# AI Usage in Mathematics Teaching and Mathematics Performance: The Role of Students Interest

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**Abstract:** This study investigated the moderating effect of students' interest in the nexus between AI usage in mathematics teaching and mathematics performance. Adopting a cross-sectional survey design, the study utilized a quantitative approach to gather and analyze data from a population of 542 students from two public senior high schools in the Ashanti Region of Ghana. Stratified and simple random sampling techniques were used to selected 230 students. A structured questionnaire was used for the data collection. A structural Equation Modeling (SEM) was utilized via Amos (v. 23). The result showed that AI usage significantly influenced students' interest in mathematics performance and hurt mathematics performance. However, students' interest positively predicted mathematics performance and significantly moderated the AI-performance nexus. The study emphasizes the need to foster students' interest alongside technology innovation to optimize learning outcomes in mathematics education.

**Keywords:** Artificial intelligence (AI) in mathematics education, Student interests, Mathematics performance, Structural equation modeling

## 1. Introduction

Digital tools in education have become more popular worldwide, particularly as Artificial Intelligence (AI) technologies become more widely available. The need for more effective. Flexible and learner-centered educational systems have fueled this digital revolution. With real-time data analysis, administrative task automation, and the capacity to tailor instruction to meet students expectation, AI has become a potent tool in the transformation of the conventional teaching and learning environment (Liu et al., 2021). The OECD (2021) reports that governments and educational institutions worldwide are investing in AI-powered solutions enhance quality and inclusive of education, especially subjects like science, technology, and mathematics, where learner disparities are more pronounced. Digital competency and AI literacy are becoming essential skills for both teachers and students, reflecting a paradigm shift in education policy and pedagogy (George, 2023). Through automated assessment tools, intelligent tutoring systems (ITS), and personalized learning, artificial intelligence (AI) has completely changed classroom procedures. AI algorithms are used in personalized learning environments to examine students' learning styles and provide feedback and content that is specifically catered to them. Intelligence tutoring programs, such as ALEKS and Carnegie Learning, mimic one-to-one human tutoring and offer instant remediation according to the learner's pace, level of difficulty, and misconceptions. Real-time grading, diagnostics feedback, and the detection of emotional stress or learning disabilities are all possible with AI-driven assessment tools. These technologies enhance teaching efficiency and direct students learning, making a shift from teacher-centered to learner-driven educational models.

A vital component of education in the twenty-first century, mathematics promotes quantitative literacy, logical reasoning, problem-solving, and critical thinking. It opens doors to STEM careers and is necessary for engagement in a global economy driven by technology. Additionally, learning mathematics helps students become more digitally fluent and cognitively flexible, which helps them deal with both personal and professional challenges. Strong math curricula are a national priority in many nations and a key objective of international education frameworks, such as Sustainable Development Goal 4 of the UN, aiming to promote quality education and opportunities for lifelong learning. Performance in mathematics is still a problem worldwide, especially in areas with low socioeconomic status, underqualified teachers, and limited resources. There are notable achievement gaps, with many students falling below basic proficiency levels, according to assessments like PISA, TIMSS, and national-level exams. These difficulties are made worse by systematic problems like packed classrooms, a lack of pedagogical support, and restricted access to educational technology. Poor performance and disengagement are caused in part by students' negative attitude toward mathematics.

By delivering individualized instruction based on each student's unique learning needs and skill level, artificial intelligence (AI) is completely changing the way that mathematics is taught. Machine learning

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algorithms are used by platforms like Carnegie Learning, Square AI, and ALEKS to monitor students' progress and recommend focused interventions. By identifying misconceptions and giving immediate feedback, the intelligence tutoring system (ITS) mimics one-to-one tutoring sessions. These AI tools support deeper mathematical understanding and engagement, particularly among low-performing students, by offering cognitive scaffolding in addition to content delivery. Traditional teaching methods are changing as a result of this change in approaches. Research indicates that AI-enhanced learning environments can increase student achievement, motivation, and confidence when combined with effective pedagogical strategies. AS AI develops, its integration holds great promise for making mathematics instruction more responsive, inclusive, and performance-oriented. These tools include automated assessment systems that grade responses, analyze errors, and generate diagnostic feedback, and chatbots like Watson Tutor Replika that provide real-time, 24/7 support to students.

