Journal of AI-Augmented Mathematics (JAAM)

https://utilitasmathematicapublishing.com

Vol: 1, ISSUE: 1, 2025

Pg No: 1-17

A Quantitative Analysis of the Impact of AI-Based Systems on Mathematical Performance in Rural Areas

S.G. Suriya [1]*, P. Anandan [2], S. Natarajan [3] and J. Raja [4]

Post Graduate Student 1, Assistant Professor 2, Professor 3, Assistant Professor 4

Department of Agronomy, Faculty of Agriculture, Annamalai University, Chidambaram, India.

1,2&3Department of Plant Pathology, Faculty of Agriculture, Annamalai University, Chidambaram, India

ABSTRACT

History: Students in grades K-12 continue to struggle with mathematics, even though there have been many improvements in the field. This is especially true in rural regions where resources are few and instructors lack the necessary expertise. There is mounting evidence that AI-based systems may improve students' mathematical performance by tailoring their learning experiences to each individual's strengths and weaknesses, which has led to their widespread use as a means of accommodating students' varied learning styles. Previous research has shown that AI-based systems may improve students' mathematical performance. Students' involvement and performance in mathematics in rural areas have not been well investigated by studies examining AI-based systems. This research fills a need in the literature by investigating the efficacy of the artificial intelligence (AI) platform Edmentum Exact Path in improving eighth graders' mathematical engagement and performance in rural Southern schools. This study investigates the function of AI-based systems in the education of students by investigating their emotional and intellectual involvement, as well as their performance in mathematics.

The purpose of this research is to determine whether or whether the artificial intelligence (AI) system Edmentum Exact Path can raise the mathematical proficiency, emotional investment, and critical thinking of eighth graders in the American South.

The research team used a quasi-experimental design to examine the effects of supplementing students' education with Edmentum Exact Path and traditional teacher-led methods on their performance compared to a control group that received only teacher-led instruction. The 78 students in the study came from economically disadvantaged backgrounds. Pre- and post-tests were used to evaluate mathematical performance, while the 5-point Student involvement Instrument (SEI) was used to measure student involvement. In order to conduct the statistical analysis, t-tests and ANOVA were used.

Final Thoughts and Findings: Both the test and control groups showed statistically significant gains in mathematical performance. There were no statistically significant changes in cognitive involvement across the groups, but there was a statistically significant improvement in emotional engagement in the group that used teacher-led teaching.

Implications: The results imply that rural students' emotional investment in mathematics might be improved by using AI-based solutions such as Edmentum Exact Path. There has to be further investigation on the effect on cognitive engagement, however. These findings provide credence to the idea that rural areas may benefit from the use of AI-based solutions to raise students' arithmetic scores.

Keywords: Edmentum Exact Path, cognitive engagement, emotional engagement, AI-based systems, mathematical accomplishment, and artificial intelligence in the classroom are all related terms.

https://utilitasmathematicapublishing.com
Vol: 1, ISSUE: 1, 2025
Pg No: 1-17

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 person- alized learning experiences and support. Indicators of socioeco- nomically 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 ac- cess 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 di- mensions 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 mathematical learning activities tend to achieve greater aca- demic success.

Students often experience fluctuations in their engagement lev- els 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 atti- tude toward mathematics, which worsens with repeated fail- ures. 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 utiliz- ing cognitive strategies in the learning process (Fine, Duggan, and Braddy 2009). Students with higher levels of cognitive en- gagement have demonstrated positive gains in mathematics achievement (Maamin et al. 2021). Traditionally, teachers have employed various effective teaching strategies to promote stu- dent engagement (Han 2021).

Traditional teaching methods often pose challenges in engag- ing 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 pop- ulation (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 con- trol 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 in- structions differ significantly in their approaches to personalized education (Jasin et al. 2023; VanLehn 2011). Edmentum Exact Path uses artificial intelligence to create individualized learn- ing pathways, adapting 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 with effective peda- gogical approaches can maximize learning outcomes through personalized feedback and enhanced engagement (Craig et al. 2013; Huang et al. 2016; Pane et al. 2014). Most empir- ical studies on the impact of AI-based systems in education have been conducted with higher education students, while sig- nificantly 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 evi- dence supporting the efficacy of AI-based systems in enhancing mathematics achievement (Clément 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 supple- mental 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 instruc- tion 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 mea- sured by the SEI, between students taught with Edmentum Exact Path and those who receive traditional teacher-led instructions?*

1.1 | AI-Based Learning Systems

Aleven et al. (2016), Appleton, Christenson, and Furlong (2008), D'Mello and Graesser (2023), Fredricks, Blumenfeld, and Paris (2004), Fung, Tan, and Chen (2018), and Khosravi, Sadiq, and Gasevic (2020) are some of the studies that discuss AI-based systems and how they use AI to create personalized learning experiences. By detecting where students are lacking information and then designing personalized learning plans to fill those gaps, these systems help students overcome learning disabilities and advance at their own speed (Terzieva, Ivanova, and Todorova 2022). In addition, systems powered by AI let instructors track their students' development and identify their areas of strength and improvement in real time via tests and feedback (Metje, Frank, and Croft 2007; Pliakos et al. 2019; Xie et al. 2019). The use of AI-based solutions allows instructors to spend more time helping students, thanks to features like automatic grading and personalized feedback (Craig et al., 2013; Feng, Huang, and Collins, 2023; Pliakos et al., 2019).

Use of technology in mathematics has been shown to have a good effect on student learning, according to empirical research (Craig et al., 2013; Huang et al., 2016; Pane et al. 2014). Several studies have re- ported the positive impact of AI-based systems in improving examination scores and test performance (Alrakhawi, Jamiat, and Abu-Naser 2023; Clément et al. 2024; Ma et al. 2014; Niño-Rojas et al. 2024; VanLehn 2011; Steenbergen-Hu and Cooper 2013), as well as significantly enhancing math learn- ing (Clément et al. 2024; Hillmayr et al. 2020; Kulik and Fletcher 2016; Ma et al. 2014; Nagashima et al. 2022; Rodrigues et al. 2023). Several studies have shown that, when compared to conventional teacher-led instructions, AI-based systems may improve students' mathematical proficiency (Craig et al. 2013; Fine, Duggan, and Braddy 2009; Hu et al. 2013; Ma et al. 2014; Wang et al. 2023a). There was no discernible difference between learning via AI-based systems and learning via human tutoring or small-group education, according to research by Ma et al. (2014). Just a few of studies (Leddo and Garg 2021; Nye et al. 2018; Olney et al. 2012; VanLehn 2011) have shown that AI-based systems are on par with teacher-led instructions.

Almoubayyed et al. (2023), Fang et al. (2019), Nitkin, Ready, and Bowers (2022), and Urbina and Polly (2017) are among the studies that found that AI-based systems like MATHia (Carnegie Learning), Edmentum Exact Path, Cognitive Tutor, Algebra I (Carnegie Learning), and Assessment and Learning in Knowledge Spaces (ALEKS) are commonly used to improve students' math achievement in K-12 classrooms in the US. Recent research by Pane et al. (2014), Phillips et al. 2020, VanLehn 2011, and Xie et al. 2019 points to the possibility that AI-based systems might improve students' learning outcomes via the provision of personalized instructions. Research conducted by Beal et al. (2010), Faber, Luyten, and Visscher (2017), Koedinger, McLaughlin, and Heffernan (2010), and Molenaar and Knoop-van Campen (2018) indicates that these systems have a favorable effect on mathematics achievement in K-12 schools. In a research comparing human instructors, Intelligent Tutoring Systems (ITS), and no tutoring at all, VanLehn (2011) found that ITS can be as successful as human tutors in educational settings. Students' mathematical performance in high school settings was shown to significantly increase in a large-scale research that examined the efficacy of Cognitive Tutor Algebra in middle and high schools (Pane et al. 2014). According to research conducted by Beal et al. (2010), Craig et al. (2013), and Hu et al. (2013), ALEKS has an impact on student learning that is similar to that of conventional teaching approaches. Edmentum Exact Path is the artificial intelligence (AI) system that is the center of this study because of its exceptional characteristics, such as adaptive diagnostic tests and tailored learning routes that allow students to learn at their own speed. Developed for use in K-12 schools, Edmentum Exact Path provides educators with useful instructional data that can be used to shape lesson plans (McLeod 2017). It was necessary to do study on the efficacy of Edmentum Exact Path in raising pupils' mathematical performance after its recent installation at a rural school in the American South. And few studies have looked at how well the Edmentum Exact approach works, especially for kids from low-income families who struggle with arithmetic.

