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The Impact of AI (Artificial Intelligence) Math Tutoring Applications on Student Learning Engagement and Academic Performance in Mathematics

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Abstract

This study investigated the relationship between students' learning engagement and their academic performance in mathematics, particularly in the context of using AI-based math tutoring applications. Using a descriptive-correlational design, data were gathered from 173 senior high school students enrolled in the STEM strand. Results revealed high levels of behavioral, cognitive, and emotional engagement, with behavioral engagement obtaining the highest mean. However, academic performance was concentrated in the satisfactory and fairly satisfactory ranges. Spearman's rho correlation analysis showed a very weak and statistically insignificant relationship with $\rho=0.048$ and $p=0.531$ between learning engagement and academic math performance. These findings suggest that while AI tools may support engagement, they do not directly translate to improved academic outcomes. The study highlights the need for more holistic integration of AI technologies, combining personalized features with teacher guidance, to enhance both engagement and achievement. Further research is recommended to explore mediating factors such as self-efficacy and learning strategies.

Keywords: *AI- Based Math Tutoring Application, Student Learning Engagement, Behavioral Engagement, Cognitive Engagement, Emotional Engagement, Math Academic Performance*

INTRODUCTION

Artificial intelligence (AI) advancements in educational technology now provide students with customized learning experiences through adaptive educational systems. The AI-based tutoring applications GeoGebra and Photo math and Symbolab and others provide effective solutions to address student learning differences and teacher shortages and rising student needs for personalized instruction. The systems apply machine learning algorithms to monitor student performance in real time for identifying individual learning strengths and weaknesses to deliver personalized feedback and guidance (Luckin et al., 2016). AI systems provide personalized educational support to students through adaptive learning which benefits math education because students need solid foundational knowledge to advance to advanced subjects.

The current research lacks sufficient data about how these promising educational tools affect student engagement levels and motivation and their lasting academic results. Academic success depends heavily on student engagement because it shows how much students actively participate and stay motivated throughout their learning activities. The ability of AI tools to enhance immediate learning results through better test scores and concept understanding faces difficulties when it comes to maintaining continuous student interaction at a meaningful level throughout extended periods (Holmes et al., 2019).

AI tools achieve student interest through individualized learning routes and interactive features and adaptive feedback systems which they implement during their initial use. The interactive learning environment created by these features helps students stay focused while meeting their individual needs during their first period of tool usage. The maintenance of student engagement throughout time requires more than basic operational features. The combination of fading novelty effects and monotonous repetitive work and insufficient social and emotional connections in learning activities leads students to stop using these tools.

Student engagement requires students to maintain both cognitive involvement through attention and effort and emotional and social participation. Students tend to lose interest in AI tools when these systems fail to recognize their changing learning preferences and do not offer team-based activities and intrinsic motivation elements. The ability of AI technologies to sustain long-term learner engagement depends on their success in handling multiple engagement aspects which include cognitive and emotional and social elements.

AI tool developers need to conduct additional research to create systems which promote enduring meaningful learner interactions that support long-term educational targets. The success of AI educational tools depends on three main factors which include interface quality and cultural background and student digital competency (Zawacki- Richter et al., 2019). The AI interface quality determines how well students can use the system because it affects both accessibility and user experience and learning engagement. A properly designed interface between students and tools results in better tool usability and accessibility which leads to enhanced user experience and longer tool engagement.

Educational tools need to match the cultural values and learning expectations of their student population to achieve success. Educational content and teaching methods that match student cultural backgrounds create familiar learning experiences which enhance their motivation to participate in class. Educational tools that do not match cultural backgrounds of students will result in lower student engagement and reduced tool effectiveness.

Student digital literacy stands as a fundamental factor which determines their ability to operate and benefit from these educational tools. Students who demonstrate strong digital skills can learn new technologies better and understand their features and solve problems which results in better use of AI-based learning platforms. Students who lack digital skills face challenges with tool operation which results in both frustration and decreased engagement. The successful implementation of AI-driven educational technologies requires designers to focus on these essential factors which will make the systems accessible and effective for all learners. Academic success in mathematics requires student engagement as an essential element because students often view math as difficult and abstract. Students who do not engage with math education show reduced motivation and lower academic achievement while developing weaker confidence in their math abilities. The resolution of these obstacles stands as a vital requirement to help students develop better comprehension and appreciation of the subject. Research findings from recent studies support this knowledge base. Liu et al. (2022) studied how students' mathematical attitudes influence their classroom participation and their academic results. Students who held favorable attitudes toward mathematics demonstrated higher engagement which produced superior academic results. The research shows that students need positive math perceptions to achieve better academic results and higher levels of engagement.

