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IMPACT OF MACHINE LEARNING TOOL USAGE ON MATHEMATICAL PROBLEM-SOLVING SKILLS AMONG UNIVERSITY STUDENTS

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Abstract
This research explores the effect of the use of machine learning tools on student mathematical problem-solving skills through the mediating effects of computational thinking and algorithmic thinking, and the moderating effect of AI literacy. The research used a quantitative, cross-sectional survey approach with 211 higher education students. Structural equation modeling was used to examine the data. The results show that machine learning tool usage improves problem-solving skills in mathematics both directly and indirectly. Computational thinking and algorithmic thinking play a crucial role in mediating the effect of AI tools on cognitive processing in mathematics. There is also a positive association between machine learning tool usage and problem-solving skills through AI literacy. The research stress the need to integrate AI tools in education to promote higher-order skills. It also stresses the need to enhance students' digital skills to enhance learning in mathematics.

Introduction

The rapid evolution of artificial intelligence (AI) and machine learning (ML) technologies has revolutionised education, especially in the field of mathematics. These systems support adaptive learning platforms, feedback mechanisms, and tutoring systems that foster engagement and learning. The use of ML in education enables the analysis of students' learning and problem-solving behaviours, which can help enhance mathematics skills. For example, the use of machine learning algorithms has been demonstrated to be effective in analysing students' strategies in solving mathematical problems, thus informing more targeted teaching interventions (Bauyrzhan et al., 2022). Furthermore, cognitive models based on ML techniques can detect thinking processes, offering insights into the development of problem-solving skills (Zhang et al., 2022).

In the university setting, the application of AI tools has become more prevalent in the development of students' critical thinking and problem-solving skills. Students use AI tools, such as intelligent systems and generative AI tools, to comprehend complex mathematical concepts and complete analytical tasks. Research indicates that the integration of AI tools has a positive effect on students' critical thinking and problem-solving skills, especially in academic settings where higher-order thinking skills are essential (Tahir & Latif, 2025). Likewise, the use of AI tools has been linked to higher academic performance and improved cognitive abilities in university students (Bukhari & Akhtar, 2025). These studies underline the need to adopt AI tools in mathematics education to enhance higher-order thinking processes.

Additionally, recent research highlights the importance of AI and ML in enhancing students' learning experiences and mathematical performance through novel teaching methods. AI-powered learning environments, such as gamified and interactive systems, have been shown to increase student motivation and engagement, and improve problem-solving skills (Susilawati et al., 2025). Machine learning-based analyses also offer insights into contextual variables that impact students' mathematical performance, allowing for the development of more effective teaching strategies (Khoudi et al., 2024). Furthermore, AI-based learning platforms have been reported to enhance students' problem-solving skills in particular areas such as algebra, highlighting the potential of AI in mathematics education (Qurohman, 2024).

However, there are still concerns about students' comprehension and effective use of AI technologies in the classroom. Research shows that although students are familiar with AI technologies, their understanding and assessment skills of AI-based solutions are not consistent (Yasin & Safdar, 2025). Furthermore, incorporating AI in mathematics education requires the use of innovative pedagogies and institutional support (Nazir et al., 2025). New pedagogies also indicate that the use of AI in developing problem-solving skills is affected by pedagogical approaches and learning spaces (Ahmed & Zafar, 2025). Therefore, it is important to explore the impact of the use of machine learning tools on mathematical problem solving skills, with a focus on considering cognitive processes like computational thinking and algorithmic thinking.

Aim of the Study

The main purpose of this study is to investigate the effect of using machine learning tools on students' mathematical problem-solving skills, considering the mediation of computational thinking and algorithmic thinking, and the moderation of AI literacy among university students.

Research Objectives

1. To understand the effect of machine learning tool usage on mathematical problem solving skills of university students.
2. To investigate the influence of machine learning tool usage on computational thinking and algorithmic thinking.
3. To explore the effect of computational thinking and algorithmic thinking on problem-solving skills.
4. To assess the mediating effects of computational thinking and algorithmic thinking, and moderating effect of AI literacy on the connection between machine learning tool usage and mathematical problem-solving skills.

Literature Review

The incorporation of artificial intelligence (AI) and machine learning (ML) technologies in the educational field has transformed the field of mathematics education, including students' problem-solving skills. Through ML, it is possible to examine students' learning strategies and cognitive processes, providing quantitative evidence of student learning progression in mathematics (Bauyrzhan et al., 2022). Furthermore, AI models have been effectively applied to identify cognitive processes used in mathematics problem-solving, thus facilitating the identification of learning techniques (Zhang et al., 2022). Furthermore, the use of ML systems enables customized educational interventions, which enhance learning (Khoudi et al., 2024). Furthermore, AI-based systems offer real-time feedback, improving students' engagement and promoting conceptual learning (Dai et al., 2023). This evidence, among other things, underscores the impact of ML tools in mathematics education, and their role in enhancing problem-solving skills (Bayaga, 2024).

