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## **AI-Enhanced Pedagogical Practices and Mathematical Language Proficiency in STEM Education**

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### **ABSTRACT**

*This study investigates the effectiveness of AI-enhanced pedagogical practices on improving the mathematical language proficiency of senior high school students in Ghana. The current research adopted a quantitative cross-sectional design, where the structural equation modeling approach was used on a sample size of 360 participants, to investigate digital literacy and learning engagement as partial mediators. As expected, results from this study show that AEPP, DL, and LE are statistically significant positive predictors of students' MLP. Additionally, digital literacy and learning engagement play a mediating role in the relationship between the AI-supported instruction and the proficiency outcomes. The findings highlighted the importance of integrating adaptive AI tools to enhance the digital literacy of the students as well as their learning engagement to improve the mathematical communication and reasoning of the senior high school students.*

**Keywords:** AI-enhanced pedagogical practices (AEPP), digital literacy, learning engagement, mathematical language proficiency, STEM education, structural equation modeling (SEM)

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## INTRODUCTION

The world of secondary education is in a state of rapid transition due to the increasing role of digital technologies in the delivery of instruction, assessment, and the learning experience of students (Arthur et al., 2025; Davor et al., 2026). In this context of transition and change, artificial intelligence (AI) has emerged as a major enabler of personalized learning, feedback (Liu et al., 2025), intelligent tutoring (Liu et al., 2025), and the presentation of content (Boadu & Boateng, 2024). In the context of mathematics education, there is an emerging role of AI in supporting the delivery of feedback, step-by-step learning, and the interactive presentation of mathematical expressions and statements (Novita & Herman, 2021). This has the potential to improve mathematical communication and reasoning, which are integral to mathematical language development.

According to Prediger et al. (2018), mathematical language proficiency may be defined as the ability to interpret, apply, and explain mathematical concepts using words and symbols, employing logical reasoning with appropriate structure. It is at the core of mathematics, especially in the secondary school levels; students continue to face problems in reading mathematical texts, explaining solution steps, and interpreting abstract terms (Eslit, 2024; Essien, 2010; Prediger et al., 2018). Several AI systems contribute towards an increase in mathematical language proficiency by considering Natural Language Processing, Symbolic Reasoning, and Explanatory Learning (Kristandl, 2025). AI teaching relies on digital literacy (Busnawir et al., 2023), the capacity to access, interpret, and employ information displayed through digital tools responsibly and efficiently. Learning engagement, including behavioral, affective, and cognitive dimensions, also influences the impact of AI teaching on learning outcomes (Sung et al., 2016). Engaged learners

will more likely focus on the lesson being taught, participate in mathematical activities, and use their minds to understand the workings of mathematical representations as well as explanations. Such activities lead to better mathematical language proficiency (Essien, 2010; Prediger et al., 2018).

Although there is growth in AI adoption, STEM education is at the center of implementing these innovative advances. However, studies on the adoption of AI in institutions of higher learning are imbalanced, favouring Europe, North America, and East Asia (Busnawir et al., 2023; Leon et al., 2025; Kotsis, 2025; Yadav, 2025; Yani et al., 2025). There remains a notable research gap in sub-Saharan Africa, as the region's overall scholarly contribution constitutes only a small proportion of the existing body of literature. Moreover, this limited body of literature is imperfectly subject to studies from South Africa and a few other countries, notably Ghana (Awofala et al., 2024; Chigona & Chigona, 2010; Li et al., 2022). The existing literature on AI-related topics and their educational applications, often framed around readiness factors such as ICT infrastructure (Chigona & Chigona, 2010), largely concentrates on AI's effects on specific mathematical outcomes, including vocabulary development, symbolic understanding, and mathematical expression (Essien, 2010). However, this body of research infrequently addresses the broader and potentially transformative influence of AI on mathematical learning processes, instructional practices, or the positioning of AI within the overall learning ecosystem.

Despite increasing integration of AI tools in mathematics classrooms, limited empirical research has modeled how AI-enhanced pedagogical practices translate into improved mathematical language proficiency, particularly within Global South contexts. This study addresses that gap by examining the direct and indirect relationships between AI-enhanced pedagogical practices, digital literacy, learning engagement, and students' mathematical language proficiency among senior high school students in Ghana. Using structural equation modeling, the study tests a mediation framework to clarify the mechanisms through which AI-supported instruction predicts mathematical communication skills. The findings contribute theoretically to AI-in-education research and practically to STEM readiness and postsecondary preparation discussions.

Although the study focuses on senior high school students, its implications extend to higher education contexts. Mathematical language proficiency developed at the secondary level forms a foundational skill for postsecondary STEM participation, teacher education programs, and entry into global STEM pipelines. Strengthening digital literacy and engagement through AI-supported instruction at the pre-university stage contributes directly to tertiary readiness and long-term STEM capacity development.

## LITERATURE REVIEW

This section synthesizes existing research across four thematic strands: AI-enhanced pedagogical practices, digital literacy, learning engagement, and mathematical language proficiency, before developing the study's mediation hypotheses.