Students in grades k–3 who finished all eight lessons of the Exact Path Diagnostic Assessment had significantly higher reading achievement than students who did not, according to a study that attempted to quantify the efficacy of Edmentum's Exact Path on reading achievement (Randel 2018). Furthermore, a correlation analysis with a large sample size (n = 6577) from various kindergarten to sixth grade schools throughout the US was carried out by McLeod (2017), an Edmentum researcher. This research found that students' performance in arithmetic, reading, and English Language Arts was significantly correlated with the Edmentum's learning route. By looking at how Edmentum Exact Path, a supplementary tool, helps children from low-income backgrounds improve their math scores, this study hopes to fill a current knowledge vacuum.

2.2 | 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 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 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 range 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 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).

2.3 | 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

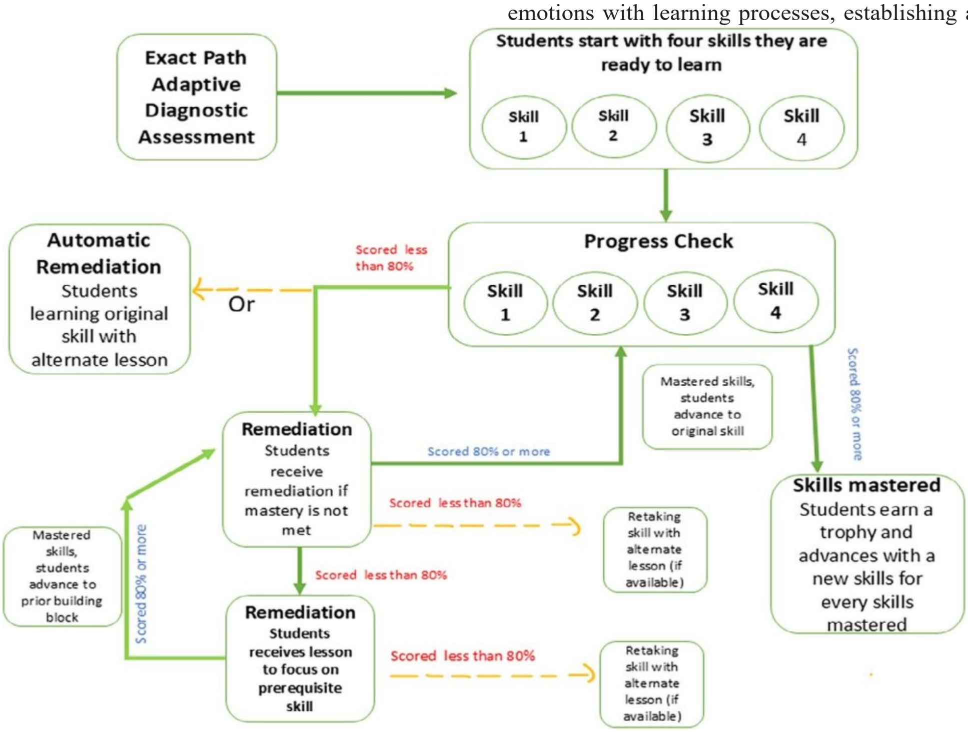

FIGURE 1 | Edmentum Exact Path Learning Progression. *Source:* Adapted from https://edmentum.com.

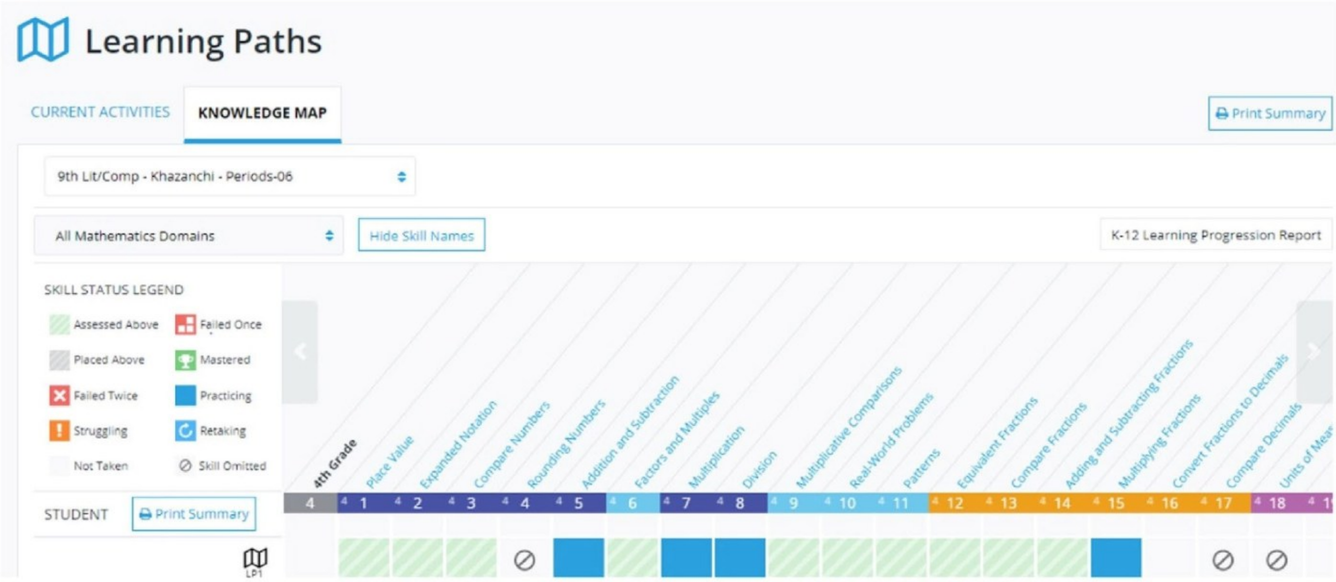

FIGURE 2 | Edmentum exact path knowledge map.

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 assess- ments (Li, Gow, and Zhou 2020).

On the other hand, the model of Affective Dynamics (D'Mello and Graesser 2012) emphasizes the impact of cognitive dis- equilibrium on deep learning. Cognitive disequilibrium oc- curs when individuals encounter obstacles to their learning goals, such as misconceptions, contradictions, or interruptions (D'Mello and Graesser 2012). The critical component of cogni- tive disequilibrium is the affective state of confusion (D'Mello and Graesser 2014), which, if left unresolved, can lead to frus- tration, boredom, and disengagement. However, when the indi- viduals 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 re- solve these difficulties. Successfully solving the problem helps students return to cognitive equilibrium, allowing them to re- main 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, cogni- tive challenges, and overall learning outcomes. It highlights the potential for adaptive learning technologies to enhance student engagement's affective and cognitive aspects, thereby improving mathematics achievements.

1 | Methodology

1.1 | 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 particu- larly 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 stan- dards, enhancing the study's ecological validity.

1.2 | 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.

1.3 | 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 disadvantaged 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 Assessment of Educational Progress (NAEP) Proficient level in mathematics. The profi- ciency levels varied significantly across different school dis- tricts: 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 per- forming at or above the proficient level (see Table 1).

1.4 | 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 exper- imental and control groups received teacher-led instruction, but the experimental group also had Edmentum Exact Path- led instruction in their math support class for the same dura- tion. In the math 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' spe- cific achievement levels. After completing each lesson, stu- dents 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 vid- eos, 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 stan- dard teaching practices.

1.5 | Assessment Development and Administration

Both experimental and control groups completed the pre-test before the instructional intervention and took the same test as the post-test upon completion of the unit. The administration of the pre-test/post-test was carried out under the supervision of the teachers, who were provided with the necessary materi- als by the researcher before the onset of the study. Although all

TABLE 1 | Student demographics: Gender, ethnicity, economically disadvantaged, and math proficiency.

Characteristics	School District 1 (Experimental Group)	School District 2 (Control Group 1)	School District 3 (Control Group 2)
Gender			
Male	54%	56%	53%
Female	46%	44%	47%
Ethnicity			
Caucasian	6.83%	24.26%	71.48%
Minority (including 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: The demographic data are from GaDOE (2022a, 2022b).

students participated in the pre-test/post-test, data collection was restricted to those who consented to participate in the re- search study. All students completed the pre-test and post-test within the 60-min testing window.

1.6 | 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 mea- sure student engagement. The SEI is a 5-point Likert scale vary- ing 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.

1.7 | Data Analyzes

This quasi-experimental study incorporates a range of descrip- tive and inferential statistics to examine the effects of Edmentum Exact Path-led versus teacher-led instructions on student en- gagement. The statistical analyzes employed include the in- dependent 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.