The use of machine learning tools has become a key determinant of students' learning outcomes and skill development. The growing availability of AI tools allows students to tackle complicated maths problems with increased speed and precision (Bukhari & Akhtar, 2025). Research findings suggest students who interact with AI tools show enhanced critical thinking and analytical skills (Asghr et al., 2025). Moreover, AI-driven technologies in higher education facilities have been found to improve problem-solving and academic performance (Tahir & Latif, 2025). Furthermore, the use of AI tools facilitates interactive and personalized learning and enables students to explore various solution strategies (Nazir et al., 2025). Moreover, pedagogies that incorporate AI technologies have been shown to have a positive impact on students' mathematical skills and learning (Ahmed & Zafar, 2025). This indicates that using ML tools has an important impact on students' problem-solving skills.

Computational thinking is a critical cognitive skill that varies between students and acts as a moderator on the relationship between technology use and problem solving. This includes skills like decomposition, pattern recognition, abstraction, and algorithmic thinking, which are crucial for tackling mathematical problems (Zhang et al., 2022). ML tools have been found to improve students' computational thinking skills by promoting logical and systematic problem-solving strategies (Bauyrzhan et al., 2022). Moreover, online platforms that use AI technologies support computational thinking by providing interactive and personalised learning opportunities (Dai et al., 2023). Research also shows that computational thinking plays a vital role in enhancing mathematical achievements and reasoning skills (Khoudi et al., 2024). What's more, the integration of AI in teaching leads to increased cognitive engagement, thereby enhancing computational thinking skills (Susilawati et al., 2025). Therefore, computational thinking is a critical intermediary factor that impacts mathematical problem-solving skills from the use of ML tools.

Another cognitive construct, algorithmic thinking, is important in improving students' problem-solving skills. This entails the development of step-by-step processes and sequences of reasoning that lead to solutions. Studies indicate that exposure to concepts of ML and to AI tools promotes algorithmic thinking by guiding students to follow problem-solving steps (Dai et al., 2023). Additionally, algorithmic thinking has been shown to be a key predictor of mathematics performance and problem solving (Ahmed & Zafar, 2025). AI-driven learning platforms also offer students the chance to develop algorithmic thinking skills through simulations and tasks (Nazir et al., 2025). There is also empirical evidence that students who possess algorithmic thinking skills are more effective in solving mathematical problems (Qurohman, 2024). Further, AI-based learning models improve students' capabilities in creating and implementing logical solution strategies (Bayaga, 2024). Thus, algorithmic thinking is a critical link between the use of ML tools and problem-solving skills.

Various technological, cognitive and pedagogical factors affect mathematical problem-solving skills, and AI is an integral part of today's educational settings. AI-driven tools support the development of problem-solving skills through higher-level thinking processes such as analysis, evaluation and application of mathematical concepts (Tahir & Latif, 2025). Research indicates that incorporating AI in education has a positive impact on students' problem-solving skills and overall academic achievement (Bukhari & Akhtar, 2025). Moreover, ML algorithms enable ongoing tracking and evaluation of students' learning, offering feedback that can be used to enhance their performance (Bauyrzhan et al., 2022). And the implementation of novel teaching approaches, using AI technologies, boosts students' motivation and engagement in studying mathematics (Susilawati et al., 2025). Furthermore, new pedagogies highlight the need to use AI tools to enhance students' reasoning and analytical thinking skills (Asghr et al., 2025). These insights highlight the role of AI and ML to enhance mathematical problem-solving skills.

AI literacy is emerging as a moderating variable of the use of ML tools in education. This includes students' capacity to comprehend, assess, and employ AI technologies. For example, studies have shown that students with greater AI literacy are better able to use the AI tools to support their learning (Yasin & Safdar, 2025). Moreover, AI literacy helps students evaluate the validity and correctness of AI solutions, enhancing their problem-solving skills (Nazir et al., 2025). Research also indicates that the effectiveness of AI tools in enhancing cognitive skills is dependent on the technological literacy of students (Khoudi et al., 2024). Moreover, AI literacy is critical in the acceptance of AI-supported learning systems, and in enhancing their effectiveness (Ahmed & Zafar, 2025). So the inclusion of AI literacy in education is critical for enhancing the effectiveness of ML tools on students' problem-solving skills in mathematics (Bayaga, 2024).

