement and improve learning outcomes. Among 42 studies reviewed, 12 studies focused on students from low socioeconomic backgrounds. The findings suggest that AI-based systems can help bridge the achievement gap by offering high-quality instruction that might otherwise be unavailable due to a shortage of highly qualified teachers or lack of resources. Through personalized support and structured learning pathways, AI-based systems have the potential to improve

mathematics achievement and promote greater educational equity.

Despite the potential, the wider implementation of AI-based system on K-12 classrooms faces several challenges including high cost, data privacy issues, and limited scalability. Many AI-based educational systems remain in experimental phases and have not yet been widely adopted in authentic classroom settings. While personalized and adaptive learning tools have shown positive results, broader studies have reported mixed outcomes. Further research is needed to explore long-term impacts of AI-based systems in K-12 classrooms, determine best practices for implementation, and ensure that these technologies are both accessible and beneficial to all students, particularly those from disadvantaged populations.

4.7 Limitations and Future Directions

The findings from this SLR suggest that AI-based systems can enhance mathematics achievement and effectively support student learning across various grade levels in K-12 classrooms. However, there are several limitations noted in the studies reviewed. One of the limitations across the studies was the small sample size, often restricted to a single classroom, school, or region. This limitation affects the generalizability of findings, particularly when studies focus on specific grade levels or mathematical domains. Some lacked control groups or used quasi-experimental designs due to constraints like the COVID-19 pandemic or ethical concerns from schools about withholding potential learning benefits from students, which impeded randomization and comprehensive data collection. These conditions limit the ability to establish causal conclusions about the effectiveness of AI-based systems.

Another significant limitation was the inconsistency in data quality and availability. Many studies lacked access to standardized test scores or demographic information such as SES, gender, or prior academic performance, making it difficult to evaluate long-term outcomes or effects on specific subgroups. Many studies relied on self-reported data and learning behaviors, which may be biased. Other limitations noted were the scope of the intervention as many studies were conducted over short durations. For example, sometimes as brief as one week or a single homework session, and often the interventions focused narrowly on one mathematical domain, limiting the findings' applicability.

Another limitation was the inconsistent implementation of AI-based systems, which was influenced by teacher quality, student engagement, and availability of technological infrastructure, which may have impacted the results. Future research should aim to address these gaps by utilizing larger and more diverse samples and rigorous experimental designs. There is a need for studies that explore the sustained use of AI-based systems across different grade levels and subject areas, particularly with low SES backgrounds. This SLR found that AI-based systems are used less frequently in high school settings than in middle and elementary schools. Therefore, future research should explore how these systems impact the mathematics achieve-

ment of high school students.

General Discussion

The objective of this doctoral thesis is to investigate how artificial based educational systems, specifically, Intelligent Tutoring Systems and Adaptive learning Systems, impacts mathematics achievement and student engagement (cognitive and affective) among underachieving students in rural South Georgia. This thesis addresses its research objectives via three distinct parts.

In Part I, we examined the role of Artificial intelligence in education (AIED), with the focus on Intelligent Tutoring systems, specifically. The use of Assessment and LEarning in Knowledge Spaces (ALEKS), as a supplemental tool to enhance mathematics achievement. The study was extended by further evaluating ALEKS as a supportive instructional tool. This study aims to investigate whether the use of ALEKS shows a statistically significant improvement in students' mathematics achievement than traditional teacher-led instruction of 8th-grade students.

Part II investigated the effect of AI-based system, Edmentum Exact Path on mathematics achievement and on students' cognitive engagement affective engagement within a socioeconomically disadvantaged rural population. This research study conducted using participants from three different school districts in the close vicinity to ensure similar student demographics. Apart from using descriptive analysis, A student engagement inventory (SEI) was utilized to measure students' affective and cognitive engagement.

Part III consists of a systematic literature review on the Impact of AI-based systems on mathematics achievement. We followed the guidelines of the Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) framework. A total of 42 studies, published between 2008 and 2023, were selected from six major databases based on clearly defined inclusion and exclusion criteria.

Main Findings

Chapter 1 - Impact of Intelligent Tutoring Systems

The first, exploratory study of this doctoral thesis, described in Chapter 1 examined the Impact of the Intelligent Tutoring System. This study used a quasi-experimental design to evaluate the efficacy of ALEKS, an intelligent tutoring system, as a supplemental tool in improving mathematics achievement among underachieving students. This study also aimed to determine whether the use of ALEKS shows improvement in mathematics achievement based on the math standards in one year period and whether gains varied by class periods. We collected data from 158 eighth-grade

students at a high school from rural South Georgia. The majority of the student population at this high school came from disadvantaged backgrounds (62-68%) with only 12 % demonstrating math proficiency. To establish a baseline, students completed a pretest at the beginning of the year to determine what they already knew and a posttest toward the end of the year to measure improvement in mathematics achievement. We compared pretest and posttest results between teacher-led instructions and ALEKS-led instructions from two consecutive years. In the first year (2019-2020), teachers used only McGraw's curriculum, *Reveal*. In the second year (2020-2021), ALEKS was implemented as a supplemental tool in a math support class for 50-minute sessions every other day throughout the year to provide support to the struggling students alongside *Reveal* curriculum. This research study also compared the pretest and posttest scores of ALEKS to evaluate whether the use of ALEKS shows significant improvement in mathematics achievement based on the math standards and class periods over the one-year period.

Findings

- The results indicated that underachieving students' mathematics performance was better in the teacher-led group as compared to ALEKS-led group, based on pretest/posttest comparisons across two consecutive years.
- A similar pattern was noted when End of Grade (EOG) state assessments data from five years (2015 to 2019), during which ALEKS was not used, were compared with data from one year (2021) when ALEKS was implemented. Students did not show a positive gain in mathematics achievement; in fact, data indicated a negative trend in mathematics achievement, even after ALEKS was employed.
- Students showed more gains in math standards that were relatively easier.
- Students in certain classes demonstrated more improvements, likely due to being grouped by ability level.

Chapter 2 - Measuring Efficacy of ALEKS

Chapter 2, Measuring efficacy of ALEKS as a supportive instructional tool was an extension of the study conducted in chapter 1. This study further evaluated the efficacy of ALEKS by comparing teacher-led instructions and ALEKS-led instructions to determine whether the use of ALEKS shows statistically significant improvement in underachieving students' mathematics achievements. This study included 158 eighth graders from a rural high school in South Georgia. This study examined whether the use of ALEKS shows statistically significant improvement in students' mathematics achievement compared to traditional teacher-led instructions, and whether it indicated statistically significant gains based on the mathematics standards over the course of one year. To address these objectives, research questions and hypotheses were formulated. This study utilized a quasi-experimental study to compare pretest/posttest results between two instructional methods. It also in-

cluded a literature review of existing studies on ALEKS, with a specific focus on K-12 classroom settings. The literature review revealed mixed findings regarding the effectiveness of ALEKS on students' mathematics achievement.

Students took a pretest at the beginning of the year (initial knowledge check) and a posttest at the end of the year (final knowledge check). The pretest and posttest data were used to determine whether there was a statistically significant improvement in students' mathematics achievement between teacher-led and ALEKS-led instruction. Also, data from five years of EOG state assessments were compared with results from one year of EOG assessments in which ALEKS was implemented. Descriptive statistics were used to analyze the data. Paired t-test and ANOVA were conducted to determine statistically significant differences in mathematics achievement based on pretest and posttest scores, as well as alignment with mathematics standards over the course of one academic year.

Findings

- Students showed highly statistically significant gains in mathematics achievement under both teacher-led and ALEKS-led instructions; however, students performed better with teacher-led instructions.
- Students who received teacher-led instructions performed better on EOG state assessments.
- Use of ALEKS indicated statistically significant improvement in mathematics achievement based on mathematics standards across all 11 math standards within five domains.

Chapter 3 - Effect of AI-Based Systems on Mathematics Achievement

In Chapter 3, we examined the effectiveness of AI-based systems on students' learning. This study aims to investigate the efficacy of Edmentum Exact Path, an adaptive learning system, on enhancing mathematics achievement and student engagement (affective and cognitive) among eighth-grade students from a rural area in the Southern United States. This quasi-experimental study included 78 students from socioeconomically disadvantaged backgrounds. This study compared students receiving Edmentum Exact Path-led instruction and traditional teacher-led methods to a control group receiving only the teacher-led instructions. This study included one experimental group (high school 1) and two control groups (high school 2 and high school 3), all located in closed proximity. The experimental group consisted of 43 students, while Control Group 1 had 15 students and Control Group 2 had 20 students. Both the experimental group and Control Group 1 were comprised entirely of economically disadvantaged students, whereas Control Group 2 included 56% economically disadvantaged students.

Based on power analysis, a sample size of 50 students needed in both the experimental and control groups. However, due to the COVID-19 pandemic during the

2021–2022 school year, many parents opted for remote learning or homeschooling, which reduced participation. Also, some students were absent during certain phases of the study due to COVID-19 infections in their families, further reducing the number of participants available and limiting data collection.

The study was conducted over five weeks, with daily sessions of 50 minutes. Teachers utilized the 8th-grade McGraw-Hill math curriculum "Reveal" and incorporated Edmentum Exact Path as a supplemental tool for the experimental group. All students received instruction using the 8th-grade *McGraw-Hill Reveal* math curriculum. The experimental group also received supplemental instruction using Edmentum Exact Path during their math support class. In the math support class, students worked at their own pace on personalized learning paths created by Edmentum Exact Path. These learning paths were created based on diagnostic assessments conducted at the beginning of the school year. Lessons in these paths were grouped into sets of three or four, targeting the students' specific achievement levels. After completing each lesson, students took a short quiz, and upon completing a set, they took a progress check. Students who scored at least 80% on the progress check were assigned a new set of lessons. Those who did not pass progress check were provided with additional lessons to develop the necessary skills.

The teacher dashboard provided an interactive, color-coded view of each student's progress, indicating whether they were struggling, had failed, mastered, or omitted lessons. Teachers could offer one-on-one help to struggling students or assign additional resources such as extra lessons or short videos, to help them understand the concepts.

Both experimental and control groups completed a pretest before the intervention and the same test as a posttest after completing the unit. Mathematics achievement was assessed using pre-test/post-test comparisons and student engagement was measured using the 5-point Student Engagement Instrument (SEI), varying from strongly agree, agree, disagree, to strongly disagree. The low scores indicate a high level of student engagement. Statistical analysis was performed using t-tests and ANOVA. The small sample size and lack of a pre-survey are limitations that may affect the study's rigor and the generalizability of its findings.

Findings

- Paired t -test results indicated that students in the experimental group using Edmentum Exact Path showed significant improvement in mathematics achievement compared to control group 1. Students in control group 2 showed significant improvement with teacher-led instructions.
- ANOVA results showed no overall statistically significant mathematics achievement for any instructional method.
- Students who received traditional teacher-led instruction showed higher levels of affective engagement.

- No statistically significant difference was found in cognitive engagement between the control groups and an experimental group.