2 | Results

Answering RQ1, we compared 8th grade arithmetic pre- and post-test scores. To compare the arithmetic performance of students taught using Edmentum Exact Path with that of students taught using more conventional methods, we used a paired sample t-test with two tails. When compared to the pre-test score of 30.76 (SD= 14.74), the experimental group utilizing Edmentum Exact Path demonstrated a mean increase of 36.05 (SD = 16.80).

on the follow-up exam, showing a considerable improvement. Significant improvements in scores were shown by a paired-sample t-test, with p-values of 0.03 (one-tailed) and 0.05 (two-tailed). With a one-tailed p value of 0.04 and a two-tailed p value of 0.09, suggesting modest improvement, Control Group 1, which received conventional teaching, showed a mean rise from 27.21 (SD = 10.03) to 38.93 (SD = 21.57). With very significant t-test findings, p = 0.002 (one-tailed), p = 0.004 (two-tailed) (see Table 2), Control Group 2, which also received conventional instruction, had a huge rise in mean score from 34.00 (SD = 13.47) to 48.53 (SD = 21.21).

Although there were notable increases in arithmetic performance using Edmentum Exact Path, the results show that conventional training, especially in Control Group 2, produced much more significant benefits. Importantly, not only did all pupils in the experimental group and Control Group 1 come from economically disadvantaged backgrounds, but their math skill was below average at 8% and 4%, respectively. The second group, Control 2, only included 56% students from low-income families. Its math competence percentage was 33.8% (refer to Table 1), which is somewhat more than the 31% state average.

Students from socioeconomically challenged families who have poor arithmetic proficiency may benefit from using AI-based systems like Edmentum Exact Path to improve their math ability, according to the results. The AI-powered system probably achieves this increase by tailoring learning routes to each student's existing knowledge. Basic arithmetic abilities are generally lacking among students from these socioeconomic backgrounds; however, AI-based solutions may help bridge this gap. In rural areas, where highly qualified teachers are often scarce, AI-based systems offer personalized learning experiences that are meaningful (Harry 2023; Terzieva, Ivanova, and Todorova 2022; García and Weiss 2020; Ingersoll and Tran 2023; Lazarev et al. 2017; Monk 2007; Shikalepo 2020). Supplementing traditional education with AI-based technologies may help schools better assist student learning and help reduce achievement disparities.

Additionally, a one-way ANOVA (Analysis of Variance) was conducted to compare the effectiveness of Edmentum Exact

TABLE 2 | *t*-test paired two sample for means indicating students' performance in the experimental and control groups.

***t*-test: Paired Two Sample for Means**

	Experimental Group		Control Group 1		Control Group 2	
	Pretest	Posttest	Pretest	Posttest	Pretest	Posttest
Mean	30.76	36.05	27.21	38.93	34	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	42	42	14	14	19	19
Pearson Correlation	0.42		−0.35		0.41	
t stat	−1.99		−1.86		−3.30	
P($T \leq t$) one-tail	0.03		0.04		0.002	
P($T \leq t$) two-tail	0.05		0.09		0.004	

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). 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.

The results may have been skewed due to the study's limited sample size and other potential confounding variables, such as participants' socioeconomic status, level of interest and motivation, and their previous academic performance in the classroom. If the students had been assigned at random, the results of this research may have turned out differently. Due to ethical concerns, this trial could not be randomized to ensure that all students had equal opportunity to acquire Edmentum Exact Path and benefit from it. For moral concerns, the school board decided against limiting students' access to the software. The results demonstrate that both the standard teacher-led instruction and the Edmentum Exact path-led instruction greatly enhanced students' mathematical performance; Nevertheless, there was no discernible variation between the two methods of education. Further research with larger samples that account for confounding factors is necessary to generalize the results of this study. When contrasted to teacher-led instructions, this will provide more definitive insights into how successful the Edmentum Exact approach is. Further investigation is needed to fully grasp how the Edmentum Exact route may be used to augment math education for kids from low-income families and improve their mathematical performance. As a result, the results of the present research will have a broader range of potential applications.

We used analysis of variance (ANOVA) on the pre-test results to confirm initial parity in mathematical competence across the three groups, which we did to assure the validity of this research. Compared to the required F value of 3.12, the F value of 0.65 is much lower. The frequently accepted significance level criterion is 0.05, and the p value of 0.53 is far higher than that (see Table 4). Results from the pre-test show that neither the experimental group nor the two control groups differed significantly from one another.

The SEI survey, which measures overall student engage- ment, was administered at the end of the post-test to address

TABLE 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				

TABLE 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				

Research Questions 2 and 3. 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 en- gagements, the three variables are Control and Relevance of Schoolwork (CRSW), Future Aspirations and Goals (FG), and Intrinsic Motivation (IM). The average affective engage- ment 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: ex- perimental 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 5). While the mean scores for affective engagement were higher in the control groups than in the experimental groups, it is im- portant to note that it is only one aspect of overall instructional effectiveness. The slight differences in mean scores do not con- clusively 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.

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 6). These findings indicate that traditional teacher-led instruction results in higher affective en- gagement compared to Edmentum Exact Path.

TABLE 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

These findings provide further evidence that the emotional bonds that students develop with their instructors in conventional classroom settings have a positive effect on students' affective engagement. It would be beneficial for future studies to include a pre-survey to measure engagement levels before the intervention and a bigger sample size. In response to RQ3, we computed the average scores and found that the experimental group had the highest (M = 3.67), followed by control group 1 with an average of 3.75, and control group 2 with an average of 3.62). For further information, refer to Table 7. In order to find out whether cognitive involvement varied significantly, a one-way ANOVA was performed. Table 7 shows that there was no statistically significant difference between the groups, with an F-value of 0.29 and a p-value of 0.74, both of which are more than the significance level of 0.05 (F critical value = 3.11). This provides further evidence that the impacts on cognitive engagement of AI-based and conventional teacher-led training are similar.

According to these results, Edmentum Exact Path promotes cognitive engagement on par with conventional teaching methods, however it could fall short when it comes to encouraging emotive involvement. Acknowledging the need for a balanced strategy that promotes both the emotive and cognitive sides of student involvement, these findings may assist educators and policymakers in incorporating AI-based learning technologies into educational environments. To fully comprehend the elements impacting cognitive engagement in the classroom, further studies and analyses of other variables are required.

3 | 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 re- search on the impact of AI-based systems on students' math- ematics 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

TABLE 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				

TABLE 7 | ANOVA: Single factor for cognitive engagement) among experimental groups 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				

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, partic- ularly among students from socioeconomically disadvantaged backgrounds. Using paired *t*-tests and ANOVA, this study ana- lyzed differences in math 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.

Although the findings were mixed overall, t-tests did show that the experimental group utilizing Edmentum Exact Path outperformed Control Group 1 in arithmetic, which is consistent with the idea that AI-based solutions may boost performance. But with teacher-led teaching, Control Group 2, which had somewhat better math performance and fewer pupils from low-income backgrounds, improved significantly. Although there were noticeable gains on an individual level, no teaching strategy emerged as clearly superior when compared across all groups, according to the analysis of variance (ANOVA). Because there were fewer pupils from socioeconomically challenged backgrounds and their baseline math ability was higher than the state average, Control Group 2 showed a substantial improvement. Haveman and Wolfe (1995), Martin et al. (2012), Reeves (2012), Sirin (2005), and Vadivel et al. (2023) all found a high association between socioeconomic status and academic success, lending credence to these aspects.

The Affective Dynamics Model provides an explanation for the contradictory findings of this research (D'Mello and Graesser 2012). Edmentum Exact Path is an AI-based system that helps students learn mathematics by addressing cognitive dis-equilibrium that arises while completing difficult tasks. According to D'Mello and Graesser (2012) and D'Mello et al. (2014), students may go back to cognitive equilibrium and stay interested in learning with the support of Edmentum Exact Path's built-in feedback, which offers suggestions on how to tackle these challenges. These results are further validated using the Stein and Levine Model. A study by Stein and Levine (2013) found that students whose objectives were clearly defined were more likely to students' passion, as their emotional states determine how well they accomplish these objectives. Teachers in more conventional classrooms are in a prime position to assist students in developing and reaching their unique learning objectives while also offering the reassurance and affirmation that students need to become emotionally invested in their learning. High levels of affective engagement in conventional education, in contrast to AI-based systems, may be explained by the presence of a caring instructor who can attend to students' intellectual and emotional needs simultaneously.

By documenting the impacts of AI-based systems on the mathematical learning of students from economically disadvantaged backgrounds, this study adds to the existing body of knowledge. Consistent with previous research, this study found that rural low-income students' arithmetic scores improved after using AI-based systems (Feng, Huang, and Collins 2023; Huang et al. 2016). Artificial intelligence systems may enhance teacher-led training to provide more tailored learning experiences (Terzieva, Ivanova, and Todorova 2022). Students from low-income families who struggle with arithmetic and may require extra help would benefit greatly from this individualized curriculum. With the aid of AI-powered tools, educators may devote more time to working with individual students who are having difficulty in the classroom. In addition, the lack of highly educated teachers in rural schools is a common issue, which may have a poor impact on kids' math performance (García and Weiss 2020; Ingersoll and Tran 2023; Lazarev et al. 2017; Monk 2007; Shikalepo 2020). The use of AI-powered technologies in the classroom might enhance learning outcomes by facilitating more individualised and relevant lessons (Harry 2023; Terzieva, Ivanova, and Todorova 2022).