### **AI-Enhanced Pedagogical Practices and Mathematical Language Proficiency**

The growing integration of artificial intelligence (AI) in secondary education has transformed instructional practices by enabling adaptive feedback, dynamic visualizations, and personalized learning pathways (Liu et al., 2025). In mathematics education, AI-enhanced pedagogical practices (AEPP) allow students to interact with intelligent tutoring systems, symbolic manipulation tools, automated reasoning environments, and real-time feedback platforms (Eslit, 2024; Liu et al., 2025). These systems help students read and build meaning from symbolic expressions, understand mathematical terminology, and clearly lay out their reasoning—the core aspects of mathematical language proficiency (Prediger et al., 2018). Studies indicate that math AI systems enhance conceptual understanding among learners and enhance the clarity and accuracy of their mathematical explanations and expressions using appropriate mathematical terminology and notation (Boateng et al., 2026; Leon et al., 2025). Capabilities that offer step-by-step solutions or identify errors in solutions while providing scaffolded hints to learners to improve their statements and enhance mathematical precision in their expressions.

From this evidence, learners who participate in AEPP are most likely to develop effective mathematical and linguistic abilities. In this study, AI-enhanced pedagogical practices (AEPP) refer specifically to instructional activities supported by adaptive or intelligent systems capable of automated feedback, personalization, and data-driven scaffolding. These differ from general digital tools (e.g., static PowerPoint slides or non-adaptive educational videos) in that AI systems dynamically respond to student input. In the Ghanaian secondary school context, AEPP included the use of AI-supported platforms that provide step-by-step solution analysis, automated error detection, personalized practice tasks, and adaptive feedback mechanisms integrated into mathematics lessons under teacher supervision. For example, during algebra instruction, students interacted with AI-enabled platforms that analyzed their symbolic steps in real time and generated corrective hints when procedural or conceptual errors were detected. Teachers facilitated these sessions by guiding students in interpreting AI-generated explanations and connecting them to formal mathematical language. Therefore, the study hypothesizes that:

*H1. AI-enhanced pedagogical practices positively predict students' mathematical language proficiency.*

## **Digital Literacy and Mathematical Language Proficiency**

Digital literacy refers to the ability to locate, appraise, and use digital technologies effectively to attain learning goals (Kristandl, 2025; Novita & Herman, 2021). For mathematics, digitally literate students navigate through AI-powered systems, understand automated feedback, work with interactive problem-solving platforms, and make use of math visualization tools (İlhan et al., 2025; Li et al., 2022). Such a skill helps learners contextualize mathematical notations, interpret explanations, and convey their reasoning accurately in mathematical language. The attribute would help learners leverage digital math resources for improving mathematical fluency and mathematical vocabulary, which would improve overall language proficiency in mathematics (Busnawir et al., 2023; Li et al., 2022). This implies that digital literacy developed by learners would help them decode digital math resources effectively for improvements in math knowledge and overall academic achievements. Accordingly:

*H2. Digital literacy positively predicts students' mathematical language proficiency.*

## **Learning Engagement and Mathematical Language Proficiency**

Engagement with learning refers to students' investment of themselves, either behaviourally, cognitively, or emotionally, in their schoolwork (Antipuesto & Tan, 2023). When students engage with their mathematics, they find themselves wanting to be involved in mathematical communication, describing their ideas related to solutions, and persevering with word or symbolic problems. Their cognitive engagement enhances the way they process vocabulary and logical elements in mathematics; it forms their behavior through frequent practice and the dissemination of mathematical ideas, and affects their emotions through the consistent motivation to be inspired while solving challenging mathematical reasoning problems. It is supported by Appleton et al. (2008) and Fung et al. (2018). As it has been proven that AI learning environments are effective in enhancing the capabilities of explaining, justifying, and symbolically solving math tasks, Antipuesto & Tan (2023) and Lijie et al. (2020) formulated the following hypothesis:

*H3. Learning engagement has a positive prediction on mathematical language proficiency.*

Moreover, there have been existing links among the above concepts explored by earlier studies. AI-facilitated teaching approaches expose scholars to digital

interactivity tools that require digital literacy, while a scholar's interaction with AI toolsets depends on familiarity with the digital environment (Davor et al., 2026; Kristandl, 2025; Leon et al., 2025). Digital literacy fosters deeper interaction since it empowers scholars to avail themselves of resources and respond to the feedback provided in AI-facilitated educational activities (Yani et al., 2025). Also, AI systems enhance engagement due to the instruction being more personalized and activities being better adapted to individual students' learning profiles. This leads to more time on task, more persistence, and more cognitive effort-engagement, eventually leading to higher cognitive effort, according to Li et al. (2022) and Martin & Dowson (2009). From this premise, the following hypotheses are developed:

*H4. Digital literacy mediates the relationship between AI-enhanced pedagogical practices and mathematical language proficiency. H5. Learning engagement mediates the relationship between AI-enhanced pedagogical practices and mathematical language proficiency.*

Digital literacy and learning engagement are the factors that define the mechanisms by which AI-enhanced teaching practices are converted into improved mathematical language skills. While digital literacy helps learners know how to interact with digital tools, learning engagement helps measure their engagement with mathematical learning.