One important element influencing students' focus, effort, and perseverance in academic assignments is their interest in learning. Interest in mathematics education is sparked by exposure to interesting, pertinent, or pleasurable material. Students who find mathematics intellectually or personally rewarding are more likely to engage in active participation, persevere through difficulties, and gain a deeper conceptual understanding. A consistent inclination towards mathematics over time can be represented by interest, which can be situational or individual. Research continuously demonstrates that students having interest in mathematics are motivated, self-reliant, and achieve better academically than less interested in mathematics. Students' use of AI-based learning resources is strongly influenced by their interest in mathematics. Deeper engagement and improved learning outcomes result from students with highly interested in mathematics being more inquisitive and willing to try out digital tools. On the other hand, if AI applications aren't made to pique their interest or fit with their objectives and preferences, disinterested students might reject or abuse them. As a result, encouraging students' interest is essential for both academic achievement and optimizing the use of AI in math classes.

Even though artificial intelligence (AI) tools are being used in education more and more, little empirical research has been done on how students' interest affects the nexus between AI usage in mathematics learning and mathematics performance, especially in developing nations and pre-tertiary education settings. The role of affective factors like interest is still poorly understood, even though AI-enhanced instruction can enhance student outcomes through personalization, instant feedback, and adaptive learning. Less attention is paid to motivational constructs influencing students' interactions with AI tools, with the majority of current research concentrating on cognitive outcomes like achievement and problem-solving abilities. Additionally, studies examining learner interest in digital learning environments are predominantly conducted in higher-income or technologically advanced contexts, overlooking diverse learning environments in developing nations. Pre-tertiary educational settings are increasingly implementing AI, more precisely in Latin America, Southeast Asia, and Sub-Saharan Africa. But little is known about how AI technologies interact with student-related elements like motivation, interest, and engagement to affect math performance. Students' focus and engagement are known to be maintained by interest, particularly when learning mathematics. This relationship hasn't been empirically examined in many studies conducted in developing nations, though. To improve mathematics performance in underresourced educational settings, policymakers and educators must close this gap and create AI-driven instruction that speaks to students' motivational profiles and learning needs. The conceptual framework for the study is shown in Figure 1.

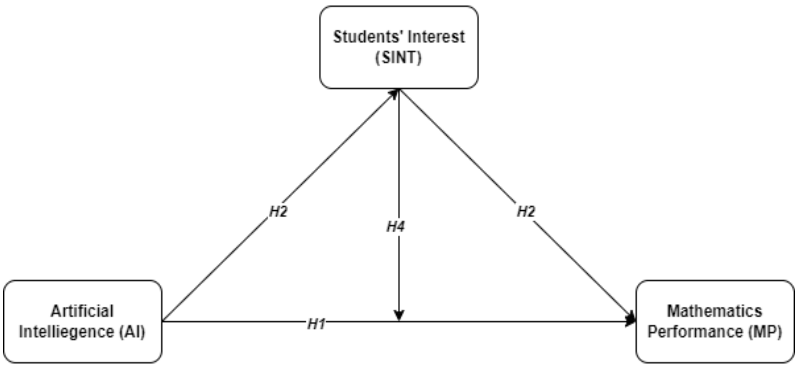


**Figure 1.** Conceptual Framework

### 1.1. Research Objectives

The objective of the study aims to;

1. Assess effect of AI usage in mathematics learning on students' mathematics performance.
2. Assess impact of AI usage in mathematics learning on students' interest.
3. Examine effect of students' interest on mathematics performance.

4. Examine the moderating effect of students' interest in the nexus between AI usage in mathematics learning and students' mathematics performance.

### 1.2. Research Hypotheses

***H**$_{1:}$* AI usage in mathematics learning significantly predicts students' mathematics performance.

***H**$_{2:}$* AI usage in mathematics learning significantly predicts students' interest.

***H**$_{3:}$* Students’ interest significantly predicts mathematics performance

***H**$_{4:}$* Students' interest moderates the nexus between AI usage in mathematics learning and students' mathematics performance.

## 2. Methodology

### 2.1. Design

Cross-sectional study was adopted by the study, to analyze data from a from the selected participant, aiming to identify the prevalence and characteristics of how students’ interest moderates the nexus between AI Usage in mathematics learning and mathematics performance.