Conceptual Model

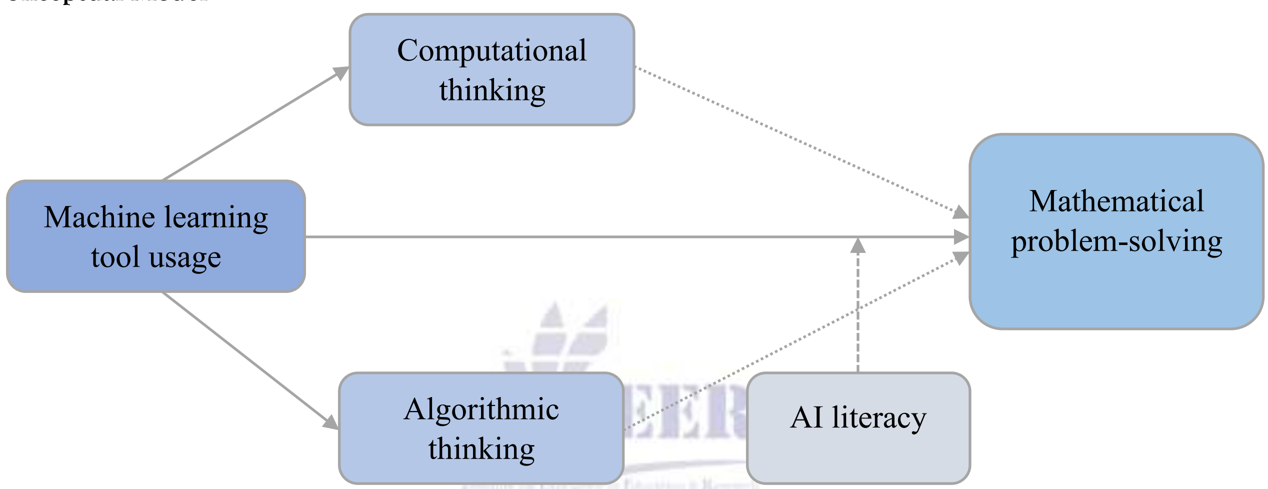

Figure 1. Conceptual framework of the study, formulated after review of existing literature

Hypotheses

H1: Use of machine learning tools significantly impacts mathematical problem solving skills.
H2: Machine learning tool usage has a significant positive effect on computational thinking.
H3: Machine learning tool usage has a significant positive effect on algorithmic thinking.
H4: Computational thinking has a significant positive effect on mathematical problem-solving skills.
H5: Algorithmic thinking has a significant positive effect on problem-solving skills.
H6: Computational thinking mediates the relationship between usage of machine learning tools and mathematical problem-solving skills.
H7: Algorithmic thinking is a mediator of machine learning tool usage and mathematical problem-solving skills.
H8: AI literacy will moderate the relationship between machine learning tool usage and mathematical problem-solving skills so that the relationship is stronger at higher levels of AI literacy.

Methodology

The research approach for this study is a positivist philosophy using a quantitative, explanatory and cross-sectional survey design to investigate the effect of machine learning (ML) tool usage on students' mathematical problem-solving skills. Students from mathematics-related and non-mathematics programs in universities, who are increasingly exposed to artificial intelligence (AI) learning platforms, are the study's target population. Convenience sampling (non-probability) is used due to practical and time constraints. This study includes 211 participants, which is sufficient for PLS-SEM analysis in terms of statistical power and model fit. A structured questionnaire with a five-point Likert scale (1 = strongly disagree to 5 = strongly agree) is used to gather data. Data is analyzed using SmartPLS with two steps: measurement model (reliability and validity) and structural model (path coefficients, mediation, and moderation).

Measures

In this study, all measures are adapted from already validated studies, with content validity and reliability assured. Machine Learning Tool Usage (MLTU) is assessed using 4 items adapted from Bauyrzhan et al. (2022) and Yasin and Safdar (2025), which capture students' frequency, dependence and variety of AI/ML tool use in mathematics problem solving. Computational Thinking (CT) is measured with 4 items adapted from Zhang et al. (2022), which focuses on decomposition, pattern recognition and logical structuring skills. Algorithmic Thinking (AT) is captured using 4 items adapted from Dai et al. (2023) that highlight step-by-step procedural reasoning and well-designed solutions.