## **Theoretical and Conceptual Framework**

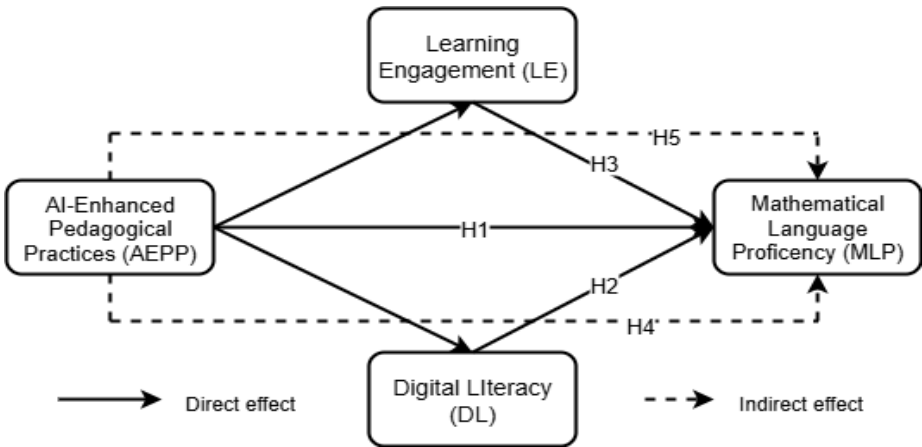
This study anchors its conceptual backbone on two much-reputed theories: Bandura's Social Cognitive Theory (Bandura, 1986) and the Engagement Theory of Martin and Dowson (2009). Social Cognitive Theory explains how what a learner believes, the processes of thinking, and the entire structure around one, impact what gets learned (Bandura, 1986). In math classrooms that integrate digital and AI tools, a student's confidence with these tools serves to colour how they explain ideas, respond to feedback, and describe their reasoning (Leon et al., 2025). Such a lens will explain why digital competence matters as a key link between AI-supported instruction and students' mathematical language skills.

Engagement theory suggests that authentic and deep learning occurs during periods of student engagement (Martin & Dowson, 2009). Students in AI-enhanced settings engage with digital explanations, automated feedback, symbolic representations, and problem-solving tools. Their thinking, actions, and feelings play a central role in how effectively students absorb math vocabulary, read and understand notations, and communicate mathematical ideas. Informed by these theories, this study considers AI-enhanced teaching methods as an exogenous variable in which students' exposure to AI-powered math instruction, automated guidance, and adaptive learning resources is reflected. Digital literacy and learning

engagement were mediators. Digital literacy captures the ability of students to navigate AI tools, while learning engagement reflects the extent to which they engage in math learning activities. Mathematical language proficiency is the ability to comprehend and produce mathematical communication with proper vocabulary, notation, and reasoning patterns.

The conceptual framework (Figure 1) assumes that AEPP influences MLP both directly and indirectly. The indirect path goes through DL and LE consecutively: AI-enhanced practices enhance digital literacy; the higher the level of digital literacy, the stronger the engagement; and the stronger the engagement, the higher the level of mathematical language proficiency. This model merges technological, cognitive, and motivational aspects of explaining how AI-supported instruction facilitates students in developing mathematical language.

**Figure 1**  
*Conceptual Framework (Source: Authors' Creation, 2025)*



## RESEARCH METHOD

### Research Design

This research employed a quantitative, cross-sectional design to investigate the relationships among AI-enhanced teaching techniques, digital literacy, student engagement, and mathematical language abilities among senior high school students. A mediation model was appropriate to apply in this research since it allows us to estimate and model direct and indirect effects simultaneously using only one structural equation model framework (Stern et al., 2024). However, because a cross-sectional study has been conducted, we cannot interpret the results

causally, as the order of events and causal relationships over time are not discernible, and mutual effects may occur.

**Population, Sample Size, Sampling Method**

The study population was made up of senior students in four public secondary schools in the Ashanti Region, amounting to a total population of 3,800 students. The students were proportionally sampled based on their streams. Even if it is estimated, based on (Krejcie & Morgan (1970) table, that a minimum of 350 participants is necessary for the given population size. It should be noted that, within SEM, it is necessary to have a power rationale related to the model. This can be accomplished via a power analysis, and in this case, it was assumed that the smallest non-centrally indexed path coefficient value is 0.15, with  $\alpha$  set at 0.05 and the power level at 0.80. If there are five latent variables within the models’ Estimated Mean, the recommended size is approximately 350-400 participants (Wolf et al., 2013), and this is met with the final sample of 360 participants.

**Table 1**  
*Students’ Background Information*

Background	Frequency (N)	Percentage (%)
Age	360	100.0
13-15	130	36.1
16-17	125	34.7
18-Above	105	29.2
Gender	360	100.0
Male	187	51.9
Female	173	48.1
Course of study	360	100.0
Home economics	65	18.1
Visual Art	55	15.3
Business	62	17.2
Technical	60	17.7
General Science	70	19.4
General Art	48	13.3

The population statistics of the study participants are presented in Table 1. They were broken down to 51.9% Males and 48.1% Females, and together they comprised the total sample. Out of their age, 130(36.1 %) were between 13-15 years old, 125(34.7 %) were between 16- 17 and 105(29.2%) were 18 years and above. In terms of the subjects offered by the students, 18.1% offered Home

Economics, 15.3% offered Visual Art, 17.2% offered Business, 17.7% offered Technical, 19.4% offered General Science, and 13.3% offered General Art.