### 2.2. Population, Sampling, and Sampling Techniques

The population of the study consists of two senior high schools in the Ashanti Region of Ghana, with a total population of five hundred and forty-two students (542). Yamane's (1967) sample size determination approach was adopted to calculated the sample size for the study with a population of 542. Which is given as;

$$n = \frac{N}{1 + Ne^2}$$

$$n = \frac{542}{1 + 542(0.05)^2} = 230.149 \approx 230$$

The selection process for respondents for the study was done through stratified simple random sampling. The stratified sampling was used to grouped students according to their course of study and their level of education. This aided the researchers to know the stratum where the participants of the study will be taken. After students were classified based on their level and course of study, the researchers used utilized simple random sampling to select participant from each stratum. Simple random sampling gives each participant the chance of being selected for the study. The selected students based on the sample size (at is, 210) will then respond to the questionnaire.

### 2.3. Questionnaire and Measures

Structured questionnaire was used as the data collection tool for the study. The questionnaire was designed based on the study constructs. The items under AI usage in teaching mathematics were adapted from the work of Bawaneh et al. (2025). Samples of the items were “I use AI-based tools (e.g., ChatGPT, Photomath, Wolfram Alpha) to support my understanding of mathematics concepts”, “AI applications have made it easier for me to solve complex mathematics problems”, “I regularly use AI-powered platforms or apps for practicing mathematics exercises”, “AI tools help me receive immediate feedback on my mathematics assignments”, and “Using AI in mathematics learning increases my confidence in solving math problems.” In additionally, items under mathematics interest were adapted from the work of Asare et al. (2023). Samples of the items were : “I enjoy solving mathematical problems during my free time,” “Mathematics is one of my favorite subjects in school,” “I feel excited when I learn new mathematical concepts,” “I am eager to attend mathematics classes,” “I often look for additional mathematics resources (books, videos, websites) outside the classroom,” “I find mathematics lessons engaging and stimulating,” “I feel motivated to improve my performance in mathematics,” and “I believe mathematics is useful and relevant to my daily life.” Furthermore, items under mathematics performance were adapted from the work of Arthur et al. (2022). Samples of the items were: “I usually score high marks in mathematics tests and exams,” “I am confident in solving mathematics problems correctly,” “I often complete my mathematics assignments successfully without assistance,” “I understand most of the mathematics topics taught in class,” “I can apply mathematical concepts to solve real-life problems,” “My performance in mathematics has improved over the past academic term,” “I am among the top-performing students in my mathematics class,” “I rarely make careless mistakes when solving mathematics questions.” The items corresponding to their respective constructs were rated using a five-point Likert Scale ranging from 1 = strongly agree to 5 = strongly disagree (5 = SD).

Instead of creating a new questionnaire, the researchers decided to alter an existing one. This choice was motivated by the desire to enhance the validity and reliability of the instruments by utilizing previously tested and validated instruments. It was easier to compare results from other studies because the study was able to maintain consistency with earlier research by using a well-established questionnaire. Additionally, using such a tool promotes both content validity, which ensures comprehensive coverage, and evaluation of the intended concepts. According to Rogoda et al. (2022), the development and validation of measurement tools can be accelerated by utilizing established scales from previous empirical research. It minimizes the need to create numerous new components while guaranteeing a high degree of precision. Despite being adapted from earlier research, the questionnaire items were changed to meet the goals and context of the current study. These changes ensured that the instrument was tailored to capture the specific construction under study without compromising the validity and robustness of the original measures.

### 2.4. Validity and Reliability

Exploratory Factor Analysis (EFA) was performed to examine the loadings of items on different factors to ascertain the underlying structure of the variables via SPSS (v.23). It determines which indicators are most closely associated with each component. The study excluded factor loadings below the minimum threshold of 0.5 or no significant loadings (de Winter et al., 2009). Factor loadings serve as a reference for enhancing the measurement model and ensure that constructs are appropriately represented in the analysis. Table 1 presents the EFA results.