Chapter 4 - Impact of Artificial Intelligence-Based systems

In Chapter 4, we conducted a systematic review of literature to identify the types of AI-based systems in mathematics that are used in K-12 classrooms, education level at which they are implemented (elementary, middle, or high school) and their impact on students' mathematics performance in K-12 classrooms. This study also examined whether AI-based systems reduce the achievement gap in mathematics among students from low socioeconomic backgrounds and which specific features contribute to that effect.

This systematic literature review followed the PRISMA framework guidelines. We searched six major databases and selected peer-reviewed articles published from 2008 to 2023. A total of 42 papers were shortlisted based on inclusion and exclusion criteria. Data from these studies were extracted and organized in a spreadsheet containing 16 variables. The dataset was then filtered to identify patterns and trends relevant to the research questions.

Findings

- The use of AI-based systems is widely used in K-12 classrooms across various countries to provide personalized and adaptive learning experiences.
- Most of the studies were conducted in the United States (29 out of 42 studies).
- The most commonly used AI-based systems include Assessment and Learning in Knowledge Spaces (ALEKS), Cognitive Tutor Algebra 1 (CTA1), ASSISTments, Helping At-Risk Students Learn Fractions (HALF), Math Nation's Intelligent Virtual Learning Environment (IVLE), MathSpring, and Decimal Point.
- Some studies incorporated adaptive learning games such as Lynnette, DragonBox, Woot Math Adaptive Learning (WMAL), and Math Whizz.
- Taiwan explored several systems, including the Model-Tracing Intelligent Tutor (MIT), dialogue-based tutors, Affective and Cognitive Factors-based Adaptive Learning System (ACALS), and Adaptive Concept-Effect Relationship (CER)-based mathematics games.
- In Germany, three studies implemented systems such as eFit, Peer Education Diagnostic and Learning Environment (PEDALE), and interactive eBooks with adaptive scaffolding.
- Brazil implemented an OLM-based ITS and the Personal Affective Tutor to Math (PAT2Math).
- In France, one study used ITS algorithms such as ZPDES and RiaRiT.
- India implemented AmritaITS to support mathematics learning.

- Several other countries were represented by a single study each: Turkey: UZWEBMAT (Adaptive and Intelligent Web-based Mathematics Teaching-Learning System), Egypt: APPEAL (Adaptive Personalized Platform for an Effective and Advanced Learning), Austria: Bettermarks, and Spain: HINTS (Hypergraph Intelligent Tutoring System.
- Middle schools emerged as the most common setting for using AI-based systems, followed by elementary and high school.
- At the elementary school level, eight studies implemented ITS, and three studies focused on ALS.
- At the middle school level, ITS has been more widely used than ALS
- At the high school level, both ITS and ALS have been employed to support mathematics; however, fewer studies have examined the role of AI-based systems in high school.
- The overall trend indicated a moderate positive effect of AI-based systems on student mathematics achievement.
- Most studies reported significant to moderate improvements in students' mathematics performance, engagement, and retention.
- AI-based tools have the potential to improve mathematics outcomes for students from low socioeconomic backgrounds.
- Several systems–including ALEKS, MathSpring, and eFit–were specifically associated with improved performance among students from low-SES populations.

Contributions of Thesis

This thesis examines the impact of AI-based systems on the mathematics achievement of underachieving students in a rural high school located in the Southern United States. Students in rural areas often lag in mathematics performance, due to limited resources and challenges in recruiting and retaining highly qualified teachers. This shortage can have a negative impact on students who are already struggling in STEM subjects, particularly in mathematics. AI-based systems, such as ITS and ALS, offer a promising solution by serving as supplemental tools alongside traditional teacher-led instruction.

In Chapters I and II, ALEKS (an ITS) was implemented as a supplemental tool. The findings suggest that while teacher-led instruction was more effective for underserved populations, students showed improvement in both instructional conditions. Chapter III explored the use of Edmentum Exact Path (an ALS) to assess its impact on mathematics achievement and student engagement. Although ANOVA results indicated no statistically significant difference among instructional methods,

the findings suggest that AI-based systems have the potential to deliver instruction comparable to that of human teachers. Students in the teacher-led instruction group exhibited higher levels of affective engagement, suggesting that teacher interaction plays a crucial role in engaging students and may enhance the overall effectiveness of instruction, especially students from disadvantaged backgrounds. The systematic literature review in Chapter IV indicated that AI-based systems are implemented in elementary, middle, and high schools globally. Overall, these systems had a moderate positive effect on students' mathematics achievement, highlighting their potential as valuable instructional tools.

In conclusion, this thesis provides evidence that AI-based systems can significantly enhance mathematics achievement among underachieving students in rural areas, where educational resources are scarce and it is challenging to recruit and retain highly qualified teachers. When used as a supplemental tool, AI-based systems can support teachers by enabling targeted feedback and providing support for struggling students. Although AI-based systems have the potential to improve math performance; however, students in the teacher-led instruction group also showed significant improvement in math performance and higher levels of affective engagement. This highlights the importance of utilizing AI-based instructions as a supplemental tool rather than replacement. Overall, this study offers data-driven insights for school leaders and policymakers considering large-scale implementation of AI-based systems in similar educational contexts.

Limitations of the Thesis

This thesis highlights the positive impact of AI-based systems on students' mathematics achievement and engagement; however, several limitations must be acknowledged. This thesis explored the use of ALEKS and Edmentum Exact Path to evaluate their effectiveness in improving mathematics achievement and enhancing student engagement.This study used a non-randomized quasi-experiemental study as school systems because school systems were hesitant to withhold the potential benefits of AI-based systems from any group of students.

In the first study, ALEKS was implemented as a supplemental tool in the math support class during the 2020-2021 academic year. Pretest and posttest data from this year were compared with teacher-led instruction data from the 2019–2020 academic year. This study took place during the COVID-19 pandemic, which significantly affected instructional delivery and grading practices. In 7th grade, these students faced complete school closures, which resulted in a loss of in-person instruction and disrupted their learning significantly. Many of these students came from disadvantaged backgrounds and lacked access to reliable internet or devices such as laptops or tablets, making it difficult to participate in remote learning. These students were promoted to 8th grade without taking state-level or school-level examinations.

The 2020–2021 school year was also the first year of ALEKS implementation, and teachers were still learning how to use the program. Teachers had limited ability to adjust or supplement ALEKS content, which may have limited their ability to meet the needs of students who were far below grade level. This limitation may have influenced the effectiveness of the intervention. This study took place in a rural setting with a disadvantaged population, which may limit the generalizability of the findings. Due to COVID-19 safety protocols, students attended in-person classes on alternating days to allow for social distancing. As a result, students received ALEKS-led instruction for only half of the academic year, which may have limited both their exposure to the program and the teachers' ability to integrate it effectively into instruction.

For the Edmentum Exact path study, a small sample size and the absence of Student Engagement Intervention (SEI) pre-survey were significant limitations. The power analysis recommended a minimum of 50 participants in each group. However, due to the COVID-19 pandemic, it was difficult to obtain consent forms, and participation was limited to students who returned them. This study used pretest/posttest design and SEI survey after students completed the posttest. Since no SEI was administered before the pretest to establish the baseline of student engagement, it was difficult to accurately assess the impact of the intervention. The differences in baseline math proficiency and socioeconomic status among participants made it challenging to interpret the results accurately.

The COVID-19 pandemic created several challenges for this study, as data were collected during the 2021-2022 school year. Many families in rural South Georgia opted for homeschooling or remote learning due to health concerns, which limited the study's sample size. Student absences due to COVID-19 infections within households disrupted participation at various stages of the study. These disruptions may have influenced both student engagement and mathematics achievement. Confounding variables such as prior academic achievement and intrinsic motivation may have influenced the outcome of this study.

In the systematic literature review (Chapter IV), several limitations were also identified. Many of the studies had small sample sizes and were limited to a single classroom, school, or region. This restricts the generalizability of findings, particularly when the focus is on specific grade levels or mathematical domains. Some studies did not include control groups or used quasi-experimental designs due to ethical concerns or pandemic-related challenges. These conditions limit the ability for randomization and comprehensive data collection. Many studies lacked access to standardized test scores and key demographic information (e.g., socioeconomic status, gender, and previous academic performance). This lack of data made it difficult to evaluate the long-term effects of AI-based systems or analyze outcomes for specific student subgroups. Self-reported learning behavior data, commonly used in several studies, may be subject to bias. With the short duration of many interventions, it is difficult to assess the long-term effectiveness of AI-based systems. The implementation of AI-based systems varied depending on teacher experience,

student participation, and the availability of technology infrastructure. These inconsistencies may have influenced the overall results.

Implications and Final Thoughts

This thesis has highlighted the importance of AI-based systems, such as ALEKS and Edmentum Exact Path in enhancing mathematics achievement and student engagement. These systems are effective when used as a supplemental tool along with teacher-led instruction. The findings are particularly relevant for underachieving students from socioeconomically disadvantaged backgrounds in rural settings.

The findings suggest that AI-based systems can provide adaptive and personalized instruction to the struggling students, especially in rural settings where limited resources and qualified teachers are scarce. In rural or under-resourced schools, AI-based systems may help bridge educational equity gaps by addressing individual learning needs. However, the cost of implementing these technologies may hinder widespread adoption in K-12 classrooms. Therefore, policymakers and educational stakeholders must carefully evaluate cost-effectiveness and sustainability when considering large-scale investments in AI-based platforms.

Although students who used AI-based systems showed improvement, students in the teacher-led instruction group demonstrated greater gains in mathematics achievement and higher levels of affective engagement. This highlights the critical role of teacher-student interaction and supports the notion that AI-based systems should augment, rather than replace, traditional instruction. Effective implementation of technology depends on teachers' ability to integrate it meaningfully into pedagogical practices.

The use of AI -based systems, including ITS and ALS, to support math learning is increasing being adopted in K-12 education. These systems have demonstrated potential to improve mathematics achievement, particularly among students who are at risk and lag in mathematics. This study contributes to the growing body of research indicating that AI-based systems can facilitate personalized learning, address foundational gaps in mathematics, and support previous findings that demonstrate significant gains in student performance on standardized mathematics assessments.

AI-based systems can deliver instruction comparable to teacher-led instruction and can be used as a supplemental tool to provide personalized learning experiences. These systems can be integrated into both in-person and remote learning environments, offering flexible instructional support tailored to each student's prior knowledge and readiness level. This type of personalized instruction is valuable for economically disadvantaged students who often lack basic math skills and may need additional support. AI-based systems can support teachers by freeing up their time allowing more time for individualized support to struggling students.

As AI-based systems continue to evolve and use innovative ways to engage students

in learning, the role of teacher-student interaction remains essential in addressing both academic and emotional needs. It is important for stakeholders to prioritize efforts to recruit and retain qualified teachers, particularly in rural areas where majority of students come from socioeconomically disadvantaged backgrounds and often lack foundational skills in mathematics. The systematic literature review revealed that the use of AI-based systems is still limited at the high school level, highlighting the need for policymakers and stakeholders to promote the broader integration of AI-based tools to enhance mathematics instruction.