Rejas and Tan (2023) investigated Grade 10 student performance and math engagement through the flipped classroom method in a real-time learning environment. The research showed that students in the flipped classroom section achieved superior results in their post-test which proves that modern educational approaches boost student involvement and academic achievement in mathematics.

The research demonstrates that student involvement stands as a vital element in mathematics education because effective engagement strategies produce better academic results. Educators who use positive math attitude promotion strategies alongside modern teaching approaches will help students overcome their math challenges which results in improved motivation and enhanced academic performance and increased mathematical self-assurance. The research examined how AI tools affect student engagement through their behavioral and emotional and cognitive responses in mathematics education. The research findings about student responses to AI technologies enable better implementation of these tools for maximizing student involvement and educational success.

The increasing importance of understanding student learning behaviors, along with the need to reevaluate academic practices in schools across the Philippines to ensure instruction is responsive to student needs, underscores the necessity of this study. This study evaluated how AI Math tutoring applications affected student learning engagement and mathematics academic performance at Samar National School throughout the SY 2023-2024.

The aim of this study is to analyze the effect of AI-based Math Tutoring applications to student learning engagement and math academic performance. Specifically, it will answer the following questions;

1.What is the academic performance (Average Math Grade) of the respondents in mathematics?

2. What is the level of perceived learning engagement attributed to AI use among respondents, in terms of cognitive, behavioral, and emotional engagement?

3.Is there a significant correlation in the learning engagement and math academic performance of respondents' using AI- based Math tutoring applications?

METHODOLOGY

Research Design

This study employed quantitative methods through descriptive-correlational design which is appropriate to allow examination of the relationships between variables without intervening or controlling them (Best & Kahn, 2006).

The research examined how students' utilization of AI-based math tutoring applications as the independent variable affects their learning engagement and math academic performance which served as the dependent variables. The study assessed learning engagement through behavioral engagement (participation and persistence and on-task behavior) and emotional engagement (interest and motivation and attitudes toward mathematics) and cognitive engagement (effort and deep learning strategies and problem-solving abilities) and math academic performance through their current mathematics final grade.

Sampling

The research employed stratified random sampling technique where the target population is divided into distinct subgroups or "strata". The researchers applied random selection to each stratum to guarantee that participants would represent their respective groups proportionally. With this method, it allows to produce reliable results because it includes all essential population subgroups in sufficient numbers (Bryan,2016).

The research employed stratified random sampling to guarantee that every grade level from the Science Technology Engineering and Mathematics (STEM) program at Samar National School received proper representation. The research included 173 participants who all reported using AI tools to enhance their math learning process. The study took place at Samar National School which was chosen as the locale of the study because of its successful performance in district mathematics competitions and its STEM curriculum which focuses on mathematics, a variable which is of interest in this study. The school also provides a STEM curriculum known for its rigor and strong mathematical focus which makes it an appropriate location for this investigation.

Instrumentation

The survey instrument contained two sections which were distributed to participants. The first section of the survey collected demographic data through questions about student grade level, age, gender, parental education, math grades and a question confirming their use of AI-based math tutoring applications, which could be answered by “yes” or “no.” The survey in Section B measured mathematics learning engagement through three dimensions which followed Delfino (2019) research framework. The survey instrument passed reliability tests and content validation procedures before researchers distributed it to participants. Three experts validated the content of the instrument through their assessment of language and mathematics expertise. The 17 items in Section B reached a Cronbach's alpha score of 0.82 which shows strong internal consistency. The instrument achieved a Content Validity Index (CVI) of 1.00 for all sections which proved its overall validity and reliability.