**Table 1.** Exploratory Factor Analysis (EFA)

| *Rotated Component Matrix* | | | |
|---|---|---|---|
| *Measurement Items* | *Component* | | |
| | *1* | *2* | *3* |
| AI2 | .855 | | |
| AI3 | .872 | | |
| AI4 | .866 | | |
| AI5 | .835 | | |
| INT2 | | | .814 |
| INT3 | | | .852 |
| INT4 | | | .809 |
| INT5 | | | .812 |
| MP3 | | .875 | |
| MP4 | | .871 | |
| MP5 | | .858 | |
| MP6 | | .851 | |

| *KMO and Bartlett's Test* | | |
|---|---|---|
| TVE | | 83.278 |
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | .906 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 2346.411 |
| | df | 66 |
| | Sig. | 0.000 |
| Determinant | | 1.27E-05 |

According to Table 1, 83.278% of the variance in the data may be explained by the Total Variance Explained (TVE). With a value close to 1, the Kaiser-Meyer-Olkin (KMO) length of sampling shows if the data is suitable for factor analysis. By assessing the identity of the correlation matrix, Bartlett’s Test of Sphericity identifies uncorrelated variables. The substantial p-value (0.000) and tiny determinant value 1.27E-05 suggested that the variables are not collinear, which is favorable for factor analysis, and why it is advised. These techniques are used to evaluate the data’s suitability for factor analysis in general.

Following the satisfactory results from the Exploratory Factor Analysis (EFA), a Confirmatory Factor Analysis (CFA) was performed using Amos (v. 23), applying the same dataset and the measurement items retained from the EFA. As with the EFA, each measurement item was expected to demonstrate a standardized factor loading of at least 0.5 (Osborne & Fitzpatrick, 2012). According to Table 2, the lowest factor loading observed was 0.843 for item INT5, indicating that all items surpassed the minimum threshold. This confirms that the retained items have a strong and positive influence on their respective latent constructs. Table 2 details the CFA outcomes, showing that three items for AI usage (AI2, AI3, and AI4), four items for students’ interest (INT2, INT3, INT4, and INT5), and four items for mathematics performance (MP3, MP4, MP5, and MP6). All met the recommended factor loading criterion of 0.5 or higher. Regarding model fit, the study followed established guidelines outlined in previous work (Amoako et al., 2022; Asare & Boateng, 2025; Bamfo et al., 2018; Marsh et al., 2020). The model showed acceptable fit indices: CMIN/DF fell within the ideal range of 1 to

3, PClose was greater than 0.5, the GFI needed to be above 0.8, and both the TLI and CFI needed to be above 0.9. Moreover, SRMR and RMSEA were both needed to be above 0.08. These results affirm that the model meets the standard criteria for good fit and it's appropriate for further analysis.

**Table 2.** Confirmatory Factor Analysis (CFA)

| **Model Fit Indices:** *CMIN = 63.733; DF = 41; CMIN/DF = 1.579; TLI = .984; CFI = .988; GFI = .946; RMR = .030; RMSEA = .052; PClose = .417* | *Std. Factor Loading(s)* |
|---|---|
| ***Artificial Intelligence (AI) Usage in Mathematics learning: CR = .920; CA = .919; AVE = .406*** | |
| AI2: I use AI-based tools (e.g., ChatGPT, Photomath, Wolfram Alpha) to support my understanding of mathematics concepts | .872 |
| AI3: I regularly use AI-powered platforms or apps for practicing mathematics exercises | .911 |
| AI4: Using AI in mathematics learning increases my confidence in solving math problems. | .888 |
| ***Students Interest (INT): CR = .928; CA = .927; AVE = .764*** | |
| INT2: I enjoy solving mathematical problems during my free time. | .872 |
| INT3: Mathematics is one of my favorite subjects in school. | .910 |
| INT4: I feel excited when I learn new mathematical concepts. | .870 |
| INT5: I am eager to attend mathematics classes. | .843 |
| ***Mathematics Performance (MP): CR = .933; CA = .933; AVE = .777*** | |
| MP3: I usually score high marks in mathematics tests and exams. | .861 |
| MP4: I understand most of the mathematics topics taught in class. | .891 |
| MP5: I am confident in solving mathematics problems correctly. | .916 |
| MP6: I can apply mathematical concepts to solve real-life problems. | .857 |

