European Institute of Knowledge & Innovation

Journal of Effective Teaching Methods (JETM)
ISSN: 2755-399X

Research Article

Innovative Teaching Methods Supported by Artificial Intelligence and Students' Mathematical Problem-Solving: The Mediating Role of Student Engagement

Francis Ohene Boateng [1], **Isaac Davor** [1,*], **and Cobbinah Appiah Manu** [1]

[1] Akenten Appiah Menka University of Skills Training and Entrepreneurial Development, Ghana
* Correspondence: davorisaac70@gmail.com

https://doi.org/10.59652/7tsj5730

Abstract: The study investigated how innovative, AI-supported teaching methods relate to the mathematics problem-solving ability of Senior High School (SHS) students in Ghana. This study examined how teachers' AI-supported pedagogical practices relate to students' problem-solving ability, the extent to which student engagement serves as an explanatory variable for that relationship, and whether students' mathematical self-belief (MSB) moderates that relationship. A quantitative cross-sectional design was employed; participants comprised 385 students from both public and private SHS. Data were collected from a structured questionnaire and analysed with structural equation modeling (SEM). The study results show that AI-supported pedagogical practices of teachers significantly enhance both student engagements in mathematics and problem-solving ability. Student engagement partially mediates the relationship between instructional practices and problem-solving ability, underscoring engagement as a critical mechanism through which effective teaching methods shape learning outcomes. MSB has a meaningful direct influence on problem-solving ability, but does not significantly modify the relationship between pedagogical practices and problem-solving ability. The study emphasises the added value of integrating AI-enhanced teaching methods with effective pedagogical principles to enhance instructional effectiveness and students' higher-order math skills in secondary education.

Keywords: effective teaching methods; AI-supported pedagogy; student engagement; mathematical self-belief (MSB); problem-solving ability

Received: July 28, 2026
Accepted: February 18, 2026
Published: February 27, 2026

1. Introduction

Effective teaching methods are important domain of modern educational discourse, especially in the teaching of mathematics, as it requires students to think critically, abstractly, and creatively in problem-solving processes (Asare et al., 2025; Cheung & Slavin, 2013; Jeong & González-Gómez, 2022). However, it is not sufficient that students merely memorize mathematical procedures and concepts, but it is essential that students are in a position to apply the concepts learned in different ways, to think logically, and to change their methods as needed in unfamiliar circumstances. In this context, the significance of the use of effective methods in the study of mathematics has been highlighted in the theories of the study of mathematics in recent times.

In the modern society, the use of artificial intelligence in the support of the learning process has been viewed as an alternative, but not in replacement of the teacher, but in aid of the teaching process, the learning process, and the engagement of the learners (Kumar et al., 2023). In the teaching of mathematics, for instance, the various teaching methods involving the use of artificial intelligence have been viewed as opportunities in the improvement of the dynamic, engaging, and effective teaching and learning processes in mathematics (Boadu & Boateng, 2024). In this regard, the potential contribution of the new forms of teaching methods involving the application of artificial intelligence in the improvement of the teaching process in mathematics has been seen with renewed interest.

From the theoretical point of view, the application of artificial intelligence in the teaching process in mathematics has been seen in consonance with the contemporary theories of learning, which emphasize the engagement in the learning process, the reasoning process, and the feedback in the learning process (Engelbrecht & Borba, 2024; Timotheou et al., 2023). In this regard, the educational value of the application of artificial intelligence in the learning process has been viewed in the way teachers apply the technology in the learning process (Tondeur et al., 2017; Yin et al., 2024), rather than in the technology applied in the learning process. From a social and practical perspective, the significance of the improvement of the teaching effectiveness in mathematics cannot be overemphasized, particularly because the ability to solve problems in mathematics represents the core purpose of the mathematics learning process, which reflects the quality of the mathematics learning process.

Effective problem-solving involves exploration, reflection, and reasoning, and these can be facilitated by the application of well-designed instruction using artificial intelligence, as discussed by Asare et al. (2025), Asiedu Menlah and Boateng (2025).

Despite the increased use of digital and AI technologies in the mathematics learning process, no significant improvement has been observed in the improvement of students' mathematical problem-solving ability. Research has indicated that no improvement can be observed in the improvement of students' mathematical problem-solving ability using technology, but rather it depends on the extent to which the teacher can engage the students in the mathematics learning process. In addition, students' engagement and their personal beliefs about their mathematical ability can also affect the improvement of their mathematical problem-solving ability using innovative instruction. Although it has been recognized that students' engagement is one of the critical factors influencing the relationship between instruction and students' learning outcomes (Fredricks et al., 2019; Fung et al., 2018), its role in the application of AI instruction in mathematics has not been clearly established. Similarly, although mathematical self-belief (MSB) has been linked to persistence and performance, its influence within AI-enhanced instructional contexts remains insufficiently understood.

Although research on digital and AI-supported instruction has increased, several gaps remain. First, many studies focus primarily on technological features rather than on the instructional processes through which AI is used to support learning. Second, relatively few studies examine how innovative, AI-supported teaching methods influence mathematics problem-solving outcomes through psychological and behavioural mechanisms such as student engagement. Third, the moderating role of MSB in AI-supported mathematics learning has received limited empirical attention, particularly at the secondary school level.

These gaps are especially evident in Sub-Saharan African contexts, where instructional conditions, teacher preparation, and access to digital resources vary considerably. There is therefore a need for empirical research that examines how AI-supported teaching methods, student engagement, and MSB interact to influence students' mathematical problem-solving ability in secondary education.

The purpose of this study is to investigate the effect of innovative teaching methods supported by artificial intelligence on senior high school (SHS) students' mathematical problem-solving ability in Ghana. Specifically, the study examines the direct effect of AI-supported teaching methods on problem-solving ability, the mediating role of student engagement in this relationship, and the moderating role of MSB.

The study is guided by the following research questions:

1. What is the effect of AI-supported teaching methods on students' mathematical problem-solving ability?
2. To what extent does student engagement mediate the relationship between AI-supported teaching methods and mathematical problem-solving ability?
3. Does MSB moderate the relationship between AI-supported teaching methods and mathematical problem-solving ability?

Based on these questions, the following hypotheses are proposed:

H1: AI-supported teaching methods have a significant positive effect on students' mathematical problem-solving ability.

H2: Teacher AI-supported pedagogical practices increase student engagement in learning mathematics

H3: Student engagement has a positive effect on students' mathematical problem-solving ability.

H4: Student engagement mediates the relationship between AI-supported teaching methods and students' mathematical problem-solving ability.

H5: MSB moderates the relationship between AI-supported teaching methods and students' mathematical problem-solving ability.