Data Analysis

The study employed descriptive statistics including frequency percentage and mean and standard deviation to present both respondent profiles and their engagement levels. The research applied Spearman’s correlations to determine how AI-based learning engagement affects students' math academic performance. The research used Spearman to evaluate learning engagement and math academic performance because this method works best with ordinal data and does not require normal distribution (Gravetter, 2017).

Ethical Considerations

The researcher completed all required documents before starting the study to meet ethical research standards. The researcher obtained ethical research board approval through an institutional ethical certificate before starting data collection.

The respondents received a consent form which they needed to sign before researchers could begin data collection. The respondents maintained their right to decline the consent form which would have excluded them from participating in the research. The researchers explained to student participants both the research objectives and data protection methods and usage procedures for their information. The consent form explained to participants how their data would be protected through confidentiality and integrity while also

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detailing research benefits and exclusive use for this study. The researchers will maintain absolute data privacy after they finish collecting information.

Results and Discussion

A. Profile of Respondents Based on Gender, Age, and Parents' Educational Attainment

The demographic profile of respondents appears in this section to establish necessary background information for research analysis. The study included gender and age and parents' educational level as variables because they affect student academic results and their ability to use AI-based math tutoring software and their educational resource access. The analysis of student learning experiences and results depends on understanding their background characteristics which help reveal patterns and inequalities.

A.1 Gender

Table 1. Distribution of Respondents' Gender

	Frequency	**%**
Male	63	36.42
Female	108	62.43
LGBTQ	2	1.15
Prefer not to say	0	0
Total	173	100.0

The data reveals that 62.423% (n=108) of 173 students who confirmed AI tool usage in math learning identified as female while 36.42% (n=63) identified as male and 1.15% (n=2) identified as LGBTQ. The data shows female students participate more actively than male students and LGBTQ students when using AI tools for mathematics learning. Research findings in gender and technology studies (Cai et al., 2021) indicate that educational technology adoption in schools leads female students to develop positive attitudes toward educational technology.

In addition, the study also reveals that students demonstrate different preferences regarding learning methods and digital educational resources based on their gender. The research indicates that female students demonstrate greater interest in AI-based learning tools for academic support even though male students show higher confidence in technology-related subjects. The study by Zhong (2020) confirms that female students demonstrate increased interest in educational technology adoption because they view these tools as beneficial for collaborative and personalized learning experiences.

Moreover, the small number of LGBTQ participants at 1.15% creates concerns about participant representation in this research. The small number of LGBTQ participants might stem from either underrepresentation in the sampling process or their reluctance to use AI-based learning platforms because of access barriers and inclusivity concerns and technology comfort issues. Future studies need to enhance participant selection methods to achieve better diversity and inclusion by including all gender identities. The research will achieve better results when it includes diverse student groups to study their AI educational platform usage patterns.

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Hence, The study demonstrates how gender affects students' willingness to adopt AI-based learning tools. The high number of male students who do not use AI creates an obstacle because males demonstrate higher resistance to AI adoption in educational contexts. Research should investigate the specific factors which lead to this phenomenon because students might doubt AI capabilities or prefer traditional learning methods or lack understanding of AI advantages. The implementation of AI literacy programs combined with personalized support that addresses male student adoption barriers could lead to increased AI adoption rates among this demographic.

The survey results demonstrate the necessity for automated integrating methods to incorporate gender identity recognition for LGBTQ students and students who identify outside traditional gender categories. AI tools need proper training to become accessible and should become accessible and fair and inclusive systems which promote acceptance and role adoption for every student.

A.2 Age

Table 2. Distribution of Respondents Age

Age (In years)	Frequency	%
15- 17	124	71.68
18- 20	31	17.92
21 & above	18	10.40
Total	173	100

The research data indicates that 71.68% of participants belong to the 15–17 age range while 17.92% belong to the 18–20 age range and 10.40% belong to the 21 years and above age range. The majority of study participants belong to their late teenage years when their cognitive abilities and digital skills and academic performance are still developing. The study requires AI-based mathematics learning tools which should be easy to use and interactive and motivational because the participants are high school students.

The age distribution of participants supports the learning theories of Piaget (1972) and Vygotsky (1978) because they stress the need for suitable learning support and teaching methods that match student development during the formal operational stage. Educational technology interventions that use AI need to design their systems with age-specific features to achieve better results and student participation.