Data collection occurred across multiple classes, and potential clustering effects were addressed in several ways. Firstly, the school coordinators ensured that the teaching approaches, assessment of the students, and curriculum followed in the selected classes remained uniform. Secondly, no class tended to influence the data collection more than the other classes, hence ensuring that there was no bias within the classes. Finally, robust standard error sandwich estimation was utilized in carrying out the SEM analysis to ensure that the likeness within the classes did not have any effect on the parameter estimation. Data collection was carried out between the 8th of August and the 10th of September 2025, and the data was collected using paper questionnaires. Indeed, 360 questionnaires were received, showing a very high response rate.

## **Research Instrument**

All data was collected through a structured questionnaire to be administered consistently and allow for comparable data analysis. The structured questionnaire was divided into five components that correlated with this study's constructs: AI-enhanced pedagogic practices (AEPP), digital literacy (DL), learning engagement (LE), and mathematical language proficiency (MLP), as well as demographic variables.

It should be noted that mathematical language proficiency was assessed through students' self-reported perceptions of their abilities. While self-perceptions provide insight into learners' communicative confidence and awareness, such measures may not fully capture actual performance. Future research may incorporate performance-based assessments, discourse analysis of written explanations, or rubric-based evaluations of mathematical reasoning to strengthen construct validity. All questions in this questionnaire were culled from existing constructs that were adjusted slightly.

AEPP items probed students' interaction with AI-enhanced instruction components such as adaptive feedback, guided explanations, and interactive math visuals (Eslit, 2024; Liu et al., 2025). DL was measured through items that tested students' understanding of operating digital environments, critically assessing online sources, and appropriately employing AI-supportive tools (Kristandl, 2025). LE was a measure that tested cognitive, behavioral, and emotional aspects related to math learning (Antipuesto & Tan, 2023; Lijie et al., 2020). MLP tested students' understanding regarding representing mathematical thoughts in suitable vocabulary, notation, or representation (Essien, 2010; Prediger et al., 2018).

Items were measured on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). Content validation was done with the input of three experts in mathematics education and measurement. The cognitive interviews were carried

out among eight older students at the high school level. The pilot study among the target population, consisting of 40 students, showed good reliability, with Cronbach's alpha above 0.70 for the measurement of each construct. Very minor adjustments were made before the final study.

### **Common Method Bias (CMB)**

As all data were collected through questionnaire responses, various procedures were adopted to alleviate common method bias (Podsakoff et al., 2012). Anonymity and confidentiality of responses were assured, with positively and negatively phrased items equally distributed across various scales of a Likert scale. Items probing AI-supported teaching approaches and digital literacy skills were distinguished from items testing learning involvement and mathematical language skills. Harman's single-factor test using exploratory factor analysis revealed that the first factor accounted for 29.6% of the variance, which was below the 50% level of concern. The confirmatory factor analysis with the latent variable approach resulted in only very small differences between the measurement model and the standard models. The differences were  $\Delta CFI = 0.008$  and  $\Delta RMSEA = 0.003$ ; that is, differences between the methods were negligible.

### **Data Analysis Methods**

The analytical procedure relied on SPSS 27 and AMOS 23. Reliability checks were carried out to ensure internal consistency, while exploratory factor analyses were conducted to conceptualize the underlying factor structure. Next, this measurement model was tested by CFA for confirmation of construct reliability, convergent validity by Average Variance Extracted (AVE), and discriminant validity (Hair et al., 2012). Once the properties of the measurement model were validated, the direct influence of AI-enhanced teaching practices on the structural model of mathematical language proficiency was checked, as well as digital literacy and learning engagement as potential mediators. The indirect effects were estimated using bootstrapping with bias-corrected confidence intervals to obtain robust mediation estimates (Hayes & Preacher, 2014). These steps together offer valid and sound measurement and structural properties, hence a clear interpretation of the proposed relationships.

## **FINDINGS**

### **Reliability and Content Validity Analysis**

The content validity was established to ensure that items are relevant to capturing focal concepts related to Artificial Intelligence in education, education

and literacy, engagement, as well as math and language proficiency in STEM education. The content was reviewed by three senior researchers and two lecturers specializing in English and Linguistics, concerned with Academic Language and Discourse Analysis. The items were fine-tuned by making some minute changes to the wording for clarity, and the constructs were retained intact. For this purpose, consistency within the study was established by using SPSS. The choice of the primary method for calculating the reliability of the constructs was based on McDonald's Omega ( $\omega$ ), which is most suitable for models with latent variables. From Table 2 above, all the constructs had values above the required threshold of 0.70.

**Table 2**  
*The Reliability Analysis*

Variables	Number of items	McDonald's Omega ( $\omega$ )
AI-enhanced pedagogical Practices (AEPP)	5	.956
Digital Literacy (DL)	5	.947
Learning Engagement (LE)	4	.938
Mathematical Language Proficiency (MLP)	4	.948

**Exploratory Factor Analysis (EFA)**

The Exploratory Factor Analysis (EFA) was conducted to clean the hidden patterns in the data pertaining to items of Artificial Intelligence-Expanded Pedagogical Practices (AEPP), Digital Literacy (DL), Learning Engagement (LE), and Mathematical Language Proficiency (MLP). Conducting the EFA here is a good fit, as there is no requirement to conform to any structural model hypothesis yet. This is consistent with best practices in early tests for construct complexity and item-type assignment for multi-construct survey research (Hair et al., 2012). Diagnostic tests for appropriateness of the data are positive here. The Kaiser-Meyer-Olkin (KMO) measure was found to be 0.928, which is excellent for sample adequacy representation, and Bartlett's Test of Sphericity was significant:  $\chi^2 (153) = 6636.65, p < .001$ , which detects excellent factorability here. The determinant of the correlation matrix, further checking for multicollinearity issues, is  $6.541E-9$ , with no indication of critical situations here.