While this study supports the use of AI-based systems as supplemental tools, their success ultimately depends on meaningful integration into existing curricula and ongoing teacher support. Further research is needed to explore long-term effects, scalability, and implementation challenges to maximize the potential of AI-based systems in improving mathematics achievement for disadvantaged student populations.

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TABLE 1.

Study Characteristics

Database	Study	Country	School level	N	Design	Duration	Types of ITS/ALS	Primary/ supplementary tool	Mathematics Performance	Socioeconomic Status	Effect Size
ScienceDirect	Özyurt et al., 2014	Turkey	High	106	Quasi-experimental	6 weeks (24 hrs.)	UZWEBMAT-ALS	Supplementary	EG outperformed CG; males > females	Not mentioned	0.59
ScienceDirect	Hwang et al., 2020	Taiwan	Elementary	162	Quasi-experimental	205 minutes	ACALS -ALS	Supplementary	Significant improvement in ACALS group; reduced anxiety	Not mentioned	0.5
Springer	Arroyo et al., 2014	USA	Middle & High	198	Quasi-experimental	one year/once per month	MathSpring-ALS	Supplementary	Improved performance, engagement, and retention scores	Low	0.35
Springer	Sayed et al., 2023	Egypt	Elementary	26	Experimental	2 months	APPEAL- ALS	Supplementary	More effective learning; reduced time; improved grades	Not mentioned	0.9
ScienceDirect	Mills, 2021	USA	High	265	Predictive correlational	2 years/ 1 hr. each day	ALEKS -ITS	Primary	Engagement time and mastery ratio predicted final grades; retention predicted PSAT math scores	Low	0.95
ERIC (EBSCO)	Clement et al., 2015	France	Elementary	400	Randomized control trial	40 minutes	ITS algorithms:ZPDES & RiaRiT	Supplementary	significant improvements in math skills	Not mentioned	0.12
Springer	Hou et al., 2022	USA	Middle	159	Experimental	6 days (1 hr./day)	Decimal Point	Primary	No significant differences in learning outcomes; learning-oriented engaged more in re-practice; enjoyment-oriented explored more mini-games	Not mentioned	0.21
ERIC (EBSCO)	Zheng et al., 2019	USA	Middle	23,374	Predictive modeling	3 years	CTA 1 -ITS	Supplementary	No significant differences in learning outcomes; learning-oriented engaged more in re-practice; enjoyment-oriented explored more mini-games	Mixed	0.11
Wiley	Leite et al., 2019	USA	Middle & High	3,987	Correlational study	Two school years (2014–2016)	Algebra Nation - ALS	Supplementary	Mixed effects; improvement index -8 to +36 percentile points	Low	0.19

TABLE 1 (CONTINUED)

Database	Study	Country	School level	N	Design	Duration	Types of ITS/ALS	Primary/ supplementary tool	Mathematics Performance	Socioeconomic Status	Effect Size
Springer	Mendiburo et al., 2014	USA	Elementary	115	Quasi-experimental	2 weeks (10 days)	HALF- ITS	Supplementary	Learning gains similar to commercial curriculum; corrected misconceptions; progressed through lessons	Low	0.14
JSTOR	Chu et al., 2021	Taiwan	Elementary	116	Quasi-experimental	2 weeks	CER-based Mathematics Game	Supplementary	Higher post-test scores in experimental group (78.37 vs. 69.48); η^2 = 0.14	Not mentioned	0.66
ScienceDirect	Waalkens et al., 2013	USA	Middle	57	Experimental	3 days (2 hrs./day)	ITS for Linear Algebraic Equations	Supplementary	All groups improved; no significant differences based on strategy freedom	Not mentioned	0.54
ACM Digital	Long & Aleven, 2017	USA	Middle	190	Randomized controlled trial	Five class periods (42 mins each)	Lynnette -ITS DragonBox-ALS (Educational Game)	Primary	Lynnette showed higher post-test gains (d = 0.41 to d = 0.84); DragonBox solved more in-game problems	Not mentioned	0.39
Springer	Graff et al., 2008	Germany	Middle	194	Quasi-experimental	9 months (2 hrs./week)	eFit -ITS	Supplementary	Treatment group significantly improved in arithmetic (d = 1.17)	Low	1.17
Springer	Ferreira da Rocha et al., 2024	Brazil	Elementary, Middle & High	39	Randomized controlled trial	4 weeks	OLM-based ITS	Supplementary	No significant differences in self-regulation or performance	Not mentioned	0.4
JSTOR	Chu et al., 2014	Taiwan	Elementary	124	Quasi-experimental	3 weeks	MIT-ITS	Primary	Experimental group scored higher (71.55 vs. 54.74)	Not mentioned	0.41
Springer	Phillips et al., 2020	USA	High	2500	Randomized control trial	Two consecutive school years	ALEKS- ITS	Supplementary	no significant effect of the ALEKS intervention on end-of-course algebra exams	Low	0.2
ERIC (EBSCO)	Kelly et al., 2014	USA	Middle	63	Randomized controlled trial	One night of homework, followed by a class review and a post-test session.	ASSISTments-ITS	Supplementary	Students in WBH group outperformed those in TH group in immediate and delayed post-tests with effect sizes of 0.52 and 0.56.	Not mentioned	0.54

TABLE 1 (CONTINUED)

Database	Study	Country	School level	N	Design	Duration	Types of ITS/ALS	Primary/ supplementary tool	Mathematics Performance	Socioeconomic Status	Effect Size
Springer	Lee et al, 2020	Taiwan and Japan	Elementary	200	Experimental	2018-2019	Intelligent agent system integrated with robotic edutainment and humanized co-learning.	Supplementary	Remedial students showed improved performance in mathematical concepts through tailored content.	Not mentioned	1.28
Eric (EBSCO)	Olsen et al.,2017	USA	Elementary	307	Quasi-experimental design	Five 45-minutes class periods	Fractions ITS	Primary	Mixed conditions led to higher learning gains than collaborative-only or individual-only conditions.	Not mentioned	1.46
Eric (EBSCO)	Fang et al., 2017	USA	Middle	275	Quasi-experimental design	Three academic years (2009-2012) with two weekly one-hour sessions over 25 weeks.	ALEKS- ITS	Primary	Persistence linked to mastering difficult topics, though no significant differences in overall achievement.	Not mentioned	0.52
ACM Digital	Fancsali & Ritter, 2014	USA	Middle	2,389	Quasi-experimental design	one year	MATHia	Supplementary	Improved problem-solving, motivation, and engagement	Not mentioned	0.2
JSTOR	Konert et al., 2012	Germany	High	210	Quasi-experimental	Three weeks	PEDALE- ALS	Primary	Peer assessment and adaptive tools enhanced understanding of mathematical functions and graphs.	Not mentioned	Not reported
ScienceDirect	Spitzer & Moeller, 2023	Austria	Elementary, Middle & High	168	Quasi-experimental	2 months	Bettermarks-ITS	Supplementary	Increased performance during closures for both below and above-average students	Not mentioned	0.45
Eric (EBSCO)	Reinhold et al., 2020	Germany	Middle	1005	Randomized control trial	Four weeks	eBook with interactive adaptive scaffolds and feedback.	Primary	Low-achieving students showed greater improvement using the scaffolded eBook. High-achieving students performed well across methods.	Mixed	0.32

TABLE 1 (CONTINUED)

Database	Study	Country	School level	N	Design	Duration	Types of ITS/ALS	Primary/ supplementary tool	Mathematics Performance	Socioeconomic Status	Effect Size
Springer	Walkington & Bernacki, 2019	USA	High	106	Quasi-experimental	1 year	CTA1 -ITS	Primary	Personalized problems advantaged; deep personalization better for high engagement students	Mixed	0.56
ScienceDirect	Suppes et al., 2014	USA	Elementary & Middle	82,132	Quasi-experimental	4 years (2007-2011)	EPGY- ALS	Supplementary	Math gains increased with correct coursework; improvements decreased with higher pre-test scores	Low	0.62
Springer	Haridas et al., 2020	India	Elementary	2,123	Quasi-experimental	3 years (2015-2017; 30 min/week)	AmritaITS -ITS	Supplementary	Improved prediction of assessment scores; effective supplement to traditional teaching	Low	0.019
ScienceDirect	Jaques et al., 2013	Brazil	Middle	43	Quasi-experimental	4 sessions (3 hrs. 20 min.)	PAT2Math-ITS	Supplementary	PAT2Math users scored higher on equation-solving tests	High	0.58
ScienceDirect	Sabo et al., 2013	USA	High	31	Quasi-experimental	14 days (4 hrs./day)	ALEKS-ITS & CTA1 - ITS	Primary	Both ITS improved arithmetic and algebra; ALEKS d=0.95, Carnegie d=1.18	Not mentioned	0.95
Wiley	Bush, 2021	USA	Elementary	297	Randomized control trial	two weeks (10 days)	WMAL-ALS	Supplementary	Higher gains after WMAL; improved fraction understanding (10.9 percentile points)	Mixed	0.6
ERIC (EBSCO)	Chakraborty et al., 2021	USA	Middle & High	16,406	Randomized control trial	1 academic year (2013-2014)	IVLE-ALS	Supplementary	Moderate engagement improved EOC scores; low engagement no benefit	Not mentioned	0.07
Springer	Salden et al., 2010	Germany & USA	Middle & High	108	Quasi-experimental and randomized controlled trial	2 lab sessions- 4hours, classroom session- 3 weeks -6 hours	CTA1-ITS	Primary	Adaptive fading showed higher immediate and delayed posttest performance	Low	0.59

TABLE 1 (CONTINUED)

Database	Study	Country	School level	N	Design	Duration	Types of ITS/ALS	Primary/ supplementary tool	Mathematics Performance	Socioeconomic Status	Effect Size
ScienceDirect	Craig et al., 2013	USA	Middle	253	Randomized controlled trial	25 weeks (after-school)	ALEKS -ITS	Primary	ALEKS and teacher-led performed similarly; ALEKS required less teacher assistance	Low	0.18
ERIC (EBSCO)	Clark & Whetstone, 2014	USA	Elementary	2,542	Quasi-experimental	3 years	Math Whizz- ITS	Supplementary	Improved math ability; 0.4 years increase; significant state assessment gains	Not mentioned	0.5
ERIC (EBSCO)	Huang et al., 2013	USA	Elementary	102	Randomized control trial	25 weeks, 2 days/week, 2 hrs./day	ALEKS-ITS	Supplementary	Improved TCAP scores, narrowed achievement gaps	Low	0.48
Springer	McDonough & Tra, 2017	USA	High	16,219	Quasi-experimental	1 year	SCIM-ITS	Supplementary	SCIM participation increased proficiency, especially for minority students	Low	0.098
JSTOR	Sales & Pane, 2019	USA	Middle & High	18,700	Randomized control	2 years	CTA1-ITS	Supplementary	Moderate positive effect on high school post-test scores; more effective for frequently promoted students	Mixed	0.22
ERIC (EBSCO)	Nagashima et al., 2021	USA	Middle	108	Randomized control	2 days	ITS with anticipatory diagrammatic self-explanation	Supplementary	Significant improvement in problem-solving performance	High	0.1
Wiley	del Olmo-Muñoz et al., 2022	Spain	Elementary	110	Quasi-experimental	8 weeks (six 45-min sessions)	HINTS -ITS	Supplementary	Improved problem-solving; especially for girls	Not mentioned	0.58
Springer	Shih et al., 2022	Taiwan	Middle	66	Quasi-experimental	2 hours	Dialogue-based mathematics-ITS	Supplementary	Experimental group significantly outperformed control group; greater impact on lower-performing students.	Not mentioned	0.15
Springer	Kessler et al., 2015	USA	Middle	7	Quasi-experimental	3 weeks	MIT	Primary	No significant overall gains in math performance; some shifts in strategy use	Not mentioned	0.04

Student Engagement Instrument

MARKING INSTRUCTIONS

- Use a No. 2 pencil or a blue or black ink pen only.
- Do not use pens with ink that soaks through the paper.
- Make solid marks that fill the response completely.
- Make no stray marks on this form.