The field research used Edmentum Exact Path to enhance students' learning while they were in school. It is difficult to ascribe learning benefits purely to AI-based systems, according to VanLehn (2011), who noted drawbacks in research comparing AI-based systems to human tutoring, such as a limited number of tests and partial replacements of activities like homework. In order to resolve these challenges and directly attribute good results to the AI-based system, the present research only uses Edmentum Exact Path for training.

When 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), a meta-analysis by Ma et al. (2014) found that AI-based systems were associated with higher achievement. Learning via AI-based systems did not vary significantly from either small-group teaching (g = 0.05) or specialized human tutoring (g = −0.11). Regardless of the context (feedback, modeling of student misunderstandings, educational level, topic area, etc.), the positive impact sizes were similar across all AI-based system implementations. Edmentum Exact Path has the potential to greatly improve student performance in the present-day classroom, according to these results, which are very pertinent to the current investigation.

A field research was carried out by Clément et al. (2024) to compare a hand-designed curriculum with and without self-choice to an automated curriculum generation system based on learning progress (LP). In addition to creating a pleasant and inspiring learning environment, the results indicated that LP-based personalization enhanced learning performance. The findings are in line with the current study that supports student learning with the use of Edmentum Exact Path, an AI-based system. The two studies show that customized AI-based solutions improve student results.

A research by Huang et al. (2016) looked at the function of Intelligent Tutoring Systems (ITS) in closing the achievement gap in mathematics instruction for sixth graders from low-income families in an after-school context. Evidence from this study revealed that ITS is especially useful for underprivileged communities and people. The current study employs an AI-based system called Edmentum Exact Path to aid students' learning, and their findings are in line with that. In an after-school context, Craig et al. (2013) assessed the effectiveness of ALEKS, an AI-based system for mathematics instruction. Neither the ALEKS-led nor the teacher-led groups performed significantly differently in mathematics. In their research assessing Cognitive Tutor Algebra's effectiveness, Pane et al. (2014) found conflicting findings; high school students did not show statistically significant differences in algebra competency after the first year, while there were substantial differences after the second year.

This research study's results (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) indicate that AI-based systems may facilitate student learning. The results of this study add to what is already known about the positive impact that AI-based systems may have on the mathematical performance of rural kids from low-income backgrounds. Nevertheless, it is important to approach our results with caution, since more research is required to confirm them in diverse settings and with other AI-powered educational resources.

A more noticeable difference was seen in emotional engagement, where there was a considerable variation across the groups, according to the ANOVA findings. Affective engagement was greater among students who received conventional teacher-led education as compared to those whose lessons were based on AI. It is in agreement with Research by Kort, Reilly, and Picard (2001), Lin, Wu, and Hsueh (2014), and Malekzadeh, Salim, and Mustafa (2014) all points to the absence of emotional awareness and empathy in AI-based systems. An essential part of learning, this discovery calls into doubt the AI-based system's ability to emotionally engage pupils (Reyes et al. 2012). These findings indicate that while AI-powered learning tools such as Edmentum Exact Path have their uses, they may fall short when it comes to addressing all elements of learning, including emotional involvement. It is clear that human connection is crucial for fostering emotional engagement. It should be noted, however, that the smaller size of the control groups and the presence of pre-existing greater engagement levels might account for the higher levels of emotional involvement in teacher-led education. The lack of a pre-survey to determine baseline involvement levels further weakens our findings.

On the other hand, there were no discernible differences in students' cognitive engagement levels across the various teaching approaches; this suggests that AI-based systems, such as Edmentum Exact Path, are just as effective as more conventional approaches in this regard. Nevertheless, the absence of noteworthy cognitive engagement implies that neither instructor-led nor AI-led education clearly promotes cognitive engagement and may even diminish it. It is challenging to derive compelling findings due to the lack of a pre-survey to establish baseline involvement levels.

A lack of emotional awareness and empathy means that AI-based systems may not significantly influence affective engagement, but they do a good job of supporting cognitive engagement by correcting cognitive dissonance. Traditional teacher-led training relies heavily on human contact, which is defined by emotional awareness and empathy (Reyes et al. 2012). Therefore, the emotional aspects of learning may be more strongly influenced by conventional teacher-led training.

Prior research has shown conflicting outcomes when comparing teacher-led education versus Edmentum Exact path-led training in terms of cognitive engagement; however, this study did not uncover a statistically significant difference. To further understand the efficacy of AI-based systems, more research into their effects on cognitive engagement is needed, taking into account factors including instructional design, student characteristics, and learning outcomes.

The capacity of AI-based systems to provide personalized instruction that takes into account each student's unique background, experiences, and requirements has led to their rise to prominence in modern K-12 classrooms. Students from low-income backgrounds in rural regions might benefit greatly from using AI-based solutions like Edmentum Exact Path to boost their engagement and math scores. The effectiveness of teacher-led instructions should not be underestimated. If lawmakers and teachers are serious about helping students from low-income families succeed in mathematics, these results should be considered. This study's real-world consequences point to the potential of AI-based solutions, such as Edmentum Exact route, as useful resources for assisting kids from low-income backgrounds in their mathematical education.

low-income origins. Additional instructional support and personalized learning experiences can be offered by incorporating AI-based systems into schools, particularly in rural areas that may have limited access to highly qualified teachers (García and Weiss 2020; Ingersoll and Tran 2023; Lazarev et al. 2017; Monk 2007; Shikalepo 2020). In addition, systems powered by AI may be useful supplementary resources in both the home and the classroom. Students who are having difficulty in the classroom may have access to credit possibilities in after-school and summer programs using AI-based systems.

The effects of artificial intelligence (AI) based systems on student engagement and achievement have been the subject of much research, and this study contributes to that body of knowledge. Additional study is necessary to investigate the wider consequences, efficacy, and possible constraints of AI-based systems in various educational settings, however the results show that Edmentum Exact Path improves mathematical proficiency. Decisions on the integration of AI-based systems to assist teaching and improve student learning outcomes may be made by educational stakeholders by using the capabilities of these systems while also acknowledging the unique contributions of instructors.

4 | Limitations and Future Directions

The results show that kids from socioeconomically disadvantaged backgrounds may benefit from AI-based solutions when it comes to arithmetic. The internal validity of the results was enhanced by the experimental design, which allowed for rigorous control over variables. This research was able to capture the real-world influence of AI-based systems on students' learning results since it was conducted in a naturalistic context. On the other hand, extrinsic variables that could affect students' performance in mathematics, such as their past academic performance, personal interests, instructional methods, teacher quality, and peer influence, might be a real problem in field research.

Nevertheless, it is important to recognize a number of constraints. Notable limitations that might affect the study's rigor and the generalizability of the results include a limited sample size and the absence of a pre-survey. Only students who returned their permission forms could participate, even though we tried our best to reach the sample size recommended by the power analysis. A bigger and more varied sample size might be considered for future research designs to increase the generalizability of results across various demographics and educational contexts. To further support the findings on the effectiveness of AI-based systems in enhancing mathematical engagement and performance, it would be beneficial to administer a pre-survey to get the average class scores before to the intervention. than conclude that AI-based training is superior than teacher-led learning based just on the criterion of emotional involvement is inadequate. Possible explanations for the greater levels of emotional involvement in teacher-led teaching include small sample sizes in the control groups and participants' already high levels of engagement, both of which might impair the reliability of our results. It is evident that none of the other teaching strategies promote or even diminish cognitive engagement, since there were no significant variations in this area. Our findings are also weak since we did not administer a pre-survey to determine baseline involvement levels. The dispersion of initial mathematical competence

differences in socioeconomic position across the categories make it difficult to draw direct comparisons and draw conclusions.

During the 2021–22 academic year, we conducted our study, although we encountered many obstacles because to the COVID-19 epidemic. A smaller sample size was observed since many parents in rural Georgia chose to homeschool or use remote learning while schools were closed (Lee et al. 2021). There was already a shortage of participants and data since some pupils missed out on the trial because they had family members infected with COVID-19. The performance and engagement metrics we used in our research were probably affected by these interruptions. If students who were previously inaccessible due to the pandemic are now able to participate, future studies should use the same sample set to provide a fuller picture of student involvement and performance.