Employing principal component extraction, the resulting five components accounted for 84.716% of the variance. Decisions to retain or not to retain components were guided by eigenvalues above one. The first solution contained highly dominant loading properties that corresponded to the study's four constructs, along with a supplementary component that corresponded to item cluster

properties. Varimax rotation with enhanced interpretability enabled the identification of dominant loading properties. Items with and lacking dominant loading properties were eliminated using item-by-item removal of components, with subsequent re-examination after deleting each item. This approach eliminated a total of six items, and the resulting stable and meaningful factor structure implies excellent initial construct validity and a solid foundation for the forthcoming confirmatory test.

**Table 3**  
*Exploratory Factor Analysis (EFA) and KMO and Bartlett's Test*

Rotated Component Matrix				
Measurement Items	Component			
	1	2	3	4
AEPP1	.874			
AEPP3	.858			
AEPP4	.853			
AEPP5	.883			
AEPP6	.874			
LE1				.880
LE2				.892
LE4				.874
LE5				.888
DL1			.713	
DL3			.899	
DL5			.886	
DL6			.899	
DL7			.889	
MLP1		.863		
MLP4		.870		
MLP5		.867		
MLP6		.883		
KMO and Bartlett's Test				
Total Variance Explained				84.71
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.				.928
Bartlett's Test of Sphericity		Approx. Chi-Square		6636.65
		df		153
		Sig		.000
Determinant				6.541E-9

## Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) run in Amos (v. 23) was performed after EFA analysis. The measurement items loaded in their rightful constructs were used to perform CFA analysis. After performing the CFA, we noticed that all the measurement items' loadings were above the minimum threshold of 0.5, as Hair et al. (2012) advised. Hair et al. (2019)'s model fit criteria were considered to determine whether the measurement items used fit the model. Confirmatory Factor Analysis (CFA) is reported in Table 4.

### Model Fitness Measures

The chi-square test calculates how well the sample covariance matrix corresponds to that of the model. The smaller the chi-square statistic, the better. However, chi-square statistics are sensitive to sample size; sometimes, although the model Chi-square statistic may not be significant, the model fit may not be too good either. Also, the chi-square value is dependent on the degrees of freedom, which in turn depend upon the observed variables and parameters in the model. The CMIN/DF ratio should lie in the range of 1 to 3 units. Since the CMIN/DF ratio is greater than 1.000 as indicated in Table 4, the result indicates an excellent fit of the model. Further, the Comparative Fit Index (CFI) judges the model's fit compared to a target (baseline) model. A CFI index greater than 0.95 is regarded as excellent; in this case, with a reading of .991, the fit is excellent. A Standardized Root Mean Square Residual (SRMR) of .017, with a reading below 0.08, denotes negligible residuals with a good fit. Also, with an RMSEA index of .036, the perfect fit is achieved since the index is below 0.06. Finally, the p-value of PClose = .796 lends support to the good fit of the model since it's not significantly different from the perfect fit (Figure 2).

**Table 4**

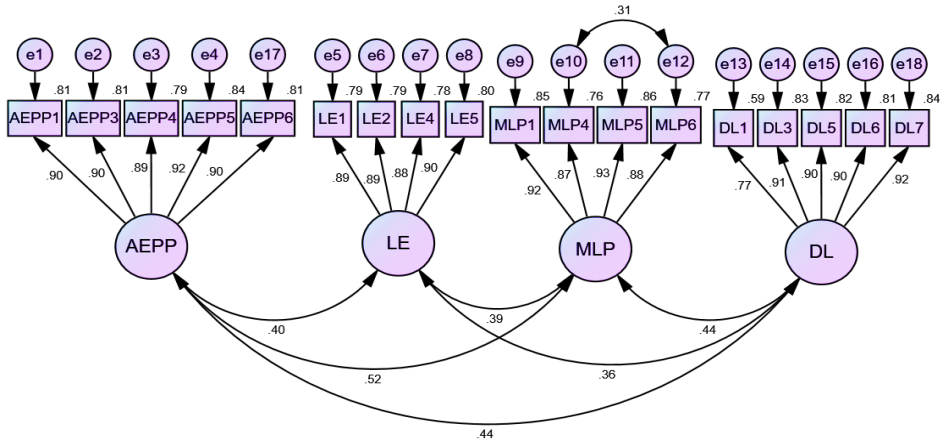
*The model Fit Indices*

Measures	Estimates	Standard	Interpretation	Source
CMIN	225.614	The smaller the better	-----	---
DF	156	The smaller the better	-----	---
CMIN/DF	1.446	Between 1 and 3	Excellent	Xia and Yang (2019)
TLI	.988	> 0.95	Excellent	Asare et al. (2025)
CFI	.991	> 0.95	Excellent	Marsh et al. (2020)