CORRECT: ● INCORRECT: ✓ ✗ ◒ ◔

	Strongly Disagree	Disagree	Agree	Strongly Agree
1. My family/guardian(s) are there for me when I need them.	①	②	③	④
2. After finishing my schoolwork I check it over to see if it's correct.	①	②	③	④
3. My teachers are there for me when I need them.	①	②	③	④
4. Other students here like me the way I am.	①	②	③	④
5. Adults at my school listen to the students.	①	②	③	④
6. Other students at school care about me.	①	②	③	④
7. Students at my school are there for me when I need them.	①	②	③	④
8. My education will create many future opportunities for me.	①	②	③	④
9. Most of what is important to know you learn in school.	①	②	③	④
10. The school rules are fair.	①	②	③	④
11. Going to school after high school is important.	①	②	③	④
12. When something good happens at school, my family/guardian(s) want to know about it.	①	②	③	④
13. Most teachers at my school are interested in me as a person, not just as a student.	①	②	③	④
14. Students here respect what I have to say.	①	②	③	④
15. When I do schoolwork I check to see whether I understand what I'm doing.	①	②	③	④
16. Overall, my teachers are open and honest with me.	①	②	③	④
17. I plan to continue my education following high school.	①	②	③	④
18. I'll learn, but only if the teacher gives me a reward.	①	②	③	④
19. School is important for achieving my future goals.	①	②	③	④
20. When I have problems at school my family/guardian(s) are willing to help me.	①	②	③	④

Please Turn Over

	Strongly Disagree	Disagree	Agree	Strongly Agree
21. Overall, adults at my school treat students fairly.	①	②	③	④
22. I enjoy talking to the teachers here.	①	②	③	④
23. I enjoy talking to the students here.	①	②	③	④
24. I have some friends at school.	①	②	③	④
25. When I do well in school it's because I work hard.	①	②	③	④
26. The tests in my classes do a good job of measuring what I'm able to do.	①	②	③	④
27. I feel safe at school.	①	②	③	④
28. I feel like I have a say about what happens to me at school.	①	②	③	④
29. My family/guardian(s) want me to keep trying when things are tough at school.	①	②	③	④
30. I am hopeful about my future.	①	②	③	④
31. At my school, teachers care about students.	①	②	③	④
32. I'll learn, but only if my family/guardian(s) give me a reward.	①	②	③	④
33. Learning is fun because I get better at something.	①	②	③	④
34. What I'm learning in my classes will be important in my future.	①	②	③	④
35. The grades in my classes do a good job of measuring what I'm able to do.	①	②	③	④

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Appendix B

Declaration of consent (in case under 18 years)[1*]

for participation in scientific research:
(*Artificial Intelligence in Education: Impact of Adaptive Learning Systems on Mathematics Achievement*

FOR THE MINOR:

- I've been given an explanation of the investigation. The letter about the research (*version code:…*) I read and had my parents read.
- I have asked any questions I may have about the investigation.
- I've been thinking about whether I want to participate in the investigation.
- I can stop the investigation at any time if I want to.
- You may use the information (e.g. the answers to the questions) that you collect from me for this research.
- I understand that you only collect the personal data as it is mentioned in the information letter. The personal data is encrypted and access to this key is limited.
- I understand you keep my data safe for 10 years.

- If you would like to participate in this research, you can sign this form. Please note, if you are not yet 16 years old, a parent/carer must also sign.

- **I'm in the investigation.**

  Name (own name):

  Date of birth:

  Signature: Date:

  Surname and initials (parent/guardian name):

1* ***This form is intended for examination with persons who have not yet reached the age of 18 but are over 11 years of age.***

* ***If you are under 16 years of age, permission must be granted by yourself and by a parent/guardian.***

* ***If you are 16 years or older, but not yet 18 years old, you only have to sign yourself. Let your parents read the information letter.***

Relationship to the participant:

Signature(s): Date:

The undersigned, responsible investigator, declares that the above person has been informed both in writing and orally about the above-mentioned research.

name:

function:

Signature: Date:

List of Tables

4.1 Impact of AI-based systems on mathematics performance at the elementary level 80
4.2 Impact of AI-based systems on mathematics performance at the middle school level 81
4.3 Impact of AI-based systems on mathematics performance at the high school level 82
4.4 Effect sizes of AI-based systems on mathematics performance (Low SES) 83

List of Figures

1.1 Comparison between teacher-led instructions versus ALEKS-led instructions 15
1.2 Comparison between End of Grade with and without ALEKS-led instructions 16
1.3 ALEKS-led improvement on mathematics standards 16
1.4 ALEKS-led improvement in mathematics achievement based on class period 17

2.1 Comparison between End of Grade with and without ALEKS-led instructions 30

3.1 Edmentum Exact Path knowledge map. 44
3.2 Edmentum Exact Path learning progression. Source: Adapted from https:// edmentum.com 44

4.1 PRISMA flow chart of the study 74
4.2 Number of studies using AI-based systems in mathematics by country 76
4.3 Distribution of AI-based systems by education level 78
4.4 Impact of AI-based systems on mathematics performance in K-12 classrooms 79
4.5 Effect sizes of AI-based systems on mathematics performance (Low SES) 83

Summary

Use of artificial intelligence in education (AIED) is growing rapidly and significantly influencing the teaching and learning processes. AI-based systems can provide immediate feedback and adapt instructions in real time, creating opportunities for interaction and engagement in the learning processes that are often difficult to achieve in traditional classroom settings, where teachers cannot always offer individualized support to struggling learners. Several research studies have shown promising results when AI-based systems are used as a supplemental tool in K-12 classrooms.

AI-based systems such as ITS and ALS have the potential to deliver adaptive and personalized learning to students, particularly in STEM subjects like mathematics, which many students find challenging. This is more evident among disadvantaged students from rural areas who frequently fall behind grade-level expectations due to limited resources, a lack of highly qualified teachers, and the effects of poverty.

The learning loss caused by the COVID-19 pandemic has significantly impacted students' mathematics performance, further widening existing achievement gaps. To address this issue and narrow the achievement gap, several schools across the United States have implemented AI-based tools to support mathematics learning. A rural high school in the southern United States piloted ALEKS, an ITS, during the 2021-2022 academic year to support struggling eighth-grade students. In the 2022–2023 academic year, the school adopted Edmentum Exact Path, an ALS, to continue providing support.

This thesis consists of four chapters: Chapter 1 discusses a study conducted with ALEKS; Chapter 2 extends the first study for journal publication; Chapter 3 examines the use of Edmentum Exact Path; and Chapter 4 presents a systematic literature review on AI-based systems and their impact on mathematics achievement.

Chapter 1 focuses on the effect of intelligent tutoring systems on the mathematics achievement of underachieving students. This quasi-experimental study used ALEKS to evaluate its impact on 158 eighth-grade students, 62–68% of whom were economically disadvantaged, with only 12% proficient in mathematics. This study aimed to 1) Compare the effectiveness of ALEKS versus traditional instruction in improving students' mathematics achievement. 2) Assess students' progress on grade-level math standards over one academic year using ALEKS. 3) Analyze differences

in achievement across class periods with ALEKS implementation.

We compared the results of pretest and posttest from teacher-led instructions and ALEKS -led instructions across two consecutive years. In the first year, only McGraw math curriculum *Reveal* was used. In the second year, ALEKS was implemented as a supplemental tool in a math support class for 50 minutes every other day, alongside the *Reveal Math* curriculum. We also analyzed five years of End-of-Grade (EOG) state assessment data (without ALEKS) and compared it to EOG data from the year ALEKS was implemented.

Findings showed that students receiving teacher-led instructions showed greater mathematics achievement than those using ALEKS-led instructions. This outcome may be attributed to ALEKS being in its pilot stage, with teachers still learning how to use it effectively. Many students were working on prerequisite skills as they were below grade level. The COVID-19 pandemic likely amplified this effect, as students were promoted to eighth grade without taking state or school exams after missing much of their seventh-grade instruction due to school closures.

This study also found that ALEKS contributed to improvement across all eleven mathematics standards within five math domains. However, most students were unable to complete all standards because ALEKS is mastery-based, requiring students to achieve 80% accuracy on prerequisite skills before progressing further. Limited access to ALEKS (only on alternate days) also restricted completion rates. Another finding indicated that high-achieving students with strong work ethics performed better compared to mixed-ability groups, which included students with disabilities.

Chapter 2 was extended for journal publication by incorporating statistical analysis, including paired t-tests and ANOVA, to evaluate the efficacy of ALEKS on students' mathematics achievement. A literature review and null hypothesis were also added. The results indicated that teacher-led instruction was more effective, showing higher test scores and lower variance compared to ALEKS. The study had two main objectives: 1) to examine whether the use of ALEKS shows a statistically significant improvement in students' mathematics achievement compared to traditional teacher-led instruction, and 2) to determine whether the use of ALEKS shows statistically significant improvement across grade-level mathematics standards over one academic year. The analysis found that both ALEKS-led and teacher-led instructions were statistically significant, with teacher-led instruction being more effective. A similar pattern was observed when comparing five years of the End of Grade (EOG) data with and without ALEKS. While the use of ALEKS significantly improved all mathematics standards, the gains varied, likely due to its mastery-based learning, which requires 80% mastery before progressing to the next topic. Since students only used ALEKS on alternate days, they were unable to complete all eleven standards.

Overall, the findings from this study provide valuable insights into the use of ITSs in K-12 classrooms. Mathematics ITSs like ALEKS offer adaptive and personalized

learning opportunities and can significantly enhance achievement among underperforming students.