To overcome these shortcomings, future studies should use random assignment to boost validity and reliability and use bigger, more varied samples. To further assess the effect of AI-based systems on student engagement, it would be helpful to conduct a pre-survey to collect the class's mean engagement ratings prior to the intervention. Students' experiences and impressions of various instructional styles might be better understood with the addition of qualitative data, such classroom observations or student interviews.

If we want to know how successful AI-based systems like Edmentum Exact Path are in raising students' mathematical performance, we need to do more research like this. In order to maximize educational results, it is essential to investigate how AI-based training might be combined with conventional approaches. To get a more complete picture of how AI-based systems affect student success, it would be beneficial to study their impacts over the long run on things like retention rates, academic achievement, and career paths. This research looks at student results, but it doesn't ask educators how they feel about using AI in the classroom. Techniques for efficiently incorporating technology into instructional practices might be informed by gaining an understanding of instructors' experiences, obstacles, and perspectives. To fully understand the implementation process and to capture these viewpoints, future study should use qualitative methodologies.

An individual's intrinsic drive and level of academic success are two of the many confounding factors that could affect the outcomes of this research. These factors should be further investigated in future studies examining the impact of Edmentum AI on the mathematical performance of South Georgian pupils. A number of factors should be taken into account, including the following: teacher effectiveness, student engagement, attendance, health and well-being, socioeconomic status, parental involvement, access to technology, learning environment, and health and wellness (Konstantopoulos 2009; Reeves 2012; Reardon 2018; Roorda et al. 2011; Singh 2015). Verifying the results and guiding methods for efficiently integrating AI-based systems in varied educational environments may be achieved by examining these factors, which will give a more thorough knowledge of the impacts on student learning and engagement.

5 | Conclusion

Researchers in this research set out to determine if artificial intelligence (AI) systems—and more specifically, Edmentum Exact Path—could improve math engagement and performance among rural kids from economically and socially disadvantaged families. The results show that these groups may greatly benefit from AI-based solutions when it comes to arithmetic. AI-powered solutions may enhance traditional teacher-led training by creating unique learning paths for each student. Economically disadvantaged pupils, who may lack fundamental arithmetic abilities and need extra guidance, benefit greatly from this personalized training.

According to Harry (2023), AI-based solutions may benefit instructors by releasing their time, which enables them to provide individualized attention to pupils who are facing difficulties. This has particular importance in rural regions, since schools in these areas often face a shortage of highly skilled educators, which has a detrimental effect on students' mathematical performance (García and Weiss 2020; Ingersoll and Tran 2023; Lazarev et al. 2017; Monk 2007; Shikalepo 2020). According to research conducted by Sutcher, Darling-Hammond, and Carver-Thomas (2016), the percentage of uncertified instructors was four times higher in schools in the United States that had a high minority population and were located in areas with high poverty.

According to D'Mello and Graesser (2023), Ma et al. (2014), and Phillips et al. (2020), AI-based systems may enhance teaching by offering tailored, high-quality education that adapts to each student's requirements. These systems can also support both conventional and remote classroom contexts. There has been a sea change in how we study and teach as a result of the revolutionary impact of new educational technology. D'Mello and Graesser (2023) and Wang et al. (2023a) found that AI-based systems can optimize learning according to individual students' knowledge, preferences, and readiness levels, and that these systems can constantly grow. According to Kinshuk et al. (2016) and Wang, Liu, and Tu (2021), teachers have a crucial role to play in improving students' learning outcomes via the integration of AI-based systems with successful pedagogical techniques. While student involvement was better in teacher-led classes, there are benefits to using any kind of education.

We should use care when interpreting these findings because of constraints such as the small sample size, absence of pre-survey data, and heterogeneity in baseline math skill and socioeconomic situation. Despite these caveats, the study adds significantly to the current literature by investigating how well Edmentum Exact Path complements traditional methods of mathematics instruction and student performance. Given the paucity of prior research on Edmentum Exact Path, this study is noteworthy for being one of the first of its kind.

Research conducted by Alrakhawi, Jamiat, and Abu-Naser (2023), Appleton, Christenson, and Furlong (2008), Pane et al. (2014), Schacter (1999), and Xie et al. (2019) has consistently shown a favorable correlation between AI-based systems and students' academic success and test scores. The success of AI-powered systems in the classroom, however, is dependent not only on the systems themselves but also on the pedagogical approaches used by individual educators.

Elementary, middle, and high school courses. In addition, Dronkers and Robert (2008) found that schools in urban regions had higher average math scores than schools in rural areas, and Miller, Votruba-Drzal, and Setodji (2013) brought attention to this correlation.

With a focus on children from low-income backgrounds, this study sheds light on how artificial intelligence-based solutions might help close the achievement gap and improve students' mathematical skills. Addressing these challenges and improving the mathematical success of students from socioeconomically disadvantaged backgrounds may be achieved via the integration of AI-based solutions, such as Edmentum Exact Path. Although this study provides valuable insights into the efficacy of Edmentum Exact Path as an auxiliary tool, further investigation into its wider implications, efficacy, and possible limits is necessary.

Additional variables including instructional design, student characteristics, and learning outcomes should be used in future studies that evaluate the effectiveness of various AI-based systems with Edmentum Exact Path. Educators and legislators can improve student learning results in mathematics and other subjects by using the capabilities of AI-based systems to make educated judgments on the appropriate integration of these developing technologies.

References

Aleven, V., E. A. McLaughlin, R. A. Glenn, and K. R. Koedinger. 2016. “Instruction Based on Adaptive Learning Technologies.” *Handbook of Research on Learning and Instruction* 2: 522–560. http://www.cs.cmu.edu/afs/.cs.cmu.edu/Web/People/aleven/Papers/2016/Aleven_etal_Handbook2016_AdaptiveLearningTechnologies_Prepub.pdf.

Almoubayyed, H., R. Bastoni, S. R. Berman, et al. 2023. “Rewriting Math Word Problems to Improve Learning Outcomes for Emerging Readers: A Randomized Field Trial in Carnegie Learning's Mathia.” In *International Conference on Artificial Intelligence in Education*, 200–205. Cham: Springer Nature. https://doi.org/10.1007/978-3-031- 36336-8_30.

Alrakhawi, H. A., N. U. R. U. L. L. I. Z. A. M. Jamiat, and S. S. Abu-Naser. 2023. “Intelligent Tutoring Systems in Education: A Systematic Review of Usage, Tools, Effects and Evaluation.” *Journal of Theoretical and Applied Information Technology* 101, no. 4: 1205–1226. https:// www.researchgate.net/profile/Hazem-Alrakhawi/publication/369019319_INTELLIGENT_TUTORING_SYSTEMS_IN_EDUCATION_A_SYSTEMATIC_REVIEW_OF_USAGE_TOOLS_EFFECTS_AND_EVALUATION/links/6404b15db1704f343fa46394/INTELLIGENT-TUTORING-SYSTEMS-IN-EDUCATION-A-SYSTEMATIC-REVIEW-OF-USAGE-TOOLS-EFFECTS-AND-EVALUATION.pdf.

Appleton, J. J., S. L. Christenson, and M. J. Furlong. 2008. “Student Engagement With School: Critical Conceptual and Methodological Issues of the Construct.” *Psychology in the Schools* 45, no. 5: 369–386. https://doi.org/10.1002/pits.20303.

Axelson, R. D., and A. Flick. 2010. “Defining Student Engagement.” *Change: The Magazine of Higher Learning* 43, no. 1: 38–43. https://doi.org/10.1080/00091383.2011.533096.

Beal, C. R., I. M. Arroyo, P. R. Cohen, and B. P. Woolf. 2010. “Evaluation of AnimalWatch: An Intelligent Tutoring System for Arithmetic and Fractions.” *Journal of Interactive Online Learning* 9, no. 1: 64–77. https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=10217608f7481735c9a82fa17d4b01ee0de85215.

Brown, T. T. 2008. *An Exploratory Study of Mathematics Engagement of Secondary Students*. Atlanta, Georgia: Georgia State University. https:// eric.ed.gov/?id=ED276149.

Clayton, J. K. 2011. “Changing Diversity in US Schools: The Impact on Elementary Student Performance and Achievement.” *Education and Urban Society* 43, no. 6: 671–695. https://doi.org/10.1177/0013124510380909.

Clément, B., H. Sauzéon, D. Roy, and P. Y. Oudeyer. 2024. “Improved Performances and Motivation in Intelligent Tutoring Systems: Combining Machine Learning and Learner Choice.” *arXiv Preprint arXiv:2402.01669*. https://arxiv.org/pdf/2402.01669.