2. Literature Review

2.1. Conceptual and Theoretical Framework

This study is anchored in Bandura's Social Cognitive Theory (Bandura, 1986) and the multidimensional model of student engagement proposed by Fredricks et al. (2004). Social Cognitive Theory explains learning as a product of reciprocal interactions among personal factors, observable behaviours, and environmental influences. In the context of mathematics education, AI-supported pedagogical practices constitute an environmental influence that can shape how students approach mathematical tasks, regulate their learning strategies, and persist in problem-solving activities. A central construct within this theory is self-efficacy, defined as learners' beliefs about their capability to perform specific tasks successfully. In mathematics learning, self-belief has been shown to influence students' effort, strategy use, and persistence when faced with challenging problems.

The engagement framework of Fredricks et al. (2004) complements this perspective by conceptualizing engagement as a multidimensional construct comprising behavioural, emotional, and cognitive components. In AI-enhanced instructional contexts, pedagogical approaches that promote interactivity, feedback, and relevance are expected to activate these dimensions of engagement, thereby supporting deeper mathematical reasoning. Figure 1 depict the conceptual framework for the study. From figure 1, teacher AI-supported pedagogical practices serve the independent variables, students' engagement as the mediator, MSB as a moderator and problem-solving ability as the dependent variable. These frameworks for the study provide a theoretical basis for examining how AI-supported pedagogical practices influence students' mathematical problem-solving ability directly and indirectly through engagement, while considering the moderating role of MSB.

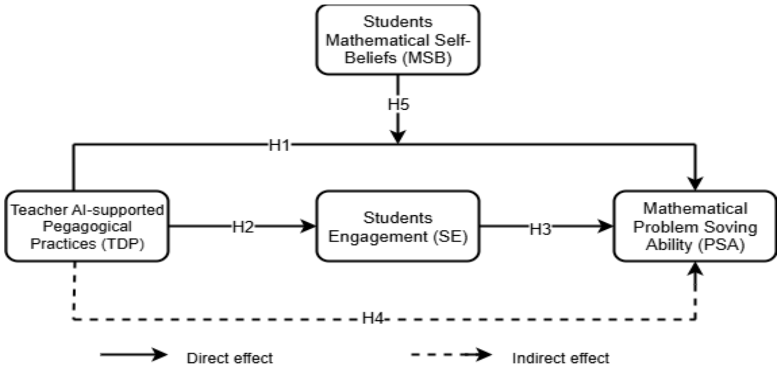

Figure 1. Conceptual framework.
Source: Authors' Creation, 2025)

2.2. Review of Key Variables

AI-supported pedagogical practices refer to the intentional integration of artificial intelligence, powered instructional tools, such as adaptive learning systems, intelligent tutoring platforms, learning analytics, and automated feedback mechanisms, into mathematics teaching to enhance learning processes and outcomes (Asiedu Menlah & Boateng, 2025; Kumar et al., 2023). Unlike conventional digital tools, AI-based systems respond dynamically to learners' inputs, offer individualized feedback, and support reasoning during problem-solving activities. These features position AI-supported pedagogy as a potentially powerful instructional approach for fostering conceptual understanding and strategic problem-solving in mathematics (Barfi et al., 2021; Bergdahl et al., 2020). Student engagement is defined as the degree of behavioural, emotional, and cognitive investment learners make in academic activities (Fredricks et al., 2004; 2019). In mathematics classrooms, engagement is particularly critical because problem-solving requires sustained attention, emotional regulation, and cognitive effort. MSB, conceptualized as students' confidence in their ability to successfully perform mathematical tasks, has also been identified as an important learner characteristic that influences responsiveness to instructional practices and persistence in problem-solving (Usher & Pajares, 2007).

2.3. Empirical Review

Empirical evidence indicates that AI-supported pedagogical practices have the potential to enhance students' mathematical problem-solving ability, particularly when such practices are embedded within carefully designed instructional activities. For instance, Lai and Hwang (2016), in their study of technology-supported mathematics classrooms, reported significant improvements in students' performance on non-routine problem-solving tasks. Their findings suggest that adaptive feedback and interactive task structures can support students' strategic thinking and transfer of mathematical knowledge. Similarly, Barfi et al. (2021) found that AI-supported instructional approaches improved students' visualization skills and conceptual understanding, which are critical components of effective mathematical problem-solving. Bergdahl et al. (2020) further demonstrated that AI-enhanced learning environments can support reasoning processes by providing dynamic representations and immediate feedback that guide students' thinking during problem-solving activities.

Despite these positive findings, the literature also reveals mixed and context-dependent outcomes. Some studies report only modest effects of AI-supported instruction on students' mathematical problem-solving performance. Asare and Boateng (2025), for example, observed limited gains in problem-solving ability when digital and AI-supported tools were implemented without deliberate instructional scaffolding. Their findings highlight that technology-supported instruction may fail to produce meaningful learning gains if teachers do not intentionally structure tasks to promote reasoning and reflection. Similarly, Bergdahl et al. (2020) and Li et al. (2022) emphasized that the presence of advanced technological features does not automatically lead to deeper understanding. Instead, they argue that pedagogical design plays a decisive role in determining whether AI-supported tools facilitate exploration, guided reasoning, and conceptual development. Collectively, these studies suggest that the effectiveness of AI-supported teaching is contingent upon how teachers integrate technology into pedagogical practices rather than on the technological tools themselves.

In addition to learning outcomes, a growing body of research has examined the relationship between AI-supported instruction and student engagement. Engagement is widely recognized as a key process variable through which instructional practices influence learning. For example, Garrison et al. (2010) demonstrated that technology-enhanced learning environments can increase learner presence and engagement by promoting interaction and sustained participation. In the context of mathematics education, Barfi et al. (2021) reported heightened levels of student engagement when AI-supported tools were used to facilitate interactive problem-solving activities and collaborative learning. Bergdahl et al. (2020) similarly found that AI-enhanced instructional approaches increased students' attention and involvement, particularly when tasks required active manipulation of mathematical representations.

However, not all studies report sustained engagement benefits. Some empirical findings suggest that engagement gains diminish when AI technologies are introduced as add-ons to traditional instructional designs rather than as integral components of pedagogical reform. This observation aligns with Bandura's (1986) Social Cognitive Theory, which posits that environmental factors influence learning outcomes through their interaction with behavioral and cognitive processes. When AI tools are not accompanied by changes in instructional strategies, their capacity to foster meaningful engagement may be limited.