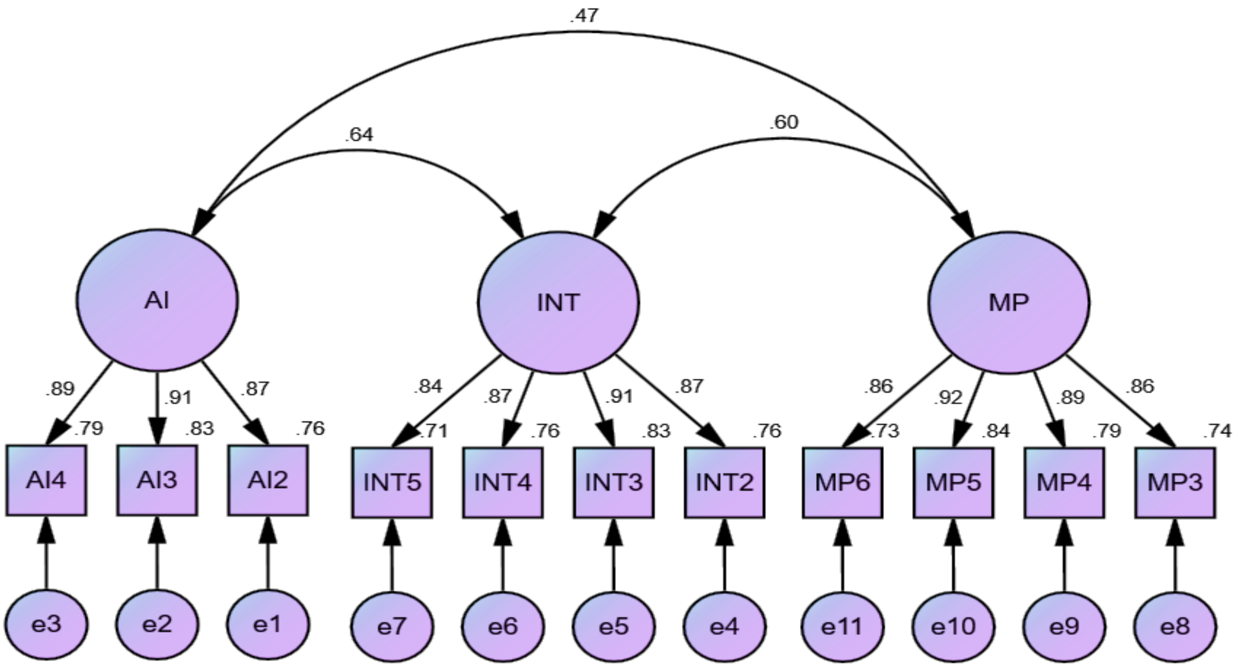


**Figure 2.** Confirmatory Factor Analysis (CFA)

Convergent validity was calculated with Average Variance Extracted (AVE) from the Confirmatory Factor Analysis (CFA) results. As presented in Table 3, every construct satisfied the minimum AVE criteria of 0.5 or more (Fornell & Larcke, 1981). By comparing the square root of each construct's AVE with the associated inter-construct correlations, discriminant validity was assessed. Discriminant validity was confirmed where smallest square root of AVE, .874, which was greater than the corresponding intercorrelation construct (.604). Furthermore, the greater observed correlation between the predictor variables was .638, which was significantly lower than the critical threshold of 0.8, indicating that multicollinearity was not an issue. Table 3 gives specifics about discriminant validity.

**Table 3.** Discriminant Validity

| Variables | CR | AVE | AI | INT | MP |
|---|---|---|---|---|---|
| AI | .920 | .406 | ***.891*** | | |
| INT | .928 | .764 | .638*** | ***.874*** | |
| MP | .933 | .777 | .468*** | .604*** | ***.882*** |

The composite reliability (CR) values, as displayed in Table 3, all exceed the recognized minimum threshold of 0.7 and range from 0.20 to 0.933. This indicates that the measurement scales are highly reliable and internally consistent. Furthermore, all of the average variance extracted (AVE) value falls above the suggested cutoff of 0.5, ranging from 0.406 to 0.776. These findings demonstrated that the constructs have strong convergent validity, meaning that each scale's items are highly correlated and accurately measure the same underlying concepts.

## 3. Results

The researchers utilized SEM to calculate the hypothesized paths, run in Amos (v. 23). The study results are presented in Table 4.