Cooper, C. E., and R. Crosnoe. 2007. “The Engagement in Schooling of Economically Disadvantaged Parents and Children.” *Youth and Society* 38, no. 3: 372–391. https://doi.org/10.1177/0044118X06289999.

Craig, S. D., X. Hu, A. C. Graesser, et al. 2013. “The Impact of a Technology-Based Mathematics After-School Program Using ALEKS on Student's Knowledge and Behaviors.” *Computers and Education* 68: 495–504. https://doi.org/10.1016/j.compedu.2013.06.010.

D'Mello, S., and A. Graesser. 2012. “Dynamics of Affective States During Complex Learning.” *Learning and Instruction* 22, no. 2: 145–157. https://doi.org/10.1016/j.learninstruc.2011.10.001.

D'Mello, S., and A. Graesser. 2014. “Confusion.” In *International Handbook of Emotions in Education*, edited by R. Pekrun and L. Linnenbrink- Garcia, 289–310. New York: Routledge.

D'Mello, S., B. Lehman, R. Pekrun, and A. Graesser. 2014. “Confusion Can Be Beneficial for Learning.” *Learning and Instruction* 29: 153–170. https://doi.org/10.1016/j.learninstruc.2012.05.003.

D'Mello, S. K., and A. Graesser. 2023. “Intelligent Tutoring Systems: How Computers Achieve Learning Gains That Rival Human Tutors.” In *Handbook of Educational Psychology*, 603–629. New York: Routledge. https://doi.org/10.4324/9780429433726-31.

Dronkers, J., and P. Robert. 2008. “Differences in Scholastic Achievement of Public, Private Government-Dependent, and Private Independent Schools: A Cross-National Analysis.” *Educational Policy* 22, no. 4: 541–577. https://doi.org/10.1177/0895904807307065.

Duncan, G. J., and K. Magnuson. 2011. *Whither Opportunity?: Rising Inequality, Schools, and Children's Life Chances*. New York: Russell Sage Foundation.

Edmentum. 2023a. “Advanced Algebra Georgia.” https://www.edmentum.com/intl/curricula-catalog/?refinementList%5Bproduct%5D%5B0%5D=Tutorials.

Edmentum. 2023b. “Unpacking Exact Path: What the Learning Path Looks Like.” https://www.edmentum.com/articles/exact-path-learning-path/.

El-Sabagh, H. A. 2021. “Adaptive E-Learning Environment Based on Learning Styles and Its Impact on Development Students' Engagement.” *International Journal of Educational Technology in Higher Education* 18, no. 1: 53. https://doi.org/10.1186/s41239-021-00289-4.

Faber, J. M., H. Luyten, and A. J. Visscher. 2017. “The Effects of a Digital Formative Assessment Tool on Mathematics Achievement and Student Motivation: Results of a Randomized Experiment.” *Computers and Education* 106: 83–96.

Fang, Y., Z. Ren, X. Hu, and A. C. Graesser. 2019. “A Meta-Analysis of the Effectiveness of ALEKS on Learning.” *Educational Psychology* 39, no. 10: 1278–1292. https://doi.org/10.1080/01443410.2018.1495829.

Feng, M., C. Huang, and K. Collins. 2023. “Promising Long Term Effects of ASSISTments Online Math Homework Support.” In *International Conference on Artificial Intelligence in Education*, 212–217. Cham: Springer Nature. https://doi.org/10.1007/978-3-031-36336-8_32.

Fine, A., M. Duggan, and L. Braddy. 2009. “Removing Remediation Requirements: Effectiveness of Intervention Programs.” *Primus* 19, no. 5: 433–446. https://doi.org/10.1080/10511970701678570.

Fredricks, J. A., P. C. Blumenfeld, and A. H. Paris. 2004. “School Engagement: Potential of the Concept, State of the Evidence.” *Review of Educational Research* 74, no. 1: 59–109. https://doi.org/10.3102/00346543074001059.

Fung, F., C. Y. Tan, and G. Chen. 2018. “Student Engagement and Mathematics Achievement: Unraveling Main and Interactive Effects.” *Psychology in the Schools* 55, no. 7: 815–831. https://doi.org/10.1002/ pits.22139.

GaDOE. 2022a. “Georgia Milestones 2021–2022 Statewide Scores.” Accessed January 13, 2023. https://www.gadoe.org/Curriculum-Instruction-and-Assessment/Assessment/Pages/Georgia_2021-2022_Assessment_Results.aspx.

GaDOE. 2022b. “The Nation's Report Card.” https://www.gadoe.org/External-Affairs-and-Policy/communications/Documents/NAEP%20Scores%202022.pdf.

García, E., and E. Weiss. 2020. *A Policy Agenda to Address the Teacher Shortage in Us Public Schools: The Sixth and Final Report in the ‘Perfect Storm in the Teacher Labor Market’ Series*. Washington, DC: Economic Policy Institute. https://files.eric.ed.gov/fulltext/ED611178.pdf.

Gopalan, M., K. Rosinger, and J. B. Ahn. 2020. “Use of Quasi-Experimental Research Designs in Education Research: Growth, Promise, and Challenges.” *Review of Research in Education* 44, no. 1: 218–243. https://doi.org/10.3102/0091732X20903302.

Grootenboer, P., and M. Marshman. 2016. “The Affective Domain, Mathematics, and Mathematics Education.” In *Mathematics, Affect and Learning*, edited by P. Grootenboer and M. Marshman, 13–33. Singapore: Springer. https://doi.org/10.1007/978-981-287-679-9_2.

Han, F. 2021. “The Relations Between Teaching Strategies, Students' Engagement in Learning, and Teachers' Self-Concept.”

Sustainability 13, no. 9: 5020. https://doi.org/10.3390/su13095020.

Hanushek, E. A., and S. G. Rivkin. 2006. *School Quality and the Black- White Achievement Gap*. Working Paper no. 12651, NBER, Cambridge, MA: National Bureau of Economic Research.

Harry, A. 2023. "Role of AI in Education." *Interdiciplinary Journal and Hummanity* 2, no. 3: 260–268. https://doi.org/10.58631/injurity.v2i3.52.

Harwell, M., and B. LeBeau. 2010. "Student Eligibility for a Free Lunch as an SES Measure in Education Research." *Educational Researcher* 39, no. 2: 120–131. https://doi.org/10.3102/0013189X10362578.

Haveman, R., and B. Wolfe. 1995. "The Determinants of Children's Attainments: A Review of Methods and Findings." *Journal of Economic Literature* 33, no. 4: 1829–1878. https://scholar.google.com/scholar?output=instlink&q=info:NzE3wLxlMDoJ:scholar.google.com/&hl=nl&as_sdt=0,11&scillfp=14595708929661686191&oi=lle.

Hillmayr, D., L. Ziernwald, F. Reinhold, S. I. Hofer, and K. M. Reiss. 2020. "The Potential of Digital Tools to Enhance Mathematics and Science Learning in Secondary Schools: A Context-Specific Meta- Analysis." *Computers and Education* 153: 103897. https://doi.org/10. 1016/j.compedu.2020.103897.

Hu, X., Y. J. Xu, C. Hall, K. Walker, and T. Okwumabua. 2013. "A Potential Technological Solution for Reducing the Achievement Gap Between White and Black Students." In *Knowledge Spaces*, 79–91. Berlin, Heidelberg: Springer. https://doi.org/10.1007/978-3-642-35329-1_5.

Huang, X., S. D. Craig, J. Xie, A. Graesser, and X. Hu. 2016. "Intelligent Tutoring Systems Work as a Math Gap Reducer in 6th Grade After- School Program." *Learning and Individual Differences* 47: 258–265. https://doi.org/10.1016/j.lindif.2016.01.012.

Hyun, J., R. Ediger, and D. Lee. 2017. "Students' Satisfaction on Their Learning Process in Active Learning and Traditional Classrooms." *International Journal of Teaching and Learning in Higher Education* 29, no. 1: 108–118. https://files.eric.ed.gov/fulltext/EJ1135821.pdf.

Ingersoll, R. M., and H. Tran. 2023. "Teacher Shortages and Turnover in Rural Schools in the US: An Organizational Analysis." *Educational Administration Quarterly* 59, no. 2: 396–431. https://doi.org/10.1177/ 0013161X231159922.

Jasin, J., H. T. Ng, I. Atmosukarto, et al. 2023. "The Implementation of Chatbot-Mediated Immediacy for Synchronous Communication in an Online Chemistry Course." *Education and Information Technologies* 28, no. 8: 10665–10690. https://doi.org/10.1007/s10639-023-11602-1.

Khosravi, H., S. Sadiq, and D. Gasevic. 2020. "Development and Adoption of an Adaptive Learning System: Reflections and Lessons Learned." In *Proceedings of the 51st ACM Technical Symposium on Computer Science Education*, 58–64. https://doi.org/10.1145/3328778.3366900.