Further evidence consistently links student engagement to mathematical problem-solving performance. Lai and Hwang (2016) found that students who demonstrated higher levels of cognitive and emotional engagement achieved superior outcomes in technology-integrated mathematics courses. Similarly, Asare et al. (2025) reported that engagement was a strong predictor of students' ability to solve unfamiliar and complex mathematical problems, underscoring its role in facilitating persistence and strategic thinking. Cheung and Slavin (2013) and Fung et al. (2018) likewise noted that instructional effectiveness in mathematics is closely tied to students' active involvement in learning tasks. These empirical studies suggest that AI-supported pedagogical practices influence mathematical problem-solving outcomes both directly and indirectly. While AI-enhanced instruction can support reasoning and conceptual understanding, its effectiveness is shaped by pedagogical design and students' engagement in learning activities. Engagement, therefore, appears to function as a critical mechanism linking instructional practices to problem-solving performance, providing a strong empirical basis for examining its mediating role in AI-supported mathematics instruction.

Based on Social Cognitive Theory and empirical evidence indicating that AI-supported pedagogy enhances reasoning and feedback during problem-solving, it is expected that such practices will positively influence students' mathematical problem-solving ability. Therefore, the following hypothesis is proposed:

H1: Teacher AI-supported pedagogical practices positively influence students' problem-solving capacity (PSA).

Given that engagement depends on how instructional technologies are pedagogically enacted, AI-supported pedagogical practices are expected to enhance students' behavioural, emotional, and cognitive engagement in mathematics learning:

H2: Teachers' AI-supported pedagogical practices have a significant positive effect on student engagement in mathematics learning.

As prior studies consistently link engagement with improved mathematical performance, particularly in problem-solving contexts, it is hypothesized that:

H3: Student engagement has a significant positive effect on students' mathematical problem-solving ability.

Although previous studies have examined digital pedagogy and engagement separately, few have empirically tested engagement as a mediating mechanism in AI-supported mathematics instruction. Drawing on theory and evidence, this study proposes that:

H4: Student engagement mediates the relationship between teachers' AI-supported pedagogical practices and students' mathematical problem-solving ability.

Finally, research on MSB suggests that students' confidence in their mathematical ability shapes their responsiveness to instructional innovations and persistence in learning (Usher & Pajares, 2007). However, its moderating role in AI-supported mathematics instruction remains underexplored. Accordingly, it is hypothesized that:

H5: MSB moderates the relationship between teachers' AI-supported pedagogical practices and students' mathematical problem-solving ability.

Therefore, the literature indicates that AI-supported pedagogical practices can enhance students' mathematical problem-solving ability, particularly when integrated into thoughtful instructional design. However, findings remain inconsistent, highlighting the need to examine mediating and moderating mechanisms. Student engagement emerges as a key pathway through which instructional practices influence learning outcomes, while MSB may condition the strength of these relationships. By integrating these perspectives, the present study addresses gaps in the literature and provides a theoretically grounded examination of AI-supported pedagogy in mathematics education.

3. Materials and Methods

3.1. Research Design

The study adopted a quantitative approach with a cross-sectional survey design. According to Kline (2023), a cross-sectional survey enables researchers to examine the relationships among constructs within a population at a single point in time. The data for the present study were collected from SHS students through a structured questionnaire designed to measure teachers' digital pedagogical practices, student engagement, mathematics self-belief, and problem-solving ability.

3.2. Population, Sample Size, and Sampling Techniques

The population of interest was SHS level students offering mathematics in some selected schools in the Ashanti Region of Ghana. In the study, the research focused on schools that integrate digital or technology-enhanced pedagogical methods into mathematics instruction. A multistage sampling technique was employed. Schools were initially stratified by ownership type (public or private). Subsequently, proportional random sampling was used to select students within each stratum. A sample size of at least 400 students was considered adequate for a population exceeding 10,000, as determined from Krejcie and Morgan (1970) sample size determination table. The questionnaires were administered in person to ensure legible responses and participation among students with limited internet connectivity. Data were collected over six weeks, from May to June 2025. Out of the 400 distributed questionnaires, 385 questionnaires were correctly filled and returned, a 95.5% response rate

3.3. Instrument Development

This study adopted a structured, self-administered questionnaire divided into five sections. Section A elicited demographic information: gender, school type (public versus private), and class level, to be used as control variables. Section B investigated AI-assisted teaching methods for teachers via modified, validated items from Lai and Hwang (2016) on aspects of design, interactivity, and feedback for secondary mathematics teaching. Section C focused on student engagement from behavioural, emotional, and cognitive perspectives, drawing on the model of Fredricks et al. (2004). Section D employed a set of self-efficacy questions for mathematics self-efficacy, adapted from Asare et al. (2025). Section E was based on the Asare et al. (2025) model for assessing students' problem-solving from a cognitive perspective. All constructs were rated on a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). The instrument was pilot-tested with 30 students to assess face validity and contextual relevance; subsequently, some items were slightly reworded prior to administration.

3.4. Common Method Bias (CMB)

Since all data for predictors, mediators, moderators, and outcomes came from self-report questionnaires, both procedures and post-hoc statistical techniques were followed to monitor and reduce common method bias effects (CMB), also called method bias effects (Podsakoff et al., 2012). Methods to reduce method bias at the design phase included ensuring confidentiality and anonymity to reduce CMB effects. A questionnaire was also used to reduce acquiescence bias by employing a combination of scales and varying item order, including both positive and negative items. In addition, psychological and temporal separation was implemented: measures of teachers' AI-supported pedagogical practices and MSB were collected in an initial session, while measures of student engagement and mathematical problem-solving ability were administered after a short time interval. Predictor and criterion variables were also placed in separate sections of the instrument and interspersed with unrelated items to reduce item-context effects. Harman's Single Factor Test indicated that only 31.8% of the total variance was accounted for by the first factor, which is below 50%. Furthermore, results from a confirmatory factor analysis using a common latent method factor model showed little change in factor loadings (0.06) and only modest improvements in model fit (0.008 in CFI and 0.004 in RMSEA). These results clearly indicate that common method variance does not appear to affect the study results.

4. Results

4.1. Validity and Reliability

Content and construct validity were assessed for the questionnaire. To conduct content validity checks on the questionnaire, advice from three senior lecturers in mathematics education or psychology was sought. They reviewed the items for clarity, relevance, and alignment with the study's purpose. Construct validity was established through confirmatory factor analysis, in which AVE values were assessed. Convergent validity was achieved as all AVE values were greater than the cut-off value of 0.50 (Hair et al., 2019).