**Table 4.** Path Analysis Results

| Path Summary | Std. Estimate | S.E. | C.R. | p-value |
|---|---|---|---|---|
| Artificial Intelligence→Students Interest_INT | .636 | .071 | 9.347 | < 0.01 |
| Artificial Intelligence→Mathematics Performance_MP | -.615 | .104 | -8.961 | < 0.01 |
| Students Interest_INT→Mathematics Performance_MP | .449 | .095 | 6.843 | < 0.01 |
| AI_INT→Mathematics Performance_MP | .671 | .010 | 14.170 | < 0.01 |

**Hypothesis One (H1):** AI usage in mathematics learning significantly predicts students' mathematics performance.

According to hypothesis 1 (H1), students' mathematics performance would be greatly impacted by the application of AI in math instruction. By investigating the direct effect of integrating AI into mathematics education on mathematics performance, this hypothesis was put to the test. A p-value of less than 0.01 ($\beta = -.615$), this indicates a significant negative direct effect of AI usage on students' mathematical performance, as presented in Table 4. As a result, the study supported hypothesis 1, showing that the use of AI in math instruction is a strong indicator of students' academic success. Therefore, Hypothesis one (H1): "AI usage in mathematics learning significantly predicts students' mathematics performance" was thus supported by this study.

**Hypothesis Two (H2):** AI usage in mathematics learning significantly predicts students' interest.

The second hypothesis (H2) states that AI usage in mathematics learning significantly predicts students' interest. To test this, the researcher examined the direct effect of AI on students' interest. As shown in Table 4, AI usage in mathematics learning had a direct significantly positive effect on students' interest with a p-value of less than 0.01 ($\beta = .636$) suggested a strong positive effect of AI usage in mathematics learning significantly predicts students' interest. Thus, the study confirmed hypothesis 2, which states that "AI usage in mathematics learning significantly predicts students' interest."

**Hypothesis Three (H3):** Students' interest significantly predicts mathematics performance.

Third hypothesis states that students' interest significantly predicts mathematics performance. This was investigated by examining the direct effect of students' interest on their mathematics performance. As shown in Table 4, students' interest had a significant positive effect on mathematics performance with a p-value of less than 0.01 ($\beta = .449$). This means that students' interest had a 44.9% positive effect on their mathematics performance. Thus, the study's data confirmed and validated hypothesis 3, which states that "students' interest significantly predicts mathematics performance."

**Hypothesis Four (H4):** Students' interest moderates the nexus between AI usage in mathematics learning and students' mathematics performance.

The moderating analysis was conducted using Amos (v. 23) as shown in Table 4, its effect on mathematics performance was investigated using the interaction term, AI_INT. This table displays the result of the moderating test. The study specifically looks into whether or not students' interest affected the nexus between AI usage in mathematics learning and their performance. The findings found that the interaction term (AI_INT) had a positive and statistically significant effect on students' mathematics performance ($\beta. = 452$). Thus, there was evidence in support of Hypothesis 4, which postulated that the nexus between AI usage in mathematics learning was moderated by students' interest.