In Chapter 3, we examined the effectiveness of *Edmentum Exact Path*, an AI-based instructional system, in enhancing mathematics achievement and engagement (affective and cognitive) among 8th-grade students in the Southern United States. This quasi-experimental study included 78 students from socioeconomically disadvantaged backgrounds. We compared an experimental group that received both traditional teacher-led instruction and Edmentum Exact Path-led instructions to a control group that received only traditional teacher-led instruction.

The three objectives for this study were 1) To compare the efficacy of Edmentum Exact Path and traditional teacher-led instruction on students' mathematics achievement. 2) To investigate differences in students' affective engagement between Edmentum Exact Path instruction and traditional teacher-led instruction. 3) To examine differences in students' cognitive engagement between Edmentum Exact Path instruction and traditional teacher-led instruction.

This intervention lasted five weeks, with a daily session of 50 minutes each. Both groups used the McGraw-Hill math curriculum *Reveal,* 8th-grade math curriculum. and incorporated Edmentum Exact Path as a supplemental tool for the experimental group. The experimental group also attended math support classes, where they worked on individualized learning pathways in Edmentum Exact Path, created based on diagnostic assessments administered at the beginning of the school year. Mathematics achievement was measured using pretests and posttests, while student engagement was measured using a 35-item, 5-point Likert-scale Student Engagement Instrument (SEI), administered following the posttest to assess affective and cognitive engagement. A significant limitation of this study is the absence of a pre-intervention SEI survey, which restricts the ability to measure changes in engagement over time.

Data were analyzed using t-tests and ANOVA. The result showed that both the experimental and control groups showed statistically significant improvements in mathematics achievement. However, the control group showed greater gains in affective engagement, whereas no statistically significant differences were observed in cognitive engagement between the two groups.

These results suggest that integrating AI-based systems like Edmentum Exact Path may enhance mathematics achievement and cognitive engagement by addressing individual learning needs. However, such tools may be less effective in increasing affective engagement, possibly due to a lack of emotional responsiveness. Further research is needed to better understand the role of AI in promoting student engagement, particularly among the underserved population in rural areas.

In Chapter 4, we conducted a systematic literature review to investigate the impact of AI-based systems on mathematics achievement in K-12 classrooms. The review was guided by the following objectives: 1) To identify what types of AI-based systems are used in mathematics education, and the educational level at which they are

implemented. 2) To identify the impact of AI-based systems on students' mathematics performance in K-12 classrooms. 3) To explore whether AI-based systems help reduce the mathematics achievement gap among students from low socioeconomic backgrounds, and which system features contribute to this effect.

We followed the PRISMA guidelines and searched six major databases: ACM Digital Library, ERIC (EBSCO), JSTOR, Wiley, ScienceDirect (Elsevier), and SpringerLink to locate peer-reviewed articles published between 2008 and 2023. An initial pool of 1,945 studies was identified based on predefined inclusion and exclusion criteria. After screening, 42 articles were selected for in-depth analysis. Data was organized and analyzed using spreadsheets.

The findings indicate that AI-based systems are widely used in K-12 classrooms across various countries to provide personalized and adaptive learning experiences to support students' mathematics learning. Most studies were conducted in the United States. Both ITS and ALS are used at the elementary, middle, and high school levels, with more frequent implementation at the middle school level and less at the high school level. Several studies also reported the use of adaptive learning games, such as Lynnette, DragonBox, Woot Math Adaptive Learning (WMAL), and Math Whizz. The most commonly used AI-based systems in the U.S. include ALEKS, CTA1, ASSISTments, HALF, Math IVLE, MathSpring, and Decimal Point. Studies from other countries reported the use of AI-based systems, such as MIT, dialogue-based tutors, ACALS, Adaptive CER-based mathematics games, PEDALE, PAT2Math, ZPDES, RiaRiT, AmritaITS, UZWEBMAT, APPEAL, and HINTS.

Overall, the findings suggest a moderately positive effect of AI-based systems on students' mathematics achievement. Most studies reported moderate to significant improvements in student performance, engagement, and retention. Several AI-based systems, such as ALEKS, MathSpring, and eFit were associated with improved outcomes among students from low socioeconomic backgrounds, highlighting their potential to support educational equity.

The discussion presents the findings of each study of this doctoral thesis, along with the contributions and the limitations of this research. Grounded in the integration of AI-based instructional systems and personalized learning frameworks, the studies demonstrate how AI-based systems can enhance student learning outcomes in mathematics. These AI-based systems show potential in enhancing students' cognitive engagement and academic performance. However, the findings also reveal limitations in promoting affective engagement, highlighting the challenges AI-based systems face in replicating the emotional connection of human teaching. The study shows limitations in affective engagement, showing the challenges of AI-based systems to replicate the emotional and relational aspects of human instruction. This dissertation adds to the broader dis, course within the AIED communities, providing empirical evidence on the pedagogical impact of AI-based instructions on students mathematics achievement and engagement in underserved population within rural educational contexts.

Future research should investigate the impact of various AI-based systems by comparing their effectiveness with ITS and ALS, such as ALEKS, and Edmentum Exact Path. It should consider factors like instructional design, student characteristics, and specific learning outcomes. By leveraging the strengths of these AI-based systems, educators and policymakers make informed decisions regarding their integration, ultimately enhancing student achievement in mathematics and related disciplines.

Samenvatting

Het gebruik van kunstmatige intelligentie (AIED) in het onderwijs groeit snel en heeft een aanzienlijke invloed op de onderwijs- en leerprocessen. AI-gebaseerde systemen kunnen direct feedback geven en instructies in realtime aanpassen, waardoor er mogelijkheden ontstaan voor interactie en betrokkenheid bij het leerproces die vaak moeilijk te realiseren zijn in traditionele klaslokalen, waar leerkrachten niet altijd individuele ondersteuning kunnen bieden aan leerlingen met leerproblemen. Verschillende onderzoeken hebben veelbelovende resultaten laten zien wanneer AI-gebaseerde systemen worden gebruikt als aanvullend hulpmiddel in klassen van het basis- en voortgezet onderwijs.

AI-gebaseerde systemen zoals ITS en ALS hebben de potentie om leerlingen adaptief en gepersonaliseerd onderwijs te bieden, met name in STEM-vakken zoals wiskunde, waar veel leerlingen moeite mee hebben. Dit is vooral duidelijk bij kansarme leerlingen uit plattelandsgebieden, die vaak achterlopen op de verwachtingen voor hun leerjaar vanwege beperkte middelen, een gebrek aan hooggekwalificeerde leraren en de gevolgen van armoede.

Het leerverlies als gevolg van de -19-pandemie heeft de wiskundeprestaties van leerlingen aanzienlijk beïnvloed, waardoor de bestaande prestatieverschillen verder zijn toegenomen. Om dit probleem aan te pakken en de prestatiekloof te verkleinen, hebben verschillende scholen in de Verenigde Staten AI-gebaseerde tools geïmplementeerd ter ondersteuning van het wiskundeonderwijs. Een middelbare school op het platteland in het zuiden van de Verenigde Staten heeft in het schooljaar 2021-2022 een pilot uitgevoerd met ALEKS, een ITS, om leerlingen uit groep 8 te ondersteunen die het moeilijk hebben. In het schooljaar 2022-2023 heeft de school Edmentum Exact Path, een ALS, geïmplementeerd om de ondersteuning voort te zetten.

Dit proefschrift bestaat uit vier hoofdstukken: Hoofdstuk 1 bespreekt een onderzoek dat met ALEKS is uitgevoerd; Hoofdstuk 2 breidt het eerste onderzoek uit voor publicatie in een tijdschrift; Hoofdstuk 3 onderzoekt het gebruik van Edmentum Exact Path; en Hoofdstuk 4 presenteert een systematisch literatuuronderzoek naar op AI gebaseerde systemen en hun impact op wiskundige prestaties.

Hoofdstuk 1 richt zich op het effect van intelligente bijlessystemen op de wiskundeprestaties van onderpresterende leerlingen. Deze quasi-experimentele studie ge-

bruikte ALEKS om de impact ervan op 158 leerlingen uit groep 8 te evalueren, van wie 62-68% in een economische achterstandspositie verkeerde en slechts 12% bekwaam was in wiskunde. Deze studie had als doel om: 1) de effectiviteit van ALEKS te vergelijken met traditioneel onderwijs ter verbetering van de wiskundeprestaties van leerlingen; 2) de voortgang van leerlingen ten opzichte van de wiskundenormen per leerjaar te beoordelen met behulp van ALEKS gedurende éénschooljaar; 3) de prestatieverschillen tussen lesperiodes te analyseren met behulp van ALEKS-implementatie.

We vergeleken de resultaten van de voor- en natoets, gebaseerd op door de docent gegeven instructies en de door ALEKS gegeven instructies, gedurende twee opeenvolgende jaren. In het eerste jaar werd alleen het *Reveal- wiskundecurriculum van McGraw* gebruikt. In het tweede jaar werd ALEKS geïmplementeerd als aanvullend hulpmiddel in een wiskundeles, gedurende 50 minuten om de dag, naast het *Reveal*-wiskundecurriculum. We analyseerden ook gegevens van vijf jaar aan het einde van het leerjaar (EOG) van de staatsexamens (zonder ALEKS) en vergeleken deze met EOG-gegevens uit het jaar waarin ALEKS werd geïmplementeerd.

De bevindingen toonden aan dat leerlingen die instructie kregen van een leerkracht, betere wiskundeprestaties lieten zien dan leerlingen die instructie kregen van een ALEKS-leerkracht. Deze uitkomst kan worden toegeschreven aan het feit dat ALEKS zich nog in de pilotfase bevond, waarbij leerkrachten nog moesten leren hoe ze het effectief konden gebruiken. Veel leerlingen werkten aan de vereiste vaardigheden omdat ze onder het niveau van hun leerjaar zaten. De COVID-19-pandemie heeft dit effect waarschijnlijk versterkt, aangezien leerlingen naar groep 8 gingen zonder staats- of schoolexamens af te leggen, omdat ze een groot deel van hun instructie in groep 7 hadden gemist vanwege schoolsluitingen.

Uit deze studie bleek ook dat ALEKS bijdroeg aan de verbetering van alle elf wiskundestandaarden binnen vijf wiskundedomeinen. De meeste leerlingen konden echter niet alle standaarden afronden, omdat ALEKS gebaseerd is op beheersing, wat betekent dat leerlingen een nauwkeurigheid van 80% moeten behalen op de vereiste vaardigheden voordat ze verder kunnen. Beperkte toegang tot ALEKS (alleen om de dag) beperkte ook de slagingspercentages. Een andere bevinding gaf aan dat hoogpresterende leerlingen met een sterke werkethiek beter presteerden in vergelijking met groepen met verschillende niveaus, waaronder leerlingen met een beperking.