4.2. Exploratory Factor Analysis (EFA)

An exploratory factor analysis (EFA) was conducted to examine the underlying factor structure and reduce measurement redundancy by prioritizing intercorrelated constructs. Hence, the factorability of the correlation matrix was confirmed, as the KMO index was 0.829, well above the threshold of 0.50. The Bartlett Test of Sphericity was also highly significant, χ^2 (105) = 2694.753, indicating sufficient inter-item correlations. Also noteworthy is that the item requirements specified a significance level of 0.001, indicating the absence of multicollinearity among the items. Four factors were obtained from principal component extraction and rotation, which accounted for only 70.49% of the cumulative variance. An iterative item refinement was also employed to ensure clarity of the construct of interest. Items were excluded if their factor loadings were less than 0.50 on more than one factor, as recommended in standard methodologies (Hair et al., 2012; 2019). Consequently, nine items were excluded due to weak discriminant properties. The final factor solution retained five indicators for teachers' AI-supported pedagogical practices, three for MSB, three for student engagement, and four for mathematical problem-solving ability, satisfying minimum indicator requirements for subsequent SEM analyses.

4.3. Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) run in Amos (v. 23) was performed after EFA analysis. The measurement items were used to conduct CFA. After performing the CFA, we observed that all loadings exceeded the minimum threshold of 0.5, as recommended by Hair et al. (2012). Hair et al. (2019) model-fit criteria were used to assess whether the measurement items fit the model. CFA is reported in table 1. Error terms e12-e14 and e13-e15 were correlated to improve model fit, consistent with modification indices and theoretical justification (see figure 2).

Table 1. CFA and KMO and Bartlett's test analysis.

Construct	Items	EFA loadings	CFA loadings	CA	CR	AVE
Teachers' AI-supported pedagogical practices				.846	.848	.530
	TDP1	.803	.734			
	TDP3	.784	.778			
	TDP4	.781	.731			
	TDP6	.791	.799			
	TDP7	.636	.579			
Students Engagement				.849	.849	.653
	SE4	.845	.801			
	SE5	.832	.796			
	SE7	.849	.826			
MSBs				.864	.865	.681
	MSB3	.883	.836			
	MSB5	.885	.854			
	MSB6	.848	.784			
Problem-Solving Ability				.851	.831	.552
	PSA2	.826	.707			
	PSA3	.790	.755			
	PSA4	.825	.729			
	PSA5	.817	.778			
KMO and Bartlett's test						
TVE				70.490%		
Kaiser-Mayer-Olkin measure of sampling adequacy					.829	
Bartlett's test of sphericity		Approx. Chi-square			2694.753	
		df			105	
		sig			.000	
Determinant					.001	

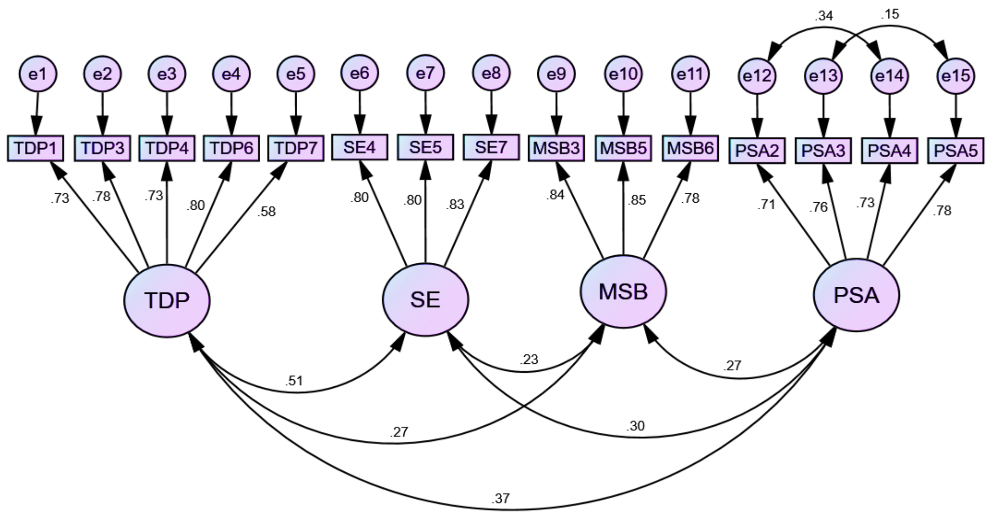

Figure 2. Confirmatory factor analysis.
Source: Authors' creation, 2026.

4.4. Discriminant Validity Analysis

Discriminant validity was assessed by comparing the square roots of the AVEs with their respective correlation coefficients. For discriminant validity to be considered good, the least value for the square root of AVE is expected to surpass the highest related correlation coefficient, as recommended by related studies (Arthur et al., 2022; Boateng et al., 2024; Davor et al., 2025).

Table 2. Discriminant validity.

Variables	TDP	SMB	SE	PSA
TDP	.728			
SMB	.271***	.808		
SE	.508***	.229***	.825	
PSA	.366***	.269***	.300***	.743

Note: ***Denotes p-value less than 1% significance level; √AVEs values are in bold and italic.

From table 2, we observed that the lowest value for the square root of AVE, namely 0.728, was greater than the highest value of the related correlation coefficient, 0.508. With this, discriminant validity is achieved. Moreover, as shown in table 3, all construct measurement items had AVE values exceeding the minimum threshold of 0.5, indicating that the measurement items for each construct are dependable and reliable, as recommended by Hair et al. (2012).

Table 3. Convergence validity.

Measurement items	Loadings
Teacher AI-supported pedagogical practices (TDP)	
TDP1: My mathematics teacher uses digital tools to make lessons more interactive.	.734
TDP3: My maths teacher uses digital platforms to help students learn on their own.	.778
TDP4: My teacher integrates technology to clearly explain mathematical concepts.	.731
TDP6: I often participate in online learning activities designed by my maths teacher	.799
TDP7: My mathematics teacher uses digital tools to assess our work and give feedback	.579
Students' Engagement (SE)	
SE4: I enjoy using digital platforms to learn mathematics.	.801
SE5: I pay full attention during mathematics lessons that involve digital activities.	.796
SE7: I put effort into completing mathematics tasks assigned online or digitally.	.826
Mathematical Self Beliefs (MSB)	
MSB3: I believe I can do well in mathematics if I put in enough effort	.836
MSB5: I feel confident when faced with challenging mathematics problems.	.854
MSB6: I feel capable of achieving high grades in mathematics.	.784
Problem-Solving Ability (PSA)	
PSA2: I can apply different strategies to solve mathematics problems.	.707
PSA3: I can identify the main ideas in a mathematics problem before solving it.	.755
PSA4: I can connect what I learn in class to solve real-life mathematics problems.	.729
PSA5: I can explain the steps I take when solving a mathematics problem.	.778