NFI	.970	> 0.90	Excellent	Davor et al. (2026)
GFI	.941	> 0.90	Good fit	Hair et al. (2012)
RMSEA	.036	< 0.08	Excellent	Xia and Yang (2019)
PClose	.796	> 0.05	Excellent	Gyimah et al. (2026)
SRMR	.017	< 0.08	Good fit	Arthur et al. (2025)

**Figure 1**

*Confirmatory Factor Analysis (Source: Authors' Creation, 2025)*



**Table 5**

*Construct Validity of Measurement Items*

Items	Loadings
AI-enhanced pedagogical Practices (AEPP); CR = .957; AVE = .813	
<i>AEPP1: The AI system gives me immediate feedback on my mathematical work</i>	.899
<i>AEPP3: The AI explains where I went wrong in a problem in math</i>	.901
<i>AEPP4: The AI offers extra practice on topics I am struggling with</i>	.891
<i>AEPP5: The AI suggests tasks that are tailored to my strengths and weaknesses</i>	.915
<i>AEPP6: The AI creates a personalized learning path for me</i>	.901
Digital Literacy (DL): CR = .946; AVE = .778	
<i>DL1: I can evaluate the credibility of digital resources (e.g., websites, apps)</i>	.771
<i>DL3: I use digital tools to organize and manage my academic materials</i>	.909

<i>DL5: I revise or edit my work using software or online tools (e.g., math apps, word processors)</i>	.903
<i>DL6: I can troubleshoot basic technical problems on my computer or device</i>	.903
<i>DL7: I use the internet ethically to solve mathematical language problems</i>	.916
Learning Engagement (LE): CR = .938; AVE = .791	
<i>LE1: I actively participate in mathematics activities when using AI.</i>	.890
<i>LE2: I try to apply new mathematical ideas that the AI shows me to solve problems.</i>	.891
<i>LE4: I feel excited when working on AI-based mathematics tasks.</i>	.882
<i>LE5: I put a lot of effort into understanding AI-generated explanations.</i>	.895
Mathematical Language Proficiency (MLP); CR = .944; AVE = .808	
<i>MLP1: I understand the precise meaning of mathematical vocabulary (e.g., 'term', 'coefficient', 'function')</i>	.919
<i>MLP4: I can accurately interpret mathematical symbols and notation used in problems</i>	.870
<i>MLP5: I use correct mathematical terms when writing or speaking about math</i>	.927
<i>MLP6: I can translate between symbolic expressions and verbal descriptions (words) of mathematics</i>	.877

## Discriminant Validity Analysis

Discriminant validity analysis was calculated by contrasting the square root of AVEs against their related correlation coefficients. For discriminant validity to be considered excellent, the least value for the square root of AVE is expected to surpass the highest related correlation coefficient, as recommended by related studies (Asare et al., 2025; Boadu & Boateng, 2024; Davor et al., 2025). From Table 6, we noticed that the lowest value for the square root of AVE, that is 0.882 (for Learning Engagement), was greater than the highest value of the related correlation coefficient, that is 0.523 (AEPP and MLP). This confirms that the constructs are statistically distinct from one another.

**Table 6**

*Discriminant Validity*

Variables	CR	AVE	AEPP	LE	DL	MLP
AEPP	0.956	0.813	.902			
LE	0.946	0.778	.402***	.882		
DL	0.938	0.791	.443***	.367***	.889	

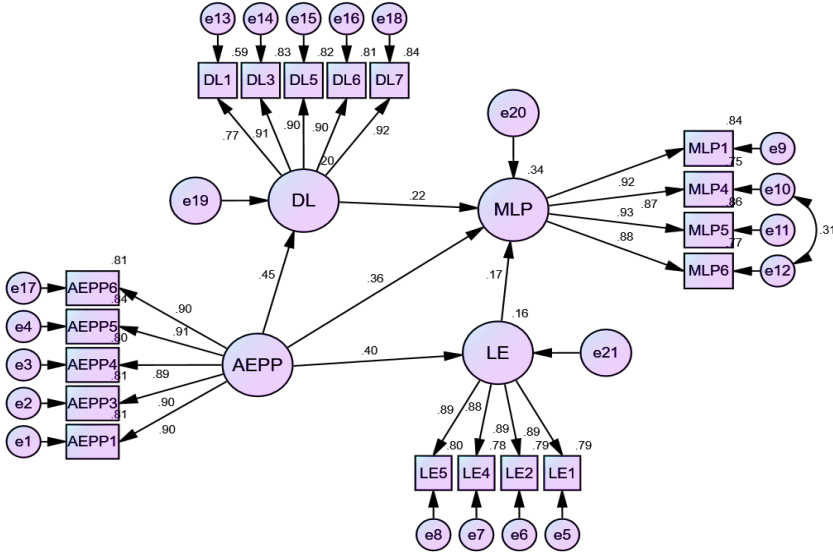
MLP	0.944	0.808	.523***	.395***	.446***	.899
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Note. \*\*\*Denotes p-value less than 1% significance level;  $\sqrt{\text{AVE}}$  values are bold and italic.

### Path Results

A structural equation model (SEM) was performed via Amos (ver. 23) to respond to the hypothesized paths. Moreover, a bootstrap of 5,000 samples and a 95% corrected confidence interval was used to estimate the indirect effect. Table 7 presents the study’s results, which are also illustrated in Figure 3.