Kinshuk, N. S. Chen, I. L. Cheng, and S. W. Chew. 2016. "Evolution Is Not Enough: Revolutionizing Current Learning Environments to Smart Learning Environments." *International Journal of Artificial Intelligence in Education* 26: 561–581. https://doi.org/10.1007/s40593-016-0108-x.

Koedinger, K. R., E. A. McLaughlin, and N. T. Heffernan. 2010. "A Quasi-Experimental Evaluation of an Online Formative Assessment and Tutoring System." *Journal of Educational Computing Research* 43, no. 4: 489–510. https://doi.org/10.1007/BF03217366.

Konstantopoulos, S. 2009. "Effects of Teachers on Minority and Disadvantaged Students' Achievement in the Early Grades." *Elementary School Journal* 110, no. 1: 92–113. https://doi.org/10.1086/598845.

Kort, B., R. Reilly, and R. W. Picard. 2001. "An Affective Model of Interplay Between Emotions and Learning: Reengineering Educational Pedagogy- Building a Learning Companion." In *Proceedings IEEE International Conference on Advanced Learning Technologies*, 43–46. IEEE. https://ieeexplore.ieee.org/iel5/7507/20425/00943850.pdf?casa_token=zMZYv4svoF8AAAAA:OSDDau1ma0MOy6Bym_TEhkLmTIuSV1CzQSBHzBFmh_iAG1AonChLUZA5ZpaSaY_N2sNo2PQ6-x7x.

Kuh, G. D. 2009. "The National Survey of Student Engagement: Conceptual and Empirical Foundations." *New Directions for Institutional Research* 141: 5–20. https://doi.org/10.1002/ir.283.

Kulik, J. A., and J. D. Fletcher. 2016. "Effectiveness of Intelligent Tutoring Systems: A Meta-Analytic Review." *Review of Educational Research* 86, no. 1: 42–78. https://doi.org/10.3102/0034654315581420.

Kumar, R. 2018. *Research Methodology: A step-by-step guide for begin- ners*. New Delhi: Sage.

Lazarev, V., M. Toby, J. Zacamy, L. Lin, and D. Newman. 2017. *Indicators of Successful Teacher Recruitment and Retention in Oklahoma Rural Schools*. REL 2018-275. Washington, DC: Regional Educational Laboratory Southwest. https://files.eric.ed.gov/fulltext/ ED576669.pdf.

Leddo, J., and K. Garg. 2021. "Comparing the Effectiveness of AI-Powered Educational Software to Human Teachers." *International*

Journal of Social Science and Economic Research 6, no. 3: 953–963. https://doi.org/10.46609/IJSSER.2021.v06i03.015.

Lee, S. J., K. P. Ward, O. D. Chang, and K. M. Downing. 2021. "Parenting Activities and the Transition to Home-Based Education During the COVID-19 Pandemic." *Children and Youth Services Review* 122: 105585. https://doi.org/10.1016/j.childyouth.2020.105585.

Li, L., A. D. I. Gow, and J. Zhou. 2020. "The Role of Positive Emotions in Education: A Neuroscience Perspective." *Mind, Brain, and Education* 14, no. 3: 220–234. https://doi.org/10.1111/mbe.12244.

Lin, H. C. K., C. H. Wu, and Y. P. Hsueh. 2014. "The Influence of Using Affective Tutoring System in Accounting Remedial Instruction on Learning Performance and Usability." *Computers in Human Behavior* 41: 514–522. https://doi.org/10.1016/j.chb.2014.09.052.

Ma, W., O. O. Adesope, J. C. Nesbit, and Q. Liu. 2014. "Intelligent Tutoring Systems and Learning Outcomes: A Meta-Analysis." *Journal of Educational Psychology* 106, no. 4: 901–918. https://psycnet.apa.org/ doi/10.1037/a0037123.

Maamin, M., S. M. Maat, and Z. H. Iksan. 2021. "The Influence of Student Engagement on Mathematical Achievement Among Secondary School Students." *Mathematics* 10, no. 1: 41. https://doi.org/10.3390/ math10010041.

Malekzadeh, M., S. S. Salim, and M. B. Mustafa. 2014. "Towards Integrating Emotion Management Strategies in Intelligent Tutoring System Used by Children." In *Pervasive Computing Paradigms for Mental Health: 4th International Symposium, MindCare 2014, Tokyo, Japan, May 8-9, 2014, Revised Selected Papers 4*, 41–50. Tokyo, Japan: Springer International Publishing.

Martin, A. J., B. Papworth, P. Ginns, L. E. Malmberg, R. J. Collie, and R. A. Calvo. 2015. "Real-Time Motivation and Engagement During a Month at School: Every Moment of Every Day for Every Student Matters." *Learning and Individual Differences* 38: 26–35. https://doi.org/ 10.1016/j.lindif.2015.01.014.

Martin, M. O., I. V. Mullis, P. Foy, and G. M. Stanco. 2012. "TIMSS 2011 International Results in Science." In *International Association for the Evaluation of Educational Achievement*. Herengracht, Amsterdam, The Netherlands: International Association for the Evaluation of Educational Achievement (IEA).

McCoy, L. P. 2005. "Effect of Demographic and Personal Variables on Achievement in Eighth-Grade Algebra." *Journal of Educational Research* 98, no. 3: 131–135. https://doi.org/10.3200/JOER.98.3.131-135.

McLeod, J. 2017. "Exact Path Research Brief: Effectiveness Study." https://cdn.edmentum.com/assets/pdf/Exact-Path-Effectiveness-Paper -FINAL_0.pdf.

Metje, N., H. L. Frank, and P. Croft. 2007. "Can't Do Maths—Understanding Students' Maths Anxiety." *Teaching Mathematics and its Applications* 26, no. 2: 79–88. https://doi.org/10.1093/teamat/ hrl023.

Miller, P., E. Votruba-Drzal, and C. M. Setodji. 2013. "Family Income and Early Achievement Across the Urban–Rural Continuum." *Developmental Psychology* 49, no. 8: 1452–1465. https://doi.org/10.1037/a0030244.

Mohammed, P. S., and E. N. Watson. 2019. "Towards Inclusive Education in the Age of Artificial Intelligence: Perspectives, Challenges, and Opportunities." In *Artificial Intelligence and Inclusive Education. Perspectives on Rethinking and Reforming Education*, edited by J. Knox, Y. Wang, and M. Gallagher. Singapore: Springer. https://doi.org/10.1007/ 978-981-13-8161-4_2.

Molenaar, I., and C. A. Knoop-van Campen. 2018. "How Teachers Make Dashboard Information Actionable." *IEEE Transactions on Learning Technologies* 12, no. 3: 347–355. https://doi.org/10.1109/TLT.2018.2851585.

Monk, D. H. 2007. "Recruiting and Retaining High-Quality Teachers in Rural Areas." *Future of Children* 17: 155–174. https://doi.org/10.1353/ foc.2007.0009.

Murray, S. 2011. "Declining Participation in Post-Compulsory Secondary School Mathematics: Students' Views of and Solutions to the Problem." *Research in Mathematics Education* 13, no. 3: 269–285. https://doi.org/10.1080/14794802.2011.624731.

Nagashima, T., J. Britti, X. Wang, et al. 2022. "Designing Playful Intelligent Tutoring Software to Support Engaging and Effective Algebra Learning." In *European Conference on Technology Enhanced Learning*, 258–271. Cham: Springer International Publishing. https:// doi.org/10.1007/978-3-031-16290-9_19.

Niño-Rojas, F., D. Lancheros-Cuesta, M. T. P. Jiménez-Valderrama, G. Mestre, and S. Gómez. 2024. "Systematic Review: Trends in Intelligent Tutoring Systems in Mathematics Teaching and Learning." *International Journal of Education in Mathematics, Science and Technology* 12, no. 1: 203–229. https://doi.org/10.46328/ijemst.3189.

Nitkin, D., D. D. Ready, and A. J. Bowers. 2022. "Using Technology to Personalize Middle School Math Instruction: Evidence From a Blended Learning Program in Five Public Schools." In *Frontiers in Education*, vol. 7, 646471. Switzerland: Frontiers Media SA. https://doi.org/10. 3389/feduc.2022.646471.

Nye, B. D., P. I. Pavlik, A. Windsor, A. M. Olney, M. Hajeer, and X. Hu. 2018. "SKOPE-IT (Shareable Knowledge Objects as Portable Intelligent Tutors): Overlaying Natural Language Tutoring on an Adaptive Learning System for Mathematics." *International Journal of STEM Education* 5: 1–20. https://doi.org/10.1186/s40594-018-0109-4.