4.5. Model Fit Measures

The chi-square test assesses the discrepancy between the model's predicted and actual covariance matrices; the lower the value, the better. It is sensitive to sample size, which may indicate a significant result even when a model fits well. The degrees of freedom are determined by the number of observed variables and model parameters. The CMIN/DF ratio assesses the general fit of the model. An excellent ratio should fall between 1 and 3. A CMIN/DF of 1.515 indicates a good fit, as shown in table 4. The Comparative Fit Index (CFI) estimates model fit relative to a baseline model; a score greater than 0.95 is considered excellent. The score of 0.984 indicates an excellent fit. The Standardized Root Mean Square Residual (SRMR) score is 0.032, which is below 0.08, indicating that the residuals are extremely small and the fit is excellent. The RMSEA index value of 0.037 indicates excellent fit; values below 0.080 are considered excellent. The PClose p-value of 0.960 indicates that the model is an excellent fit, as the RMSEA would not differ statistically from an excellent fit (see figure 2). Moreover, model fit was assessed using the Goodness-of-Fit Index (GFI) and the Normed Fit Index (NFI). The GFI, which shows the percentage of variance and covariance in the sample data explained by the model, was 0.947 (table 5). A value above 0.80 signifies a strong fit. The NFI, which assesses the proposed model against a null model, was 0.955 (see Table 4). A value greater than 0.80 indicates an acceptable fit, whereas a value greater than 0.90 indicates a good fit. Generally, these indices indicate that the model is consistent with the observed data.

Table 4. The model fit indices.

Measures	Estimates	Standard	Interpretation	Source
CMIN	124.198	The smaller the better		-------
DF	82	The smaller the better		-------
CMIN/DF	1.515	Between 1 and 3	Excellent	Hair et al. (2012)
TLI	.979	> 0.95	Excellent	Hair et al. (2019)
CFI	.984	> 0.95	Excellent	Marsh et al. (2020)
NFI	.955	> 0.90	Excellent	Arthur et al. (2022)
GF1	.947	> 0.80	Good fit	Xia and Yang (2019)
RMSEA	.037	< 0.08	Excellent	Hu and Bentler (1999)
PClose	.960	> 0.05	Excellent	Asare et al. (2025)
SRMR	.032	< 0.08	Good fit	Marsh et al. (2020)

4.6. Statistical Modeling and Estimation Methodology

The hypothesized relationships among the study variables were estimated using covariance-based structural equation modeling (CB-SEM) in Amos (v.27). CB-SEM is appropriate for testing theoretical models involving both observed and unobserved constructs, as it provides reliable estimates of complex relationships. Model estimation employed bias-corrected (BC) percentile bootstrapping with 5,000 bootstrap samples at the 95% confidence level. The results are presented in table 5.

Table 5. Path summary.

Direct Effect	Std. Est.	S.E.	C.R.	p-value
TDP→ PSA	.289	.079	3.778	***
TDP→ SE	.508	.067	8.149	***
SE→ PSA	.154	.069	2.114	.035
Indirect Effect	**Std. Est.**	**L. B**	**U. B**	**p-value**
TDP→SE→PSA	.253	0.069	.252	.003

H1: Teacher AI-supported pedagogical practices positively influence students' PSA.

H1 posited that teacher AI-supported pedagogical practices (TDP) would have a significant effect on students' PSA. The rationale for this assumption is that when digital pedagogical tools are used effectively by teachers, students develop stronger analytical and critical-thinking skills, which in turn enhance their PSA. As shown in table 6, TDP had a significant positive effect on PSA ($\beta = 0.289$, C.R. = 3.778, $p < 0.001$). This finding confirms hypothesis H1, which posits that the use of AI-supported pedagogical practices substantially contributes to increasing students' problem-solving ability.

H2: Teacher AI-supported pedagogical practices increase student engagement in learning mathematics

H2 hypothesized that TDP would positively influence student engagement (SE). That is, instructors who embrace digital content and pedagogically interactive methods will feel encouraged to design more participatory learning environments that provoke learners' engagement and interest. The results presented in Table 6 indicate a significant and positive correlation between TDP and SE ($\beta = 0.508$, C.R. = 8.149, $p < 0.001$). Thus, H2 is confirmed, since pedagogic innovation in electronic format significantly enhances student engagement.

H3: Student engagement positively affects students' problem-solving ability.

Hypothesis three assumed that student engagement would play a significant role in promoting problem-solving ability. This is supported by the conclusion that greater student engagement is associated with greater mental effort, thereby enhancing their capacity to analyze and solve intellectual problems. The SEM analysis supports that SE has a significant, positive effect on PSA ($\beta = 0.154$, C.R. = 2.114, $p = 0.035$).

H4: Student engagement mediates the relationship between teachers' AI-supported pedagogical practices and students' problem-solving ability.

H4 examined the indirect effect of TDP on PSA through student engagement. The mediation result, derived using BC bootstrapping, indicates that the indirect effect is significant ($\beta = 0.253$, 95% CI [0.069, 0.252], $p = 0.003$). This result suggests an improvement in the student's problem-solving ability through AI-supported teaching, an effect achieved both directly and by enhancing the student's engagement. Therefore, H4 is confirmed by the data on the mediating effect of student engagement on the relationship in question.

H5: Mathematics self-belief moderates the relationship between teachers' digital pedagogical practices and *students' problem-solving ability.*

The hypothesis predicted that MSB would mediate the direction and strength of the relationship between TDP and students' problem-solving ability (PSA). A positive moderating effect would imply higher levels of self-belief, indicating an increase in the relationship between teachers' use of AI-supported pedagogical practices and problem-solving performance of students. From figures 3-4 and table 6, TDPxMSB is the interaction term between teacher AI-supported pedagogical practices and MSB.

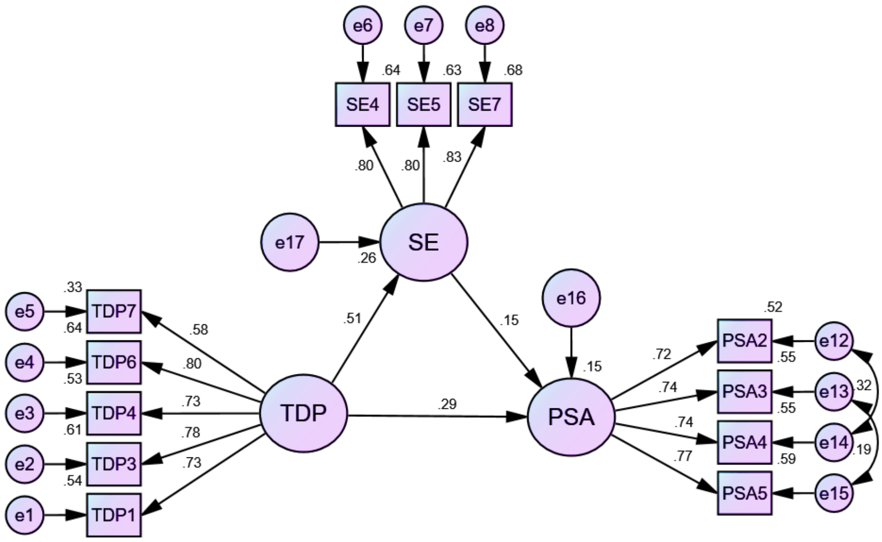

Figure 3. Path analysis.
Source: Authors' creation, 2026.