Hoofdstuk 2 werd uitgebreid voor publicatie in tijdschriften door statistische analyse, waaronder gepaarde t-toetsen en ANOVA, te integreren om de effectiviteit van ALEKS op de wiskundeprestaties van leerlingen te evalueren. Een literatuuronderzoek en een nulhypothese werden ook toegevoegd. De resultaten gaven aan dat door de leraar geleide instructie effectiever was, met hogere testscores en een lagere variantie in vergelijking met ALEKS. De studie had twee hoofddoelen: 1) onderzoeken of het gebruik van ALEKS een statistisch significante verbetering in de wiskundeprestaties van leerlingen liet zien in vergelijking met traditionele door de leraar geleide instructie, en 2) bepalen of het gebruik van ALEKS een statistisch sig-

nificante verbetering liet zien over de wiskundestandaarden van alle leerjaren heen over éénschooljaar. De analyse wees uit dat zowel door ALEKS als door de leraar geleide instructie statistisch significant was, waarbij door de leraar geleide instructie effectiever was. Een vergelijkbaar patroon werd waargenomen bij vergelijking van vijf jaar aan gegevens over het einde van het leerjaar (EOG) met en zonder ALEKS. Hoewel het gebruik van ALEKS alle wiskundestandaarden aanzienlijk verbeterde, varieerde de winst, waarschijnlijk vanwege het op beheersing gebaseerde leren, waarbij 80% beheersing vereist is voordat naar het volgende onderwerp kan worden doorgegaan. Omdat leerlingen ALEKS slechts om de dag gebruikten, konden ze niet alle elf standaarden afronden.

Over het geheel genomen bieden de bevindingen van deze studie waardevolle inzichten in het gebruik van ITS-systemen in het basis- en voortgezet onderwijs. Wiskunde-ITS-systemen zoals ALEKS bieden adaptieve en gepersonaliseerde leermogelijkheden en kunnen de prestaties van onderpresterende leerlingen aanzienlijk verbeteren.

In hoofdstuk 3 onderzochten we de effectiviteit van *Edmentum Exact Path* , een op AI gebaseerd instructiesysteem, in het verbeteren van de wiskundeprestaties en -betrokkenheid (affectief en cognitief) onder leerlingen in groep 8 in het zuiden van de Verenigde Staten. Deze quasi- experimentele studie omvatte 78 leerlingen uit sociaaleconomisch achtergestelde milieus. We vergeleken een experimentele groep die zowel traditionele, door de leerkracht geleide instructie als door Edmentum Exact Path geleide instructie kreeg, met een controlegroep die alleen traditionele, door de leerkracht geleide instructie kreeg.

De drie doelstellingen van dit onderzoek waren: 1) Het vergelijken van de effectiviteit van Edmentum Exact Path en traditioneel, door docenten geleid onderwijs op de wiskundeprestaties van leerlingen. 2) Het onderzoeken van de verschillen in affectieve betrokkenheid van leerlingen tussen Edmentum Exact Path-onderwijs en traditioneel, door docenten geleid onderwijs. 3) Het onderzoeken van de verschillen in cognitieve betrokkenheid van leerlingen tussen Edmentum Exact Path-onderwijs en traditioneel, door docenten geleid onderwijs.

Reveal- wiskundecurriculum van McGraw-Hill , een wiskundecurriculum voor groep 8 , en integreerden Edmentum Exact Path als aanvullend instrument voor de experimentele groep. De experimentele groep volgde ook ondersteunende wiskundelessen, waar ze werkten aan geïndividualiseerde leerpaden in Edmentum Exact Path, ontwikkeld op basis van diagnostische beoordelingen die aan het begin van het schooljaar werden afgenomen. De wiskundige prestaties werden gemeten met behulp van pretests en posttests, terwijl de betrokkenheid van de leerlingen werd gemeten met een 35-items, 5-punts Likert-schaal Student Engagement Instrument (SEI), afgenomen na de posttest om affectieve en cognitieve betrokkenheid te beoordelen. Een belangrijke beperking van deze studie is de afwezigheid van een SEI-enquéte vóor de interventie, wat de mogelijkheid beperkt om veranderingen in betrokkenheid in de loop van de tijd te meten.

De gegevens werden geanalyseerd met behulp van t-toetsen en ANOVA. Het resultaat toonde aan dat zowel de experimentele als de controlegroep statistisch significante verbeteringen in wiskundeprestaties lieten zien. De controlegroep liet echter een grotere winst zien in affectieve betrokkenheid, terwijl er geen statistisch significante verschillen werden waargenomen in cognitieve betrokkenheid tussen de twee groepen.

Deze resultaten suggereren dat de integratie van AI-gebaseerde systemen zoals Edmentum Exact Path de wiskundeprestaties en cognitieve betrokkenheid kan verbeteren door in te spelen op individuele leerbehoeften. Dergelijke tools zijn echter mogelijk minder effectief in het vergroten van de affectieve betrokkenheid, mogelijk vanwege een gebrek aan emotionele responsiviteit. Verder onderzoek is nodig om de rol van AI bij het bevorderen van de betrokkenheid van leerlingen beter te begrijpen, met name onder de achtergestelde bevolking in plattelandsgebieden.

In hoofdstuk 4 hebben we een systematisch literatuuronderzoek uitgevoerd om de impact van AI-gebaseerde systemen op de wiskundeprestaties in klassen van het basis- en voortgezet onderwijs te onderzoeken. Het onderzoek was gericht op de volgende doelstellingen: 1) Identificeren welke soorten AI-gebaseerde systemen worden gebruikt in het wiskundeonderwijs en op welk onderwijsniveau ze worden geïmplementeerd. 2) De impact van AI-gebaseerde systemen op de wiskundeprestaties van leerlingen in het basis- en voortgezet onderwijs identificeren. 3) onderzoeken of op AI gebaseerde systemen de kloof in wiskundeprestaties onder leerlingen uit lage sociaaleconomische milieus helpen verkleinen, en welke systeemkenmerken hieraan bijdragen.

We volgden de PRISMA-richtlijnen en doorzochten zes belangrijke databases: ACM Digital Library, ERIC (EBSCO), JSTOR, Wiley, ScienceDirect (Elsevier) en SpringerLink om peer-reviewed artikelen te vinden die tussen 2008 en 2023 zijn gepubliceerd. Een eerste pool van 1945 studies werd geïdentificeerd op basis van vooraf gedefinieerde inclusie- en exclusiecriteria. Na screening werden 42 artikelen geselecteerd voor diepgaande analyse. De gegevens werden georganiseerd en geanalyseerd met behulp van spreadsheets.

De bevindingen geven aan dat AI-gebaseerde systemen op grote schaal worden gebruikt in klassen van het basis- en voortgezet onderwijs in verschillende landen om gepersonaliseerde en adaptieve leerervaringen te bieden ter ondersteuning van het wiskundeonderwijs van leerlingen. De meeste onderzoeken zijn uitgevoerd in de Verenigde Staten. Zowel Intelligent Tutoring Systems (ITS) als Adaptive Learning Systems (ALS) worden gebruikt op de basisschool, middelbare school en middelbare school, met een frequentere implementatie op de middelbare school en minder op de middelbare school. Verschillende onderzoeken meldden ook het gebruik van adaptieve leergames, zoals Lynnette, DragonBox, Woot Math Adaptive Learning (WMAL) en Math Whizz. De meest gebruikte AI-gebaseerde systemen in de VS zijn ALEKS, CTA1, ASSISTments, HALF, Math IVLE, MathSpring en Decimal Point. Uit onderzoeken uit andere landen blijkt dat er gebruik wordt gemaakt van AI-gebaseerde systemen zoals MIT, dialooggebaseerde docenten, ACALS, adaptieve

CER-gebaseerde wiskundespellen, PEDALE, PAT2Math, ZPDES, RiaRiT, AmritaITS, UZWEBMAT, APPEAL en HINTS.

Over het algemeen suggereren de bevindingen een matig positief effect van AI-gebaseerde systemen op de wiskundeprestaties van leerlingen. De meeste studies rapporteerden matige tot significante verbeteringen in de prestaties, betrokkenheid en retentie van leerlingen. Verschillende AI-gebaseerde systemen, zoals ALEKS, MathSpring en eFit, werden geassocieerd met verbeterde resultaten bij leerlingen met een lage sociaaleconomische achtergrond, wat hun potentieel om onderwijsgelijkheid te ondersteunen onderstreept.

De discussie presenteert de bevindingen van elk onderzoek in dit proefschrift, samen met de bijdragen en beperkingen van dit onderzoek. Gebaseerd op de integratie van AI-gebaseerde instructiesystemen en gepersonaliseerde leerkaders, tonen de studies aan hoe AI-gebaseerde systemen de leerresultaten van leerlingen in wiskunde kunnen verbeteren. Deze AI-gebaseerde systemen tonen potentieel in het verbeteren van de cognitieve betrokkenheid en academische prestaties van leerlingen. De bevindingen onthullen echter ook beperkingen in het bevorderen van affectieve betrokkenheid, en benadrukken de uitdagingen waarmee AI-gebaseerde systemen worden geconfronteerd bij het repliceren van de emotionele connectie van menselijk lesgeven. De studie toont beperkingen in affectieve betrokkenheid en laat de uitdagingen zien van AI-gebaseerde systemen om de emotionele en relationele aspecten van menselijk lesgeven te repliceren. Dit proefschrift draagt bij aan het bredere discours binnen de AIED-gemeenschappen en levert empirisch bewijs voor de pedagogische impact van AI-gebaseerde instructies op de wiskundeprestaties en betrokkenheid van leerlingen in kansarme bevolkingsgroepen in landelijke onderwijscontexten.

Toekomstig onderzoek zou de impact van verschillende AI-gebaseerde systemen moeten onderzoeken door hun effectiviteit te vergelijken met ITS en ALS, zoals ALEKS en Edmentum Exact Path. Hierbij zouden factoren zoals instructieontwerp, leerlingkenmerken en specifieke leerresultaten in aanmerking moeten worden genomen. Door de sterke punten van deze AI-gebaseerde systemen te benutten, kunnen docenten en beleidsmakers weloverwogen beslissingen nemen over de integratie ervan, wat uiteindelijk de prestaties van leerlingen in wiskunde en aanverwante disciplines verbetert.