A.3. Parent's Highest Educational Attainment

Table 3. Distribution of Respondents' Parents Educational Attainment

	Educational Attainment	Frequency	%
Father	Elem. Level/Graduate	13	7.51
	Secondary Level/Graduate	35	20.23
	College Level/Graduate	106	61.27
	Post Graduate (Master's or Doctorate	19	10.99
Total		173	100
	Elem. Level/Graduate	27	15.61
	Secondary Level/Graduate	32	18.49

Mother	College Level/Graduate	96	55.49
	Post Graduate (Master's or Doctorate	18	10.41
Total		173	100

Most study participants reported their fathers and mothers achieved college degrees with 61.27% and 55.49% respectively and 10.99% of fathers and 10.41% of mothers earned postgraduate degrees. The survey results show that elementary education reached only 7.51% of fathers yet 15.61% of mothers. The research data shows that most students in this study originate from families which hold educational achievements ranging from moderate to high levels.

Research studies from Chowa et al. (2018) and LeFevre & Shaw (2020) demonstrate that parental education levels determine student academic involvement and their ability to access educational resources including digital tools. Parents who achieved higher education levels tend to prioritize education while supporting technology-based learning and fostering beneficial learning practices at home. The level of parental education strongly affects student engagement with AI-based math tutoring applications and their academic achievement. The evaluation of AI educational effectiveness requires knowledge about family backgrounds because it helps explain why students exhibit different learning behaviors and attitudes.

B. Respondents' Mathematics Academic Performance

Table 4. Distribution for Respondents' Math Grades

Grade Scale	Frequency	%	Descriptor
90-100	6	3.47	Outstanding
85-89	33	19.08	Very Satisfactory
80-84	70	40.46	Satisfactory
75-79	55	31.79	Fairly Satisfactory
Below 75	9	5.20	Did Not Meet expectations
Total	173	100	

The academic performance of respondents through their grades shows that most students received Satisfactory (40.46%) and Fairly Satisfactory (31.79%) grades which correspond to scores between 75 and 84. The Very Satisfactory level was reached by 19.08% of students yet 3.47% of respondents received Outstanding grades. The K–12 grading system considers scores below 75 as failing marks because 5.20% of respondents fell into this category.

The majority of students show basic math competence and only a small group demonstrates exceptional performance. The small number of students who reached outstanding performance levels indicates possible advanced thinking abilities and greater access to technology. Same as those who did not meet expectation, which are seen as the ones with restricted opportunities for advanced learning and access to technology, as 7 out of 9 of them have parents in the elementary level, which might have an effect to students' academic performance. This supports to the claim of Acosta and Acosta (2019) that students' academic success depends heavily on their learning environment together with their access to technology and their individual level of engagement. The students who failed to meet expectations and those in lower achievement bands require specific intervention methods such as adaptive learning technologies and AI-based math tutoring

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applications which offer customized instruction and immediate feedback. The tools demonstrate their ability to connect students with different learning levels while helping them achieve mathematical understanding (Alon-Barkat & Busuioc, 2021). The performance distribution helps educators identify specific areas that need improvement through better instructional support and technological integration and curriculum adaptation.

C. Learning Engagement of Respondents Using AI Math Tutoring Applications

The section examines how users of AI-based math tutoring applications engage with their learning content. The analysis of learning engagement through behavioral and cognitive and emotional dimensions help to understand how AI tools affect student participation in mathematics education. The study by Henrie, Halverson and Graham (2015) defines learning engagement as the combination of students' visible classroom activities and their mental dedication and emotional responses to academic work.