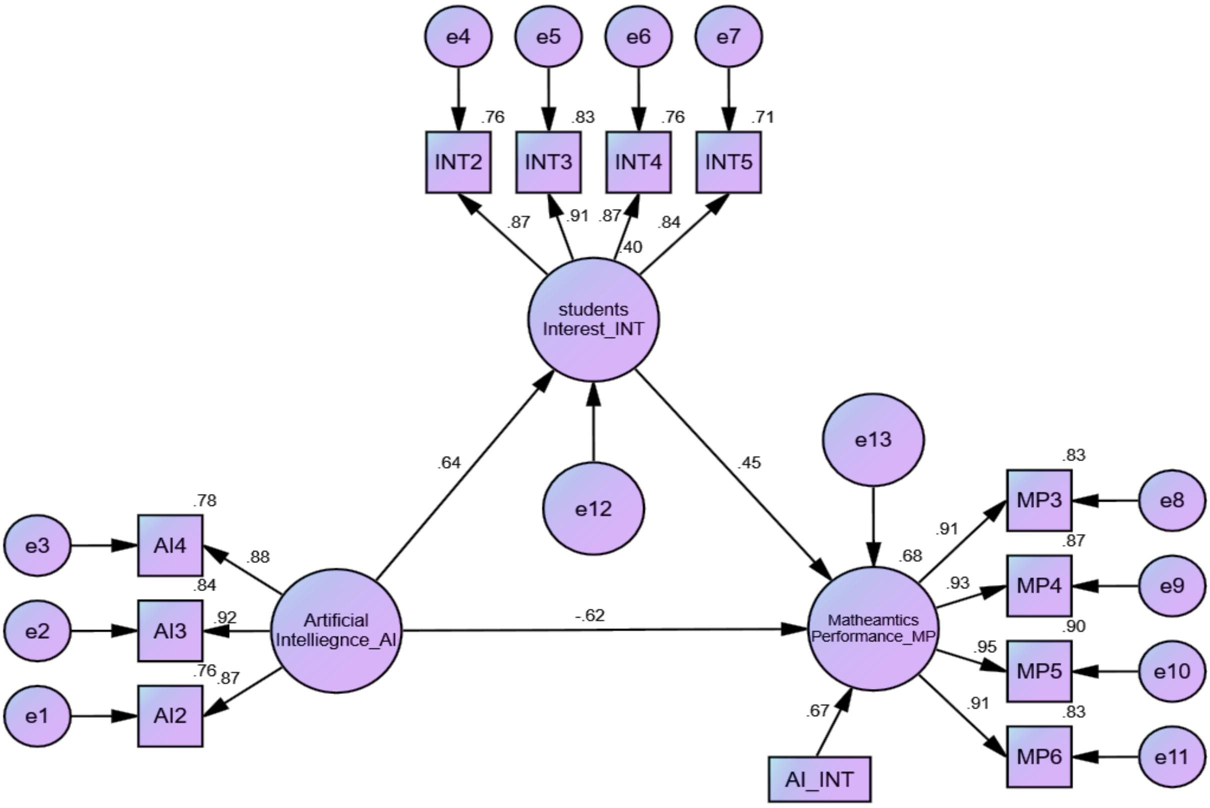


**Figure 3.** Path Summary

## 4. Discussions

### 4.1. Hypothesis One (H1): AI usage in mathematics learning significantly predicts students' mathematics performance

According to the study, incorporating artificial intelligence (AI) into math classes has a detrimental effect on students' performance, suggesting that overuse of AI could impair conceptual knowledge and problem-solving skills. This might be the result of an over-reliance on AI technologies, which could restrict opportunities for deeper learning and active cognitive engagement. Osamor et al. (2023) backed up this opinion by warning that AI tools that don't have enough instructional design and direction can end up being more detrimental than helpful. In a systematic review, Nnadi et al. (2024) noted that a large number of AI applications in education have poor contextual adaptability, which can have a detrimental effect on learning outcomes. Similarly, Cruz-Jesus et al. (2020) found that the use of AI in Chinese secondary mathematics classrooms was linked to poor academic performance. especially when AI took the place of human scaffolding and feedback. On the other hand, research like that conducted by Xu et al. (2023) emphasized that the combination of AI and successful teacher engagement increases the likelihood of the best results. These results are theoretically in line with constructivist learning principles, which place a strong emphasis on social interaction, dialogue, and active participation in the learning process. These aspects may be lessened when instruction is mediated primarily by artificial intelligence.

### 4.2. Hypothesis Two (H2): AI usage in mathematics learning significantly predicts students' interest

The second hypothesis (H2) posits that the usage of AI in mathematics learning significantly influences students' interest. The result of the current study supports this hypothesis, revealing a strong and statistically significant positive effect of AI on students' interest. This outcome aligns with prior research. For instance, Opesemowo and Ndlovu (2024) highlighted that AL-driven educational systems enhance students' engagement through adaptive and responsive feedback. In a similar vein, Alrashedi et al. (2024) found that students exposed to gamified AL learning platforms demonstrated heightened interest in academic tasks. Wei (2023) also underscored that AI technologies, by addressing individual learning needs, can foster greater intrinsic motivation. More recently, Yurt and Kasarci (2024) reported a positive correlation between the use of AI tools and increased students' interest. Additionally, Rane (2024) observed that adaptive AI systems sustain student engagement through continuous, personalized interactions. Theoretically, these results were well-explained by

Self-Determination Theory, which emphasizes the role of autonomy and competence in fostering motivation. AI application, by offering personalized learning experiences and instant feedback, empowers students to feel more autonomous and capable, thereby students' perceived usefulness and ease of use of AI tools likely contribute to their favorable attitude and increased interest in classroom activities.