सारांश

शिक्षा में कृत्रिम बुद्धिमत्ता (AI) का उपयोग तेज़ी से बढ़ रहा है और शिक्षण एवं अधिगम प्रक्रियाओं को महत्वपूर्ण रूप से प्रभावित कर रहा है। AI-आधारित प्रणालियाँ तत्काल प्रतिक्रिया प्रदान कर सकती हैं और वास्तविक समय में निर्देशों को अनुकूलित कर सकती हैं, जिससे अधिगम प्रक्रिया में अंतःक्रिया और सहभागिता के अवसर पैदा होते हैं, जो पारंपरिक कक्षाओं में अक्सर प्राप्त करना मुश्किल होता है, जहाँ शिक्षक हमेशा कठिनाई से जूझ रहे शिक्षार्थियों को व्यक्तिगत सहायता प्रदान नहीं कर पाते हैं। कई शोध अध्ययनों ने K-12 कक्षाओं में पूरक उपकरण के रूप में AI-आधारित प्रणालियों के उपयोग से आशाजनक परिणाम दिखाए हैं।

ITS और ALS जैसी एआई-आधारित प्रणालियाँ छात्रों को अनुकूल और व्यक्तिगत शिक्षा प्रदान करने की क्षमता रखती हैं, खासकर गणित जैसे STEM विषयों में, जिन्हें कई छात्र चुनौतीपूर्ण पाते हैं। यह ग्रामीण क्षेत्रों के वंचित छात्रों के बीच अधिक स्पष्ट है, जो सीमित संसाधनों, उच्च योग्य शिक्षकों की कमी और गरीबी के प्रभाव के कारण अक्सर ग्रेड-स्तर की अपेक्षाओं से पीछे रह जाते हैं।

कोविड -19 महामारी के कारण हुई सीखने की क्षमता में कमी ने छात्रों के गणित प्रदर्शन को काफ़ी प्रभावित किया है, जिससे मौजूदा उपलब्धि अंतराल और भी बढ़ गया है। इस समस्या का समाधान करने और उपलब्धि अंतराल को कम करने के लिए, संयुक्त राज्य अमेरिका के कई स्कूलों ने गणित सीखने में सहायता के लिए AI-आधारित उपकरण लागू किए हैं। दक्षिणी संयुक्त राज्य अमेरिका के एक ग्रामीण हाई स्कूल ने आठवीं कक्षा के छात्रों की सहायता के लिए शैक्षणिक वर्ष 2021-2022 के दौरान ALEKS, एक ITS, का संचालन किया। शैक्षणिक वर्ष 2022-2023 में, स्कूल ने सहायता प्रदान करना जारी रखने के लिए एडमेंटम एक्ज़ैक्ट पाथ, एक ALS को अपनाया।

इस थीसिस में चार अध्याय हैं: अध्याय 1 में स्कूल ने आठवीं कक्षा के छात्रों की सहायता के लिए शैक्षणिक वर्ष 2021-2022 के दौरान ALEKS के साथ किए गए एक अध्ययन पर चर्चा की गई है; अध्याय 2 में जर्नल प्रकाशन के लिए पहले अध्ययन का विस्तार किया गया है; अध्याय 3 में एडमेंटम एक्ज़ैक्ट पाथ के उपयोग की जांच की गई है; और अध्याय 4 में AI-आधारित प्रणालियों और गणित की उपलब्धि पर उनके प्रभाव पर एक व्यवस्थित साहित्य समीक्षा प्रस्तुत की गई है।

अध्याय 1 कम अंक प्राप्त करने वाले छात्रों की गणित उपलब्धि पर बुद्धिमान शिक्षण प्रणालियों के प्रभाव पर केंद्रित है। इस अर्ध-प्रयोगात्मक अध्ययन में आठवीं कक्षा के 158 छात्रों पर इसके प्रभाव का मूल्यांकन करने के लिए ALEKS का उपयोग किया गया, जिनमें से 62-68% आर्थिक रूप से वंचित थे और केवल 12% ही गणित में कुशल थे। इस अध्ययन का उद्देश्य था: 1) छात्रों की गणित उपलब्धि में सुधार लाने में पारंपरिक शिक्षण की तुलना में ALEKS की प्रभावशीलता की तुलना करना। 2) ALEKS का उपयोग करके एक शैक्षणिक वर्ष में कक्षा-स्तरीय गणित मानकों पर छात्रों की प्रगति का आकलन करना। 3) ALEKSके कार्यान्वयन के साथ कक्षा अवधियों में उपलब्धि में अंतर का विश्लेषण करना।

हमने लगातार दो वर्षों में शिक्षक-निर्देशित निर्देशों और ALEKS-निर्देशित निर्देशों से प्राप्त पूर्व-परीक्षण और पश्चात-परीक्षण के परिणामों की तुलना की। पहले वर्ष में, केवल मैकग्रा गणित पाठ्यक्रम रिवील का उपयोग

किया गया था। दूसरे वर्ष में, रिवील गणित पाठ्यक्रम के साथ-साथ, ALEKS को हर दूसरे दिन 50 मिनट के लिए एक गणित सहायता कक्षा में एक पूरक उपकरण के रूप में लागू किया गया था । हमने पाँच वर्षों के कक्षा-अंत (EOG) राज्य मूल्यांकन आँकड़ों ALEKS के बिना का भी विश्लेषण किया और उनकी तुलना उस वर्ष के EOG आँकड़ों से की, जिस वर्ष ALEKS लागू किया गया था।

निष्कर्षों से पता चला कि शिक्षक-निर्देशित निर्देश प्राप्त करने वाले छात्रों ने ALEKS-निर्देशित निर्देशों का उपयोग करने वालों की तुलना में गणित में बेहतर प्रदर्शनकिया। यह परिणाम ALEKS के अपने प्रायोगिक चरण में होने के कारण हो सकता है, जहाँ शिक्षक अभी भी इसे प्रभावी ढंग से उपयोग करना सीख रहे हैं। कई छात्र पूर्व-आवश्यक कौशल पर काम कर रहे थे क्योंकि वे कक्षा स्तर से नीचे थे। कोविड-19 महामारी ने संभवतः इस प्रभाव को और बढ़ा दिया, क्योंकि स्कूल बंद होने के कारण सातवीं कक्षा के अधिकांश निर्देश छूट जाने के बाद छात्रों को राज्य या स्कूल की परीक्षा दिए बिना ही आठवीं कक्षा में पदोन्नत कर दिया गया।

इस अध्ययन में यह भी पाया गया कि ALEKS ने पाँच गणित क्षेत्रों में सभी ग्यारह गणित मानकों में सुधार में योगदान दिया। हालाँकि, अधिकांश छात्र सभी मानकों को पूरा नहीं कर पाए क्योंकि ALEKS निपुणता-आधारित है, जिसके लिए छात्रों को आगे बढ़ने से पहले पूर्वापेक्षित कौशलों में 80% सटीकता प्राप्त करनी होती है। ALEKS तक सीमित पहुँच (केवल एक दिन छोड़कर) ने भी पूर्णता दर को सीमित कर दिया। एक अन्य निष्कर्ष ने संकेत दिया कि मजबूत कार्य नैतिकता वाले उच्च-प्राप्ति वाले छात्रों ने मिश्रित-क्षमता वाले समूहों की तुलना में बेहतर प्रदर्शन किया, जिसमें विकलांग छात्र भी शामिल थे।

अध्याय 2 को सांख्यिकीय विश्लेषण को शामिल करके जर्नल प्रकाशन के लिए विस्तारित किया गया था, जिसमें युग्मित टी-परीक्षण और एनोवा शामिल थे, ताकि छात्रों की गणित की उपलब्धि पर ALEKS की प्रभावकारिता का मूल्यांकन किया जा सके। साहित्य समीक्षा और शून्य परिकल्पना को भी जोड़ा गया। परिणामों से संकेत मिलता है कि शिक्षक के नेतृत्व वाला निर्देश अधिक प्रभावी था, जो एएलईकेएस की तुलना में उच्च परीक्षण स्कोर और कम विचरण दर्शाता है। अध्ययन के दो मुख्य उद्देश्य थे: 1) यह जांचना कि क्या एएलईकेएस का उपयोग पारंपरिक शिक्षक के नेतृत्व वाले निर्देश की तुलना में छात्रों की गणित की उपलब्धि में सांख्यिकीय रूप से महत्वपूर्ण सुधार दिखाता है, और 2) यह निर्धारित करना कि क्या एएलईकेएस का उपयोग एक शैक्षणिक वर्ष में ग्रेड-स्तर के गणित मानकों में सांख्यिकीय रूप से महत्वपूर्ण सुधार दिखाता है। विश्लेषण में पाया गया कि एएलईकेएस के नेतृत्व वाले और शिक्षक के नेतृत्व वाले निर्देश दोनों सांख्यिकीय रूप से महत्वपूर्ण थे, जिसमें शिक्षक के नेतृत्व वाला निर्देश अधिक प्रभावी था। हालाँकि ALEKS के इस्तेमाल से गणित के सभी स्तरों में उल्लेखनीय सुधार हुआ, लेकिन ये लाभ अलग-अलग थे, संभवतः इसकी महारत-आधारित शिक्षा के कारण, जिसमें अगले विषय पर आगे बढ़ने से पहले 80% महारत हासिल करना ज़रूरी है। चूँकि छात्रों ने ALEKS का इस्तेमाल केवल एक-एक दिन छोड़कर किया था, इसलिए वे सभी ग्यारह स्तर पूरे नहीं कर पाए।

कुल मिलाकर, इस अध्ययन के निष्कर्ष K-12 कक्षाओं में ITS के उपयोग के बारे में बहुमूल्य जानकारी प्रदान करते हैं। ALEKS जैसे गणित ITS अनुकूली और व्यक्तिगत शिक्षण के अवसर प्रदान करते हैं और कम प्रदर्शन करने वाले छात्रों की उपलब्धि में उल्लेखनीय वृद्धि कर सकते हैं।

अध्याय 3 में उत्तरी अमेरिका के दक्षिण में में आठवीं कक्षा के छात्रों के बीच गणित की उपलब्धि और जुड़ाव (भावनात्मक और संज्ञानात्मक) को बढ़ाने में, एडमेंटम एक्ज़ैक्ट पाथ , एक *AI*-आधारित शिक्षण प्रणाली की प्रभावशीलता का परीक्षण किया । इस अर्ध- प्रयोगात्मक अध्ययन में सामाजिक-आर्थिक रूप से वंचित पृष्ठभूमि के 78 छात्र शामिल थे। हमने एक प्रायोगिक समूह, जिसे पारंपरिक शिक्षक-नेतृत्व वाली शिक्षा और एडमेंटम एक्ज़ैक्ट पाथ-नेतृत्व वाली शिक्षा, दोनों प्राप्त हुईं, की तुलना एक नियंत्रण समूह से की, जिसे केवल पारंपरिक शिक्षक-नेतृत्व वाली शिक्षा प्राप्त हुई।

इस अध्ययन के तीन उद्देश्य थे: 1) छात्रों की गणित उपलब्धि पर एडमेंटम एक्ज़ैक्ट पाथ और पारंपरिक शिक्षक-नेतृत्व वाले निर्देश की प्रभावकारिता की तुलना करना। 2) एडमेंटम एक्ज़ैक्ट पाथ निर्देश और पारंप-

रिक शिक्षक-नेतृत्व वाले निर्देश के बीच छात्रों की भावनात्मक संलग्नता में अंतर की जांच करना । 3) एडमेंटम एक्ज़ैक्ट पाथ निर्देश और पारंपरिक शिक्षक-नेतृत्व वाले निर्देश के बीच छात्रों की संज्ञानात्मक संलग्नता में अंतर की जांच करना।