Table 6. Moderating effects.

Moderating effect	Std. Estimate	S. E	CR	p-value
TDPxMSB→PSA	.027	.071	.527	.598

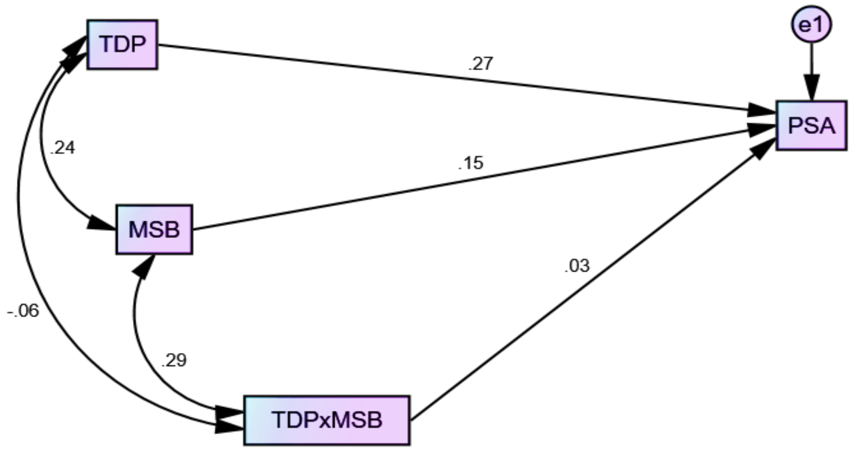

Figure 4. Moderation path analysis.
Source: Authors' creation, 2026.

Again, 0.027 is the magnitude of the moderating effect, and the standard error of 0.071 is the variability of the estimate. The C.R. of 0.527 and the p-value of 0.598 indicate that the interaction effect is not significant. As the C.R. value is less than ±1.96, there is insufficient evidence to support the conclusion that MSB significantly moderates the relationship between teachers' AI-supported pedagogical practices and students' problem-solving ability.

Figure 5 indicates the design of this relationship. Both lines of low and high MSB exhibit a positive slope, indicating that students' problem-solving potential is enhanced when teachers employ more innovative AI-supported pedagogical practices. The lines also lie nearly parallel, indicating that the range of self-belief levels is limited. The trend suggests that, although MSB is positively related to students' learning, it contributes little to the effect of teachers' AI-supported pedagogical practices on students' problem-solving ability.

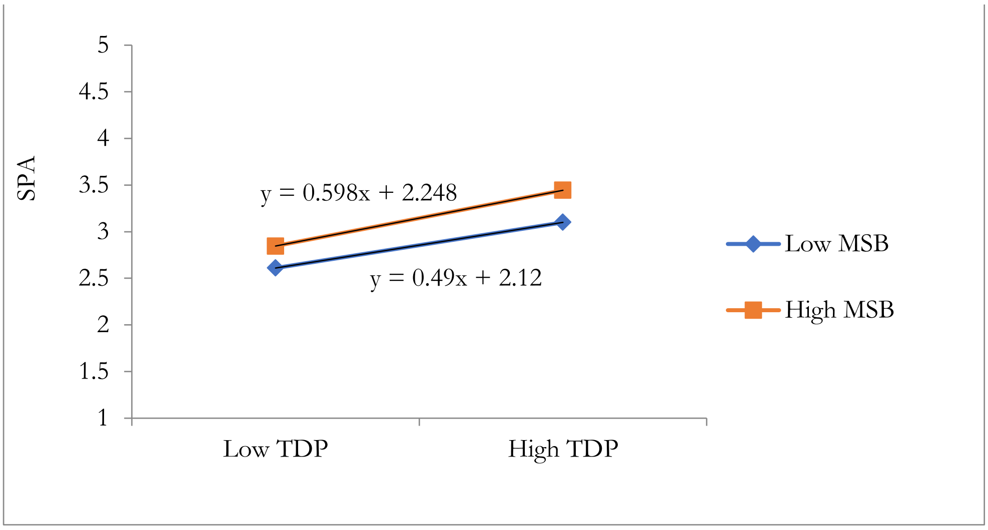

Figure 5. Two-way interaction plot for the moderation effect (MSB).
Source: Authors' creation, 2026.

The result therefore, indicates that students benefit from teachers' AI-supported pedagogical practices irrespective of their level of self-belief in mathematics. Even though self-belief remains a prominent psychological variable in learning, its moderating role on the teacher's AI-supported pedagogical practices-student problem-solving ability relationship is not significant. The hypothesis that MSB would moderate the relationship between teacher AI-supported pedagogical practices and students' problem-solving ability was therefore not supported.

5. Discussion

This study contributed to the knowledge base of effective teaching by revealing the impact of innovative teaching approaches supported by artificial intelligence on students' capacity to solve mathematical problems, from classroom and psychological perspectives. It advances the argument that the true power of artificial intelligence is not just in technology-in-the-trenches as a panacea to the challenges facing education, but actually embedded in the methodologies that a teacher undertakes when providing the education supported by the technology, an argument that was advanced previously by various scholars (Li et al., 2022; Tondeur et al., 2017). The strong positive effect on students' mathematics problem-solving competence demonstrates the added value of innovative didactics. This can also be supported theoretically by Social Cognitive Theory (Bandura, 1986), which emphasizes that learning is explained by the dynamic interaction among the learning environment, students' behavior, and their personal characteristics. Here, the AI-based didactics can be classified as a specific learning environment. All such conditions enhance self-regulation and strategic thinking, two main enablers of mathematical problem-solving processes (Kumar et al., 2023). Such a finding is further consistent with other studies reporting increases in reasoning and problem-solving associated with technology-enhanced instruction with explicit pedagogical scaffolding (Akma et al., 2025; Asiedu Menlah & Boateng, 2025; Boadu & Boateng, 2024).