Table 5. Respondents' Level of Engagement

Using AI	Behavioral Engagement	Cognitive Engagement	Emotional Engagement
N	173	173	173
Mean	3.8560	3.6095	3.5152
Std. Deviation	.49171	.55639	.70112
Interpretation	HE	HE	HE

Legend: 1.0 – 1.80 - Very Low Engagement **(VLE)**
1.81 – 2.60 - Low Engagement (**LE)**
2.61 – 3.40 - Moderate Engagement (**ME**)
3.41 – 4.20 - High Engagement (**HE**)
4.21 - 5.00 - Very High Engagement (**VHE)**

The research shows that students demonstrate high levels of engagement through all three measurement dimensions. Students show the highest level of behavioral engagement through their consistent active learning participation and effort and persistence when using AI tools according to their mean score of 3.8560 (SD = 0.49171). The students demonstrate strong mental involvement through cognitive engagement with a mean score of 3.6095 (SD = 0.55639) while using learning strategies. The emotional engagement scores the lowest at 3.5152 (SD = 0.70112) but still falls under the high engagement category because students show less emotional involvement through enjoyment or enthusiasm.

Research from Holstein et al. (2019) and Li et al. (2021) confirms that AI-based platforms boost students' mathematical learning behaviors and mental engagement during mathematics tasks. The results indicate that AI systems excel at maintaining student focus and mental effort but they need additional affective design elements to create emotional connections with users. In addition, Tzafilkou et al. (2022) stated that students achieve better emotional engagement and sustained motivation through the combination of personalized feedback and gamification and social presence features in their learning environment. The research demonstrates that AI should function as a complete learning companion which fulfills behavioral and cognitive (Zekaj,2023) requirements while supporting emotional student needs.

D. Correlation of Respondents' Learning Engagement and Math Academic Performance

Table 6. Correlation Between the Respondents' Learning Engagement and Math Performance

Correlations				
			Mean_Learning Engagement	Mean_Math Academic Performance
Spearman's rho	Mean_Engagement	Correlation Coefficient	1.000	.048
		Sig. (2-tailed)	.	.531
		N	173	173
	Mean_MathPerform	Correlation Coefficient	.048	1.000
		Sig. (2-tailed)	.531	.
		N	173	173

The research used Spearman's rank-order correlation to study how student engagement in learning affects their math academic results. The researchers selected this non-parametric test because the engagement data from Likert-scale responses maintained an ordinal scale.

The study results presented in the table demonstrated a very weak positive relationship between student engagement and math performance through $\rho=0.048$ and $p=0.531$. The calculated correlation value failed to reach statistical significance at the 0.05 level. The study results show that student engagement levels do not create a significant patterned connection with their mathematics test results.

The research results indicate that engagement holds theoretical value but failed to establish a direct connection between student grades and their math performance in this particular study. Research by Trowler (2015) and Fredricks et al. (2019) supports the finding that academic achievement depends on multiple factors beyond student engagement because prior knowledge and instructional quality and learning strategies also influence results.

Conclusion

The findings of this study show how students use AI-based math tutoring applications to determine their learning engagement levels and their mathematics academic results. The study participants belonged to the 15–17 age range while their parents held college degrees or higher which indicates typical access to educational resources.

The survey results showed students demonstrated strong engagement in all three areas with behavioral engagement at the highest level (M = 3.8560) followed by cognitive engagement (M = 3.6095) and emotional engagement (M = 3.5152) which all fell into the "High Engagement" range. The majority of students received Satisfactory (40.46%) and Fairly Satisfactory (31. 79 %). The results showed that only a small number of students achieved Outstanding (3.47%) performance.

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The Spearman's rho correlation analysis showed no significant relationship between student engagement and their math grades because the correlation coefficient was 0.048 with a p-value of 0.531. The study shows that students remain engaged when using AI tools but their engagement level fails to predict their math grades. Student performance might also depends on their initial math skills and classroom teaching methods and learning environment than their level of engagement with AI tools.

Recommendations

1. The developers of AI math tutoring applications need to improve their tools by adding personalized feedback and gamification elements and social presence features to enhance emotional engagement since this dimension showed the lowest scores.

2. Teachers need to combine AI tools with their own instruction and feedback and scaffolding methods because AI engagement by itself does not lead to better academic results.

3. Research should investigate how different variables including study habits and socioeconomic status and learning preferences and technology availability affect the relationship between student engagement and academic achievement.

4. The 5.20% of students who failed to meet expectations require AI diagnostic data for schools to create individualized intervention programs.

5. Research studies should use mixed-methods approaches to gain deeper understanding of student experiences with AI-supported math education and their encountered difficulties.

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