Olney, A. M., S. D'Mello, N. Person, et al. 2012. "Guru: A Computer Tutor That Models Expert Human Tutors." In *Intelligent Tutoring Systems: 11th International Conference, ITS 2012, Chania, Crete, Greece, June 14–18, 2012. Proceedings 11*, 256–261. Heidelberg, Germany: Springer. https://doi.org/10.1007/978-3-642-30950-2_32.

Pane, J. F., B. A. Griffin, D. F. McCaffrey, and R. Karam. 2014. "Effectiveness of Cognitive Tutor Algebra I at Scale." *Educational Evaluation and Policy Analysis* 36, no. 2: 127–144. https://doi.org/10. 3102/0162373713507480.

Phillips, A., J. F. Pane, R. Reumann-Moore, and O. Shenbanjo. 2020. "Implementing an Adaptive Intelligent Tutoring System as an Instructional Supplement." *Educational Technology Research and Development* 68: 1409–1437. https://doi.org/10.1007/s11423-020-09745-w.

Pliakos, K., S. H. Joo, J. Y. Park, F. Cornillie, C. Vens, and W. Van den Noortgate. 2019. "Integrating Machine Learning Into Item Response Theory for Addressing the Cold Start Problem in Adaptive Learning Systems." *Computers and Education* 137: 91–103. https://doi.org/10. 1016/j.compedu.2019.04.009.

Randel, B. 2018. "Impacts of Edmentum's Exact Path on Student Mathematics Achievement." Online Submission. ERIC. https://files. eric.ed.gov/fulltext/ED605132.pdf.

Reardon, S. F. 2018. "The Widening Academic Achievement Gap Between the Rich and the Poor." In *Social Stratification*, 536–550. New York: Routledge.

Reeves, E. B. 2012. "The Effects of Opportunity to Learn, Family Socioeconomic Status, and Friends on the Rural Math Achievement Gap in High School." *American Behavioral Scientist* 56, no. 7: 887–907. https://doi.org/10.1177/0002764212442357.

Reyes, M. R., M. A. Brackett, S. E. Rivers, M. White, and P. Salovey. 2012. "Classroom Emotional Climate, Student Engagement, and Academic Achievement." *Journal of Educational Psychology* 104, no. 3: 700–712. https://doi.org/10.1037/a0027268.

https://utilitasmathematicapublishing.com
Vol: 1, ISSUE: 1, 2025
Pg No: 1-17

Rodrigues, L., F. D. Pereira, M. Marinho, et al. 2023. "Mathematics Intelligent Tutoring Systems With Handwritten Input: A Scoping Review." *Education and Information Technologies* 29: 11183–11209. https://doi.org/10.1007/s10639-023-12245-y.

Rogers, J., and A. Revesz. 2019. "Experimental and Quasi-Experimental Designs." In *The Routledge Handbook of Research Methods in Applied*

Linguistics, 133–143. New York: Routledge. https://doi.org/10.4324/ 9780367824471-12.

Roorda, D. L., H. M. Koomen, J. L. Spilt, and F. J. Oort. 2011. "The Influence of Affective Teacher-Student Relationships on Students' School Engagement and Achievement: A Meta-Analytic Approach." *Review of Educational Research* 81, no. 4: 493–529. https://doi.org/10. 3102/0034654311421793.

Schacter, J. 1999. "The Impact of Education Technology on Student Achievement: What the Most Current Research Has to Say." *Milken Exchange of Educational Technology*: 1–13. https://files.eric.ed.gov/fullt ext/ED430537.pdf.

Sedlak, M. W. 1986. *Selling Students Short: Classroom Bargains and Academic Reform in the American High School*. New York: Teachers College Press.

Shikalepo, E. E. 2020. "Challenges Facing Teaching at Rural Schools: A Review of Related Literature." *International Journal of Research and Innovation in Social Science* 4, no. 5: 211–218. https://www.academia. edu/download/63487885/Challenges_Facing_Teaching_at_Rural_ Schools20200531-17223-d5g6c.pdf.

Singh, M. 2015. "Influence of Socioeconomic Disadvantages on Mathematics Achievement: A Multilevel Cohort Analysis." *Journal of Educational Research* 108, no. 5: 347–357. https://doi.org/10.1080/00220 671.2014.899956.

Sirin, S. R. 2005. "Socioeconomic Status and Academic Achievement: A Meta-Analytic Review of Research." *Review of Educational Research* 75, no. 3: 417–453. https://doi.org/10.3102/00346543075003417.

Song, C., S. Y. Shin, and K. S. Shin. 2024. "Implementing the Dynamic Feedback-Driven Learning Optimization Framework: A Machine Learning Approach to Personalize Educational Pathways." *Applied Sciences* 14, no. 2: 916. https://doi.org/10.3390/app14020916.

Steenbergen-Hu, S., and H. Cooper. 2013. "A Meta-Analysis of the Effectiveness of Intelligent Tutoring Systems on K-12 Students' Mathematical Learning." *Journal of Educational Psychology* 105, no. 4: 970–987. https://doi.org/10.1037/a0032447.

Stein, N. L., and L. J. Levine. 1999. "The Early Emergence of Emotional Understanding and Appraisal: Implications for Theories of Development." *Handbook of Cognition and Emotion*: 383–408. https:// doi.org/10.1002/0470013494.ch19.

Stein, N. L., and L. J. Levine. 2013. "Making Sense out of Emotion: The Representation and Use of Goal-Structured Knowledge." In *Psychological and Biological Approaches to Emotion*, 45–74. New York: Psychology Press. https://doi.org/10.4324/9780203761588.

Sutcher, L., L. Darling-Hammond, and D. Carver-Thomas. 2016. *A Coming Crisis in Teaching? Teacher Supply, Demand, and Shortages in the U.S.* Palo Alto, CA: Learning Policy Institute.

Terzieva, V., T. Ivanova, and K. Todorova. 2022. "Personalized Learning in an Intelligent Educational System." In *Novel and Intelligent Digital Systems Conferences*, 13–23. Cham: Springer International Publishing. https://doi.org/10.1007/978-3-031-17601-2_2.

Urbina, A., and D. Polly. 2017. "Examining Elementary School Teachers' Integration of Technology and Enactment of TPACK in Mathematics." *International Journal of Information and Learning Technology* 34, no. 5: 439–451. https://doi.org/10.1108/IJILT-06-2017-0054.

Vadivel, B., S. Alam, I. Nikpoo, and B. Ajanil. 2023. "The Impact of Low Socioeconomic Background on a Child's Educational Achievements." *Education Research International* 2023, no. 1: 6565088. https://doi.org/ 10.1155/2023/6565088.

VanLehn, K. 2011. "The Relative Effectiveness of Human Tutoring, Intelligent Tutoring Systems, and Other Tutoring Systems." *Educational Psychologist* 46, no. 4: 197–221. https://doi.org/10.1080/00461520.2011. 611369.

Wang, H., A. Tlili, R. Huang, et al. 2023a. "Examining the Applications of Intelligent Tutoring Systems in Real Educational Contexts: A Systematic Literature Review From the Social Experiment Perspective." *Education and Information Technologies* 28, no. 7: 9113–9148. https:// doi.org/10.1007/s10639-022-11555-x.

Wang, N., G. Rebolledo-Mendez, V. Dimitrova, N. Matsuda, and O. C. Santos, eds. 2023b. "Artificial Intelligence in Education." In *Posters and Late Breaking Results, Workshops and Tutorials, Industry and Innovation Tracks, Practitioners, Doctoral Consortium and Blue Sky: 24th International Conference, AIED 2023, July 3–7, 2023, Proceedings*. Switzerland: Springer Nature. https://doi.org/10.1007/978-3-031- 36336-8.

Wang, S., C. Christensen, W. Cui, et al. 2023c. "When Adaptive Learning Is Effective Learning: Comparison of an Adaptive Learning System to Teacher-Led Instruction." *Interactive Learning Environments* 31, no. 2: 793–803. https://doi.org/10.1080/10494820.2020.1808794.

Wang, Y., C. Liu, and Y. F. Tu. 2021. "Factors Affecting the Adoption of AI-Based Applications in Higher Education." *Educational Technology and Society* 24, no. 3: 116–129. https://www-jstor-org.ezproxy.elib10.ub. unimaas.nl/stable/pdf/27032860.pdf.

Xie, H., H. C. Chu, G. J. Hwang, and C. C. Wang. 2019. "Trends and Development in Technology-Enhanced Adaptive/Personalized Learning: A Systematic Review of Journal Publications From 2007 to 2017." *Computers and Education* 140: 103599. https://doi.org/10.1016/j. compedu.2019.103599.