**Figure 3**  
*Path Analysis (Source: Authors’ Creation, 2025)*



**Table 7**  
*Path Summary*

Direct Effect	Std. Est.	S.E.	C.R.	p-value
AEPP→ MLP	.361	.059	6.119	***
DL→ MLP	.224	.070	3.200	***
LE→ MLP	.167	.054	3.093	.001
Indirect Effect	Std. Est.	L. B	U. B	p-value
AEPP→DL→ <b>MLP</b>	.170	0.103	.259	.000
AEPP→LE→ <b>MLP</b>	.168	0.096	.227	.000

*H1. AI-enhanced pedagogical practices positively predict students' mathematical language proficiency.*

The analysis presented in Table 7 indicates that AI-enhanced pedagogical practices had a positive and statistically significant direct effect on mathematical language proficiency ( $\beta = 0.361$ ). The results show a SE of 0.059, a CR value of 6.119, and a p-value of less than 0.001. Based on what we established, hypothesis H1 remains valid. Students exposed to AI-enhanced classroom instruction tended to report stronger mathematical vocabulary use, improved symbol interpretation, and clearer mathematical communication. The magnitude of this effect suggests a meaningful association between AI-enhanced pedagogy and students' mathematical language proficiency.

*H2. Digital literacy positively predicts students' mathematical language proficiency.*

From Table 7, it is evident that digital literacy positively and significantly affects mathematical language proficiency since the beta value is 0.224. Since the standard error is 0.070 with a critical ratio of 3.200 and a significance level less than 0.001, it indicates that this result tests the hypothesis H2. It is therefore safe to say that those who are digitally literate can easily understand the math explanations offered by AI or express math concepts symbolically. This clearly signifies that digital literacy is paramount for students to benefit from math learning supported by AI.

*H3. Learning engagement has a positive prediction on mathematical language proficiency.*

The data in Table 7 above also reveal that the positive relationship between learning engagement and mathematical language proficiency is statistically significant, with a  $\beta$  value of 0.167. The standard error for the path is 0.054, the critical ratio is 3.093, and the p-value for the result is 0.001. Therefore, it can be concluded that H3 is true, as the more the students behaviourally, cognitively, and emotionally engage with AI-assisted math learning processes, the more they develop proficiency in their mathematical language.

*H4. Digital literacy mediates the relationship between AI-enhanced pedagogical practices and mathematical language proficiency.*

From the results of the mediation model, there is a significant indirect relationship from AI-enriched teaching practices to mathematics language proficiency as encouraged by digital literacy ( $\beta = 0.170$ , 95% CI [0.103, 0.259], p

< 0.001). As the confidence interval is non-zero, the result is significant, thereby indicating that being mathematics language proficient is crucial, as it is affected by AI-related teaching practices that make students more proficient in digital literacy. The magnitude of the indirect is an indicator that digital literacy is a crucial component that bridges AI teaching practices to math language proficiency.

*H5. Learning engagement mediates the relationship between AI-enhanced pedagogical practices and mathematical language proficiency.*

As shown in Table 7 above, there is a significant mediation effect of learning engagement ( $\beta = 0.168$ , 95%CI [0.096, 0.227],  $p < 0.001$ ). Therefore, H5 is supported. The results indicate that the use of AI-based teaching methods to improve learning engagement leads to improved mathematical language proficiency indirectly. It appears that when mathematical language proficiency is enhanced using AI-based teaching methods, a higher level of engagement leads to greater cognitive processes being undertaken to express mathematical concepts, resulting in enhanced mathematical language proficiency.

## DISCUSSION

*H1. AI-enhanced pedagogical practices positively predict students' mathematical language proficiency.*

This research indicates the predictive capacity of AI-enhanced teaching concerning students' understanding and expression of mathematical concepts. When students engage with mathematical concepts through AI-enhanced teaching practices, their understanding and expression of mathematical concepts improve. This is in line with the messages academics have been sending: learning environments with the assistance of AI help learners reason mathematically and articulate it better, which is the assistance with the interpretation of symbols and the formation of expressions (Eslit, 2024; Li et al., 2022; Liu et al., 2025). It is also consistent with the principles established in Social Cognitive Theory, which states that the capabilities and learning abilities we have are enabled and disabled based on the learning facilities derived (Bandura, 1986). This study contributes evidence to the existing literature within the Ghanaian context, which suggests the efficiency of AI-assisted learning practices in enhancing the linguistic capabilities related to math in the Ghanaian learning framework.

*H2. Digital literacy positively predicts students' mathematical language proficiency.*

The results further reveal that digital literacy is a strong predictor of mathematical language proficiency. That is, students who can better interact with digital systems, evaluate digital information critically, and apply AI tools proficiently are better equipped to understand symbolic representations and express mathematical ideas. It confirms existing research that has suggested digital literacy enhances students' capacity to interactively participate with tech-intensive learning environments to produce desired academic results (Davor et al., 2026; Kristandl, 2025; Novita & Herman, 2021; Yani et al., 2025). In the context of AI-based mathematics learning environments, digital literacy is thereby identified as an influential building block skill that empowers students to fully immerse themselves in the instructive potential of AI-provided feedback and mathematical explanations. The current research, therefore, contributes to the existing body of knowledge, indicating that digital literacy is more than an academic skill that matters greatly to define mathematical language proficiency within an AI-enriched secondary education environment.