यह हस्तक्षेप पांच सप्ताह तक चला, प्रत्येक सत्र 50 मिनट का था। दोनों समूहों ने मैकग्रा-हिल गणित पाठ्यक्रम रिवील, 8वीं कक्षा के गणित पाठ्यक्रम का इस्तेमाल किया और प्रायोगिक समूह के लिए पूरक उपकरण के रूप में एडमेंटम एक्ज़ैक्ट पाथ को शामिल किया । प्रायोगिक समूह ने गणित सहायता कक्षाओं में भी भाग लिया, जहां उन्होंने एडमेंटम एक्ज़ैक्ट पाथ में व्यक्तिगत शिक्षण पथों पर काम किया, जो स्कूल वर्ष की शुरुआत में किए गए नैदानिक आकलन के आधार पर बनाया गया था। गणित की उपलब्धि को प्रीटेस्ट और पोस्टटेस्ट का उपयोग करके मापा गया, जबकि छात्र संलग्नता को 35-आइटम, 5-पॉइंट लिकर्ट-स्केल स्टूडेंट एंगेजमेंट इंस्ट्रूमेंट (SEI) का उपयोग करके मापा गया, जो कि पोस्टटेस्ट के बाद भावात्मक और संज्ञानात्मक संलग्नता का आकलन करने के लिए दिया गया था।

आँकड़ों का विश्लेषण किया गया । परिणामों से पता चला कि प्रायोगिक और नियंत्रण दोनों समूहों ने गणित की उपलब्धि में सांख्यिकीय रूप से महत्वपूर्ण सुधार दिखाया। हालाँकि, नियंत्रण समूह ने भावात्मक जुड़ाव में अधिक लाभ दिखाया, जबकि दोनों समूहों के बीच संज्ञानात्मक जुड़ाव में कोई सांख्यिकीय रूप से महत्वपूर्ण अंतर नहीं देखा गया।

ये परिणाम बताते हैं कि एडमेंटम एक्ज़ैक्ट पाथ जैसी एआई-आधारित प्रणालियों को एकीकृत करने से व्यक्तिगत शिक्षण आवश्यकताओं को पूरा करके गणित की उपलब्धि और संज्ञानात्मक जुड़ाव में वृद्धि हो सकती है। हालाँकि, भावनात्मक प्रतिक्रिया की कमी के कारण, ऐसे उपकरण भावात्मक जुड़ाव बढ़ाने में कम प्रभावी हो सकते हैं। छात्र जुड़ाव को बढ़ावा देने में, विशेष रूप से ग्रामीण क्षेत्रों में वंचित आबादी के बीच, एआई की भूमिका को बेहतर ढंग से समझने के लिए और अधिक शोध की आवश्यकता है।

अध्याय 4 में, हमने K-12 कक्षाओं में गणित की उपलब्धि पर AI-आधारित प्रणालियों के प्रभाव की जाँच के लिए एक व्यवस्थित साहित्य समीक्षा की। इस समीक्षा के निम्नलिखित उद्देश्य थे: 1) यह पहचान करना कि गणित शिक्षा में किस प्रकार की AI-आधारित प्रणालियों का उपयोग किया जाता है, और उन्हें किस शैक्षिक स्तर पर लागू किया जाता है। 2) K-12 कक्षाओं में छात्रों के गणित प्रदर्शन पर AI-आधारित प्रणालियों के प्रभाव की पहचान करना। 3) यह पता लगाना कि क्या एआई-आधारित प्रणालियाँ निम्न सामाजिक-आर्थिक पृष्ठभूमि वाले छात्रों के बीच गणित में उपलब्धि के अंतर को कम करने में सहायक होती हैं, तथा कौन सी प्रणाली विशेषताएँ इस प्रभाव में योगदान करती हैं।

हमने PRISMA दिशानिर्देशों का पालन किया और 2008 और 2023 के बीच प्रकाशित सहकर्मी-समीक्षित लेखों को खोजने के लिए छह प्रमुख डेटाबेस: ACM डिजिटल लाइब्रेरी, ERIC (EBSCO), JSTOR, Wiley, ScienceDirect, Elsevier, और SpringerLink में खोज की। पूर्वनिर्धारित समावेशन और बहिष्करण मानदंडों के आधार पर 1,945 अध्ययनों का एक प्रारंभिक समूह पहचाना गया। स्क्रीनिंग के बाद, गहन विश्लेषण के लिए 42 लेखों का चयन किया गया। स्प्रेडशीट का उपयोग करके डेटा को व्यवस्थित और विश्लेषित किया गया।

निष्कर्ष बताते हैं कि छात्रों की गणित सीखने में सहायता के लिए व्यक्तिगत और अनुकूली शिक्षण अनुभव प्रदान करने हेतु विभिन्न देशों में K-12 कक्षाओं में AI-आधारित प्रणालियों का व्यापक रूप से उपयोग किया जाता है। अधिकांश अध्ययन संयुक्त राज्य अमेरिका में किए गए। इंटेलिजेंट ट्यूटरिंग सिस्टम (ITS) और अडैप्टिव लर्निंग सिस्टम (ALS) दोनों का उपयोग प्राथमिक, मध्य और उच्च विद्यालय स्तरों पर किया जाता है, जिनका कार्यान्वयन मध्य विद्यालय स्तर पर अधिक और उच्च विद्यालय स्तर पर कम होता है। कई अध्ययनों में लिनेट, ड्रैगनबॉक्स, वूट मैथ अडैप्टिव लर्निंग (WMAL), और मैथ व्हिज़ जैसे अनुकूली शिक्षण खेलों केउपयोग की भी रिपोर्ट की गई है। अमेरिका में सबसे अधिक उपयोग की जाने वाली AI-आधारित प्रणालियों में ALEKS, CTA1, ASSISTments, HALF, Math IVLE, MathSpring, और Decimal Point शामिल हैं। अन्य देशों के अध्ययनों में एआई-आधारित प्रणालियों जैसे एमआईटी, संवाद-आधारित

ट्यूटर्स, एसीएएलएस, अनुकूली सीईआर-आधारित गणित खेल, पेडल, पैट2मैथ, जेडपीडीईएस, रियारिट, अमृताआईटीएस, यूजेडवेबमैट, अपील और हिंट्स के उपयोग की सूचना दी गई है।

कुल मिलाकर, निष्कर्ष छात्रों की गणित उपलब्धि पर AI-आधारित प्रणालियों के मध्यम सकारात्मक प्रभाव का संकेत देते हैं। अधिकांश अध्ययनों में छात्रों के प्रदर्शन, जुड़ाव और धारणा में मध्यम से लेकर महत्वपूर्ण सुधार की सूचना मिली है। कई एआई-आधारित प्रणालियाँ, जैसे कि एएलईकेएस, मैथस्प्रिंग और ईफिट, निम्न सामाजिक-आर्थिक पृष्ठभूमि वाले छात्रों के बीच बेहतर परिणामों से जुड़ी हुई थीं, जो शैक्षिक समानता को बढ़ावा देने की उनकी क्षमता को उजागर करती हैं।

चर्चा इस डॉक्टरेट थीसिस के प्रत्येक अध्ययन के निष्कर्षों के साथ-साथ इस शोध के योगदान और सीमाओं को प्रस्तुत करती है। AI-आधारित शिक्षण प्रणालियों और व्यक्तिगत शिक्षण ढाँचों के एकीकरण पर आधारित, ये अध्ययन दर्शाते हैं कि कैसे AI-आधारित प्रणालियाँ गणित में छात्रों के सीखने के परिणामों को बेहतर बना सकती हैं। ये AI-आधारित प्रणालियाँ छात्रों की संज्ञानात्मक संलग्नता और शैक्षणिक प्रदर्शन को बेहतर बनाने की क्षमता दर्शाती हैं। हालाँकि, निष्कर्ष भावात्मक संलग्नता को बढ़ावा देने की सीमाओं को भी उजागर करते हैं, और मानव शिक्षण के भावनात्मक जुड़ाव को दोहराने में एआई-आधारित प्रणालियों के सामने आने वाली चुनौतियों पर प्रकाश डालते हैं। अध्ययन भावात्मक संलग्नता की सीमाओं को दर्शाता है, और मानव शिक्षण के भावनात्मक और संबंधपरक पहलुओं को दोहराने में AI-आधारित प्रणालियों की चुनौतियों को दर्शाता है। यह शोध प्रबंध AIED समुदायों के भीतर व्यापक विमर्श में योगदान देता है, और ग्रामीण शैक्षिक संदर्भों में वंचित आबादी में छात्रों की गणित उपलब्धि और संलग्नता पर AI-आधारित निर्देशों के शैक्षणिक प्रभाव पर अनुभवजन्य साक्ष्य प्रदान करता है।

भविष्य के शोध में विभिन्न AI-आधारित प्रणालियों के प्रभाव की जाँच, उनकी प्रभावशीलता की तुलना आईटीएस और एएलएस, जैसे एएलईकेएस और एडमेंटम एक्ज़ैक्ट पाथ से करके की जानी चाहिए। इसमें शिक्षण डिज़ाइन, छात्र विशेषताओं और विशिष्ट शिक्षण परिणामों जैसे कारकों पर विचार किया जाना चाहिए। इन AI-आधारित प्रणालियों की खूबियों का लाभ उठाकर, शिक्षक और नीति-निर्माता उनके एकीकरण के बारे में सूचित निर्णय ले सकते हैं , जिससे अंततः गणित और संबंधित विषयों में छात्रों की उपलब्धि में वृद्धि होगी।

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My PhD journey began with inspiration from the work of Prof. dr. Paul A. Kirschner. After reaching out to him and persisting with my request, he graciously agreed to be my mentor and introduced me to Prof. dr. Marcus Specht. Although our collaboration was brief as Prof. Specht transitioned to a new role shortly after, we remained connected. He then introduced me to Prof. dr. Drachsler, under whose mentorship I found direction and clarity. It was Prof. Drachsler who introduced me to Prof. dr. Di Mitri, completing the team that guided me forward.

At the time, I was teaching in a K–12 classroom and had always been passionate about integrating technology into my pedagogical practice. Following the complete school closures of 2019–2020 due to COVID-19 pandemic, a high school in a rural area of the Southern United States adopted the ALEKS, an ITS, to supplement mathematics instruction in 2021 to address pandemic-related learning gaps. Curious about how this AI-based system could support student learning, I embarked on this research journey.

I come from a family of educators and have always aspired to pursue a PhD. My late father, Dr. Sunder Lal Jain, was a professor of sociology, and I grew up witnessing his students successfully complete their doctoral journeys. My younger brother and sister are both college professors. I was raised in Rajasthan, India, and completed my master's degree in Organic Chemistry. After marriage, I moved to Delhi, where I earned a postgraduate diploma in Health Psychology and Behavior Modification. My research during that program, titled *"A Comparative Study of Anxiety and Depressive Disorder Patients: Familial and Psychosocial Factors,"* further deepened my interest in academic research. Over the years, I began presenting papers at various national and international conferences, where I was introduced to the influential

work of Prof. dr. Kirschner.

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2017

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2021

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