### 4.3. Hypothesis Three (H3): Students' interest significantly predicts mathematics performance

The study found that students' interest significantly predicts their mathematics performance. Increased interest in mathematics may improve student engagement, motivation, perseverance in solving problems, and encourage the use of successful learning techniques, all of which lead to improved performance results. This result confirmed with earlier studies. For example, Tambunan (2018) found that a strong motivating factor that is strongly associated with higher achievement in mathematics in secondary school is student interest. In a similar vein, Wong and Wong (2019) discovered that a robust positive nexus existing between students' interest and their performance in solving problems. Additionally, Capinding (2022) highlighted that these students who show a strong interest in mathematics are more likely to develop a positive attitude toward the subject and perform better academically. In support of this, Haeger et al. (2024) concluded that increasing STEM subjects, especially mathematics, is crucial for improving academic achievement and reducing dropout rates. Moreover, Rad (2025) emphasized mathematics' pivotal role in student success by highlighting its mediating role in the nexus between academic achievement and self-efficacy. Despite the general agreement, some academics (Mejeh et al., 2024; Villagrán et al., 2024) contend that unless interest is accompanied by successful teaching strategies and the growth of self-regulated learning abilities, it may not be sufficient to ensure better performance. according to Eccles and Wigfield (2002) Expectancy-Value Theory of achievement, motivation, students' engagement, perseverance, and academic performance in subjects like mathematics are greatly influenced by the perception of task value, such as interest. The finding is consistent with this theory.

### 4.4. Hypothesis Four (H4): Students' interest moderates the nexus between AI usage in mathematics learning and students' mathematics performance.

From the result, the interaction term (AI_INT) significantly moderate the nexus between AI usage in mathematics learning and mathematics performance. This suggests that students' interest greatly increases the benefits of integrating AI into math education. Stated differently, more interested students in mathematics are likely to perform better when AI tools are used in teaching and learning. This result contributes to the body of literature by revealing a positive and significant moderating effect of students' interest in the nexus between AI usage in mathematics teaching and mathematics performance. Previous studies have looked at both the independent nexus between students' interest and mathematical performance (Arhin & Gideon, 2020; Arthur, 2022) as well as the direct effects of AI integration on mathematics teaching and performance (Egara & Mosimege, 2024b; Kumar Kanvaria & Tarance Suraj, 2024). Previous studies had not addressed this point of view, and a significant gap in the literature was filled. This suggests that when students demonstrate a higher level of interest in the subject, the positive effects of utilizing AI in mathematics learning on their mathematics performance are amplified. However, when interest is low, AI methods might not have as much of an effect on performance. this moderating factor gives educators, researchers, and policymakers a fresh perspective by highlighting how important it is to pique students' interest to minimize the benefits of AI in mathematics education.

## 5. Conclusion

This study aimed to examine the moderating effect of students' interest in the nexus between AI usage in mathematics and performance. Structural Equation Modeling (SEM) was employed to analyze the hypothesized relationships among AI usage, students' interest, and mathematics performance. The findings reveal that AI usage in mathematics learning positively and significantly predicted students' interest. Surprisingly, AI usage had a significant but negative direct effect on students' mathematics performance. Students' interest, however, positively and significantly influenced mathematics performance. Most notably, the interaction term (AI_INT) significantly predicted mathematics performance, confirming the moderating effect of students' interest.

## 6. Limitations and Suggestions for Further Studies

One major setback of the study lies in the cross-sectional research design, which captures data at a single point in time. While statistical associations were identified, this design cannot conclusively determine whether AI usage directly affects performance or if other latent factors may contribute to the observed outcomes. A longitudinal approach would have provided a better framework for tracking changes over time and establishing causal relationships. Furthermore, the study relied exclusively on self-reported data through questionnaires, which may be influenced by social desirability bias or misinterpretation of items by respondents. In addition, including qualitative methods such as interviews or classroom observations would provide deeper insight into students' actual interactions with AI tools and how these shape their learning experiences and motivation. Further research should also consider expanding the sample frame and geographical scope by including multiple regions, a large number of schools, and varied school types (urban, rural, public, and private). This broader scope would enhance the external validity of findings and allow for regional comparisons. Moreover, demographic variables such as gender, prior academic achievement, access to technology, and socio-economic background could be examined as potential moderators to uncover nuanced relationships in AI adoption and learning outcomes. In addition, further studies may explore different dimensions or types of AI tools used in mathematics instruction, such as adaptive learning platforms, chatbots, or AI-powered problem solvers, and examine their specific impacts on cognitive and affective learning outcomes.

**Funding:** The study received no funding support.

**Ethics Declaration:** All participants into the current study were given a consent form and asked to opt in whether they wanted to participate. No additional ethical approval was ¬required to conduct the study.

**Data Availability:** The corresponding author has access to the data supporting the findings of this study upon request.

**Conflict of Interest:** The author affirms that there were no conflicts of interest associated with the study.

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