Again, the strong positive relationship between teachers' innovative teaching methods and student engagement further reinforces engagement as a key indicator of instructional effectiveness. Consistent with Fredricks et al. (2004) multidimensional model of student engagement, AI-supported pedagogical practices appear to activate behavioral, emotional, and cognitive engagement by encouraging participation, sustaining interest, and fostering deeper cognitive investment in learning tasks. Prior studies have similarly reported that interactive and adaptive instructional approaches enhance students' engagement in mathematics learning environments (Barfi et al., 2021; Bergdahl et al., 2020; Fung et al., 2018). Importantly, these findings suggest that engagement is not an automatic outcome of technology use, but rather a pedagogical outcome shaped by teaching methods and instructional design.

Moreover, the mediating role of student engagement provides important insight into how effective teaching methods operate in AI-supported mathematics classrooms. Studies have found that innovative teaching methods have a positive, indirect effect on students' problem-solving abilities through increased engagement. This was in line with what prior studies had found on the relationship between the engagement of the students and their learning, with studies indicating that engagement can be viewed as a bridge between the quality of teaching received by a student and the quality of learning (Fredricks et al., 2019). From a pedagogical perspective, effective teaching goes beyond the immediate lesson; it lays the groundwork for developing students' sustained effort, strategic approaches, and perseverance, which are essential for mastering problem-solving skills.

Furthermore, MSB did not significantly moderate the relationship between teachers' innovative teaching methods and students' problem-solving ability, contrary to expectations. Self-belief was seen to have a significant direct effect on the students' problem-solving ability. This finding could also be explained by (Bandura, 1986) argument that self-efficacy is a gradual process learned through experience. In emerging AI-supported instructional contexts, such as Ghanaian SHSs, students' self-belief may not yet be sufficiently differentiated to condition the effects of instructional innovation. Other studies have found the same, showing that the influence of design and engagement on learning outcomes is more immediate than that of learner beliefs in technology-enhanced learning environments (Asare et al., 2025; Jeong & González-Gómez, 2022). Furthermore, the studies demonstrate the primary pedagogical nature of the instructional design in AI-supported learning environments.

The study reinforces the argument that effective teaching methods, characterized by purposeful instructional design, engagement-oriented practices, and guided feedback, are central to improving mathematical problem-solving outcomes. By empirically demonstrating that student engagement mediates the relationship between teaching methods and learning, this study responds to calls for process-oriented research that explains how teaching methods influence learning, rather than focusing solely on outcomes.

6. Conclusions

The study investigates the effectiveness of innovative teaching methods enabled by artificial intelligence in promoting students' mathematical problem-solving capabilities in SHSs. The results of the research have illustrated the effectiveness of teachers' artificial intelligence-facilitated teaching methods in promoting students' mathematical problem-solving outcomes, both directly and indirectly through students' engagement. The research results have also highlighted the significance of teaching methods in promoting students' mathematics outcomes. From a pedagogical perspective, the study under consideration highlights the significance of student engagement as a vital mechanism for linking teaching methods with learning outcomes. Teaching methods, such as AI-powered feedback, interactive learning, and adaptive instruction, have the potential to enhance cognitive engagement and persistence skills, which are principal ingredients of success in problem solving. The study results have implications for teaching methods and teacher development. Teacher training programs should focus on teaching methods rather than on the ability to use artificial intelligence tools. Teaching methods should be emphasized, including lesson design, feedback mechanisms, and student engagement strategies.

For educational policy and curriculum development, the study provides empirical support for integrating AI-supported teaching methods into mathematics instruction to enhance instructional effectiveness rather than merely increasing technological exposure. In contexts such as Ghanaian SHSs, where access and preparedness may vary, prioritizing pedagogically driven integration can ensure that digital innovations contribute meaningfully to the quality of education. In conclusion, this study advances understanding of effective teaching methods in AI-supported learning environments by demonstrating that instructional effectiveness depends on pedagogical design and student engagement. By foregrounding teaching methods rather than technology alone, the study aligns with contemporary educational research priorities and offers practical guidance for improving mathematics teaching and learning in secondary education.

Ethical Statement: Ethical approval for this study was obtained from the [BLENDED]. All participants provided written informed consent before their inclusion in the study. Consent was also obtained from the heads of departments and lecturers, as well as from the participating students, in accordance with the ethical standards outlined by the Committee and the Declaration of Helsinki.

Conflict of Interest: The author confirms that there were no conflicts of interest related to the study.

Data Availability: The data supporting the findings of this research can be obtained from the corresponding author upon request.

Funding: No financial support was provided for the study.

Generative AI Statement: No generative AI tools were used in writing this manuscript. Conventional tools, including spell-check, grammar software, and Mendeley for reference management, were used solely for editing and formatting. All analysis, interpretation, and writing were completed solely by the authors.

References

Akma, A. U., Asrizal, A., & Lufri, L. (2025). Structural equation modeling of the contextual teaching-digital learning framework: Predicting 21st century skills development in pre-service elementary teachers. *International Journal of Innovative Research and Scientific Studies, 8*(6), 1941-1949. https://doi.org/10.53894/ijirss.v8i6.10047

Arthur, Y. D., Appiah, S. K., Amo-Asante, K., & Asare, B. (2022). Modeling student's interest in mathematics: Role of history of mathematics, peer-assisted learning, and student's perception. *Eurasia Journal of Mathematics, Science and Technology Education, 18*(10), em2168. https://doi.org/10.29333/ejmste/12458

Asare, B., & Boateng, F. O. (2025). Self-awareness and self-regulatory learning as mediators between ChatGPT usage and pre-service mathematics teacher's self-efficacy. *Journal of Pedagogical Research, 9*(2), 38-54. https://doi.org/10.33902/JPR.202530637

Asare, B., Dissou Arthur, Y., & Adu Obeng, B. (2025). Mathematics self-belief and mathematical creativity of university students: the role of problem-solving skills. *Cogent Education, 12*(1). https://doi.org/10.1080/2331186X.2025.2456438

Asiedu Menlah, C. K., & Boateng, F. O. (2025). Examining the effect of AI-based tutoring systems on students' mathematical problem-solving skills: The moderating role of mathematics anxiety. *Journal of Pedagogical Sociology and Psychology, 7*(3), 5-17. https://doi.org/10.33902/jpsp.202536137

Bandura, A. (1986). The explanatory and predictive scope of self-efficacy theory. *Journal of Social and Clinical Psychology, 4*(3), 359-373. https://doi.org/10.1521/jscp.1986.4.3.359

Barfi, K. A., Bervell, B., & Arkorful, V. (2021). Integration of social media for smart pedagogy: initial perceptions of senior high school students in Ghana. *Education and Information Technologies, 26*(3), 3033-3055. https://doi.org/10.1007/s10639-020-10405-y