### *H3. Learning engagement has a positive prediction on mathematical language proficiency.*

Consistent with expectations, engagement with learning emerges as a very important, positive predictor of mathematical language proficiency. This means that students who are engaged mentally, behaviourally, and emotionally with AI-enhanced mathematical learning are more likely to invest efforts in making sense of mathematical language, symbolic expressions, and their justifications. Consistent with previous studies, this finding underlines the central role of engagement in profound mathematical learning and mathematical communication (Awofala et al., 2024; Antipuesto & Tan, 2023; Lijie et al., 2020). Interestingly, in AI-enhanced environmental conditions, engagement might even be of greater significance because, in this case, students need to engage with digital mathematical explanations and mathematical problems actively, which might be very important.

This implies that they do not simply receive information passively but need to act and work with this information actively. Collectively, these findings suggest that AI-enhanced pedagogical practices do not operate in isolation but function within a broader cognitive-motivational system. Digital literacy enables effective interaction with adaptive technologies, while learning engagement transforms technological exposure into meaningful communicative competence. This layered mechanism advances understanding of how AI-supported instruction contributes to the development of mathematical language proficiency beyond mere procedural achievement.

*H4: Digital literacy mediates the relationship between AI-enhanced pedagogical practices and mathematical language proficiency*

A key contribution of this study lies in demonstrating that digital literacy mediates the relationship between AI-enhanced pedagogical practices and mathematical language proficiency. This implies that the more tech-based learning is applied, the better the mathematical language skills, indirectly, with the ability to promote mathematical skills more by developing the digital literacy of the student, which is crucial if the AI-based learning approach is to be applied. This is connected to the Social Cognitive Theory, whereby learning is influenced by the interaction between the environment and personal characteristics (Bandura, 1986). The research clearly indicates that the more the digital literacy skills are enhanced by the AI-based learning approach, the better the ability to read the results, explain graphics, or explain mathematical concepts.

*H5. Learning engagement mediates the relationship between AI-enhanced pedagogical practices and mathematical language proficiency.*

Also, the study reveals that the mediating variable, learning engagement, explains how AI-augmented teaching increases language proficiency in math. It appears that AI-augmented teaching practices produce a level of improvement and enhancement in the development of mathematical language proficiency by raising the level of engagement with activities, lessons, and mathematical problems. As defined by Engagement Theory, more involved and participative individuals attain a far more significant level of outcome and growth throughout the process (Martin & Dowson, 2009). There seems to exist the power of AI-based systems and processes to grab the attention of the students and hence enhance their ability to articulate mathematical concepts effectively.

Importantly, the study advances the field by modeling technological, cognitive, and motivational constructs simultaneously within a unified structural framework. Rather than treating AI integration as a direct instructional intervention, the findings emphasize the importance of intermediary competencies that translate technological affordances into linguistic and communicative mathematical outcomes. This integrative perspective provides a more nuanced understanding of AI's educational value.

While the findings are promising, AI integration in Ghanaian senior high schools operates within broader structural constraints. Variations in internet connectivity, disparities in ICT infrastructure across schools, and differences in teacher preparedness for AI-supported instruction may influence the strength of observed relationships. These contextual realities should be considered when interpreting the findings and may function as moderating variables in future research. Incorporating school-level contextual indicators in multilevel analyses

would provide a more comprehensive understanding of AI implementation in developing-country settings.

## CONCLUSIONS

This study examined how AI-enhanced pedagogical practices, digital literacy, and learning engagement jointly predict students' mathematical language proficiency, both directly and indirectly. The findings indicate that digital literacy and learning engagement function as key intermediary mechanisms through which AI-enhanced pedagogical practices influence students' mathematical language proficiency. The findings suggest the data to be accurate as per the mediator pattern, as AI-supported, positive learning conditions enhance skill levels in mathematical languages, and this is further strengthened by digital literacy and active learning.

Although structural equation modeling enabled examination of direct and indirect predictive relationships, the cross-sectional design limits causal inference. The relationships identified should therefore be interpreted as associations rather than definitive causal effects. Future studies employing longitudinal, experimental, or quasi-experimental designs would allow stronger conclusions regarding temporal ordering and causal mechanisms. Such approaches would further clarify how AI-enhanced pedagogical practices influence digital literacy, engagement, and mathematical language development over time.

Practically, the scope of implications is evident in the realm of teaching. Adaptive feedback, visual interpretation, and problem-solving guidance provided through AI features can enhance students' Mathematical Vocabulary and Symbol Fluency. Basically, effectiveness can be amplified through increased internet literacy and more engaging AI-assisted learning activities. This research, based on the Ghanaian senior high school context, provides evidence-informed guidance for integrating AI tools into mathematics classrooms to support students' mathematical language proficiency.

Beyond the Ghanaian context, the findings offer insight for other developing and emerging economies seeking to integrate AI into secondary mathematics education. As global education systems invest in digital transformation, understanding the mediating roles of digital literacy and engagement becomes essential for designing scalable and equitable AI-supported STEM initiatives. The study, therefore, contributes to broader international discussions on sustainable AI integration and global STEM development.

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