Bergdahl, N., Nouri, J., & Fors, U. (2020). Disengagement, engagement and digital skills in technology-enhanced learning. *Education and Information Technologies, 25*, 957-983. https://doi.org/10.1007/s10639-019-09998-w

Boadu, S. K., & Boateng, F. O. (2024). Enhancing students' achievement in mathematics education in the 21st century through technology integration, collaborative learning, and student motivation: The mediating role of student interest. *Eurasia Journal of Mathematics, Science and Technology Education, 20*(11), em2534. https://doi.org/10.29333/ejmste/15622

Boateng, F. O., Bandoh, S. O., Kwarteng, S., & Lotey, E. K. (2024). Impact of Parent Interest in Mathematics and Students Mathematics Interest on Student Mathematics Achievement. *Mathematics Education Journal, 8*(2), 206-220. https://doi.org/10.22219/mej.v8i2.33182

Cheung, A. C. K., & Slavin, R. E. (2013). The effectiveness of educational technology applications for enhancing mathematics achievement in K-12 classrooms: A meta-analysis. *Educational Research Review, 9*, 88-113. https://doi.org/10.1016/j.edurev.2013.01.001

Davor, I., Boateng, F. O., & Lotey, E. K. (2025). The mediating role of metacognitive thinking in the relationship between attributional beliefs, academic buoyancy, error-management mindset, and mathematics achievement. *European Journal of Mathematics and Science Education, 6*(4), 239-253. https://doi.org/10.12973/ejmse.6.4.239

Engelbrecht, J., & Borba, M. C. (2024). Recent developments in using digital technology in mathematics education. *ZDM – Mathematics Education, 56*(2), 281-292. https://doi.org/10.1007/s11858-023-01530-2

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School Engagement: Potential of the Concept, State of the Evidence. *Review of Educational Research, 74*(1), 59-109. https://doi.org/10.3102/00346543074001059

Fredricks, J. A., Reschly, A. L., & Christenson, S. L. (2019). Interventions for student engagement: Overview and state of the field. In J. A. Fredricks, A. L. Reschly, & S. L. Christenson (Eds.), *Handbook of student engagement interventions: Working with disengaged students* (pp. 1-11). Elsevier Academic Press. https://doi.org/10.1016/B978-0-12-813413-9.00001-2

Fung, F., Tan, C. Y., & Chen, G. (2018). Student engagement and mathematics achievement: Unraveling main and interactive effects. *Psychology in the Schools, 55*(7), 815-831. https://doi.org/10.1002/pits.22139

Garrison, D. R., Cleveland-Innes, M., & Fung, T. S. (2010). Exploring causal relationships among teaching, cognitive and social presence: Student perceptions of the community of inquiry framework. *The Internet and Higher Education, 13*(1-2), 31-36. https://doi.org/10.1016/j.iheduc.2009.10.002

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review, 31*(1), 2-24. https://doi.org/10.1108/EBR-11-2018-0203

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science, 40*, 414-433. https://doi.org/10.1007/s11747-011-0261-6

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1-55. https://doi.org/10.1080/10705519909540118

Jeong, J. S., & González-Gómez, D. (2022). Mathematics self-belief comparison and examination of pre-service teacher (PST) through a flipped-open calculation based on numbers (ABN) learning method. *Heliyon, 8*(7), e09806. https://doi.org/10.1016/j.heliyon.2022.e09806

Kline, R. B. (2023). *Principles and Practice of Structural Equation Modeling.* Guilford Publications.

Krejcie, R. V., & Morgan, D. W. (1970). Determining Sample Size for Research Activities. *Educational and Psychological Measurement, 30*(3), 607-610. https://doi.org/10.1177/001316447003000308

Kumar, S., Gupta, U., Singh, A. K., & Singh, A. K. (2023). Artificial Intelligence: Revolutionizing Cyber Security in the Digital Era. *Journal of Computers, Mechanical and Management, 2*(3), 31-42. https://doi.org/10.57159/gadl.jcmm.2.3.23064

Lai, C., & Hwang, G. (2016). A self-regulated flipped classroom approach to improving students' learning performance in a mathematics course. *Computers & Education, 100*, 126-140. https://doi.org/10.1016/j.compedu.2016.05.006

Li, L., Tong, Y., Wei, L., & Yang, S. (2022). Digital technology-enabled dynamic capabilities and their impacts on firm performance: Evidence from the COVID-19 pandemic. *Information & Management, 59*(8), 103689. https://doi.org/10.1016/j.im.2022.103689

Marsh, H. W., Guo, J., Dicke, T., Parker, P. D., & Craven, R. G. (2020). Confirmatory Factor Analysis (CFA), Exploratory Structural Equation Modeling (ESEM), and Set-ESEM: Optimal Balance Between Goodness of Fit and Parsimony. *Multivariate Behavioral Research, 55*(1), 102-119. https://doi.org/10.1080/00273171.2019.1602503

Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of Method Bias in Social Science Research and Recommendations on How to Control It. *Annual Review of Psychology, 63*, 539-569. https://doi.org/10.1146/annurev-psych-120710-100452

Timotheou, S., Miliou, O., Dimitriadis, Y., Sobrino, S. V., Giannoutsou, N., Cachia, R., Monés, A. M., & Ioannou, A. (2023). Impacts of digital technologies on education and factors influencing schools' digital capacity and transformation: A literature review. *Education and Information Technologies, 28*, 6695-6726. https://doi.org/10.1007/s10639-022-11431-8

Tondeur, J., van Braak, J., Ertmer, P. A., & Ottenbreit-Leftwich, A. (2017). Understanding the relationship between teachers' pedagogical beliefs and technology use in education: a systematic review of qualitative evidence. *Educational Technology Research and Development, 65*, 555-575. https://doi.org/10.1007/s11423-016-9481-2

Usher, E. L., & Pajares, F. (2007). Self-Efficacy for Self-Regulated Learning: A Validation Study: A Validation Study. *Educational and Psychological Measurement, 68*(3), 443-463. https://doi.org/10.1177/0013164407308475

Xia, Y., & Yang, Y. (2019). RMSEA, CFI, and TLI in structural equation modeling with ordered categorical data: The story they tell depends on the estimation methods. *Behavior Research Methods, 51*, 409-428. https://doi.org/10.3758/s13428-018-1055-2

Yin, X., Bin Mohd Saad, M. R., & Binti Abdul Halim, H. (2024). Technology-enhanced social learning (TSL) to foster critical thinking dispositions and thinking in writing. *Cogent Education, 11*(1). https://doi.org/10.1080/2331186X.2024.2341584