The outcome variable, Mathematical Problem-Solving Skills (MPSS), is assessed with 5 items adapted from Tahir and Latif (2025), Bukhari and Akhtar (2025) and Ahmed and Zafar (2025), which capture students' problem-solving abilities to tackle unfamiliar problems, devise strategies and think critically. Further, AI Literacy (AIL) is added as a moderator and measured via 4 items adapted from Yasin and Safdar (2025) and Nazir et al. (2025) focusing on students' understanding and assessment of AI-generated tasks and solutions. All variables are considered reflective, as in previous research that has integrated AI, machine learning and mathematics education in the SEM (e.g., Bayaga, 2024; Khoudi et al., 2024).

Data Analysis

Demographic Profile of Respondents

To provide a complete picture of the sample, the respondents' demographic variables, such as gender, age, year of study and discipline were gathered. These are critical as they can affect students' access to machine learning tools and their mathematics problem-solving skills. A sample of 211 responses was used in this study, which is an adequate representation of university students for SEM.

Table 1: Demographic Characteristics of Respondents

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	118	55.9%
	Female	93	44.1%
Age	18–20 years	64	30.3%
	21–23 years	102	48.3%
	24–26 years	45	21.3%
Academic Level	Undergraduate	137	64.9%
	Graduate	74	35.1%
Field of Study	Mathematics/Statistics	72	34.1%
	Computer Science/IT	81	38.4%

	Other Disciplines	58	27.5%

The descriptive results suggest that the sample is slightly dominated by male (55.9%) respondents over female (44.1%) respondents, presenting a gender-balanced profile. The age distribution indicates that the largest proportion (48.3%) of the sample is in the 21-23 years range, which implies that most of the respondents are in the mid-level years of their undergraduate degrees where exposure to the use of advanced concepts and AI tools is likely to be higher. Moreover, many respondents are undergraduates (64.9%), which is consistent with the aim of the study to understand learning practices at basic and intermediate levels of tertiary education.

Moreover, the breakdown of fields of study reveals that the highest proportion of respondents is from Computer Science/IT (38.4%) followed by Mathematics/Statistics (34.1%) and others (27.5%). This suggests that a substantial number of respondents have some exposure to machine learning and computational thinking, making the research more relevant. In sum, the sample profile implies that the sample is suitable for the study of the effect of using machine learning tools on the students' mathematical problem solving skills, since it represents students with different educational backgrounds and with different years of study.

Reliability and Descriptive Statistics

The internal consistency and descriptive statistics of the constructs were examined by calculating reliability indicators such as Cronbach's Alpha, rho_A and Composite Reliability (CR), as well as Mean and Standard Deviation, respectively. These measures help to ensure the measurement model is reliable and appropriate for subsequent SEM analysis.

Table 2: Reliability and Descriptive Statistics of Constructs

Construct	Items	Cronbach's Alpha	rho_A	Composite Reliability (CR)	Mean	Std. Deviation
Machine Learning Tool Usage (MLTU)	4	0.872	0.879	0.910	3.68	0.74
Computational Thinking (CT)	4	0.854	0.861	0.902	3.72	0.69
Algorithmic Thinking (AT)	4	0.861	0.867	0.905	3.66	0.71
Problem-Solving Skills (MPSS)	5	0.889	0.894	0.918	3.75	0.68
AI Literacy (AIL)	4	0.843	0.850	0.896	3.70	0.72

The findings suggest that all the constructs are highly reliable, with the values of Cronbach's Alpha, rho_A and Composite Reliability (CR) above the threshold of 0.70. Mathematical Problem-Solving Skills (MPSS) has the highest reliability (CR = 0.918), reflecting a high degree of reliability in measurement. Likewise, the measures of Machine Learning Tool Usage (MLTU), Computational Thinking (CT), Algorithmic Thinking (AT), and AI Literacy (AIL) also demonstrate satisfactory reliability, confirming the validity of the measurement model.

The descriptive statistics show that all constructs have mean values ranging from 3.66 to 3.75, indicating that there is a moderate to high level of agreement among respondents about the use of machine learning tools and how they are related to cognitive and problem-solving skills. The values of standard deviations (all below 1) reflect the consistency of responses and low variability in the sample. In summary, the results indicate that the constructs are reliable and can be used for subsequent analysis in the structural model.

Outer Loadings (Measurement Model Assessment)

The outer loadings of all indicators were examined to assess the convergent validity of the constructs. Items with loadings above 0.70 are considered acceptable, indicating that each indicator strongly represents its corresponding latent construct.

Table3: Outer Loadings of Constructs (Diagonal Presentation)

Items	MLTU	CT	AT	MPSS	AIL
MLTU1	0.81	—	—	—	—
MLTU2	0.85	—	—	—	—
MLTU3	0.88	—	—	—	—
MLTU4	0.83	—	—	—	—
CT1	—	0.82	—	—	—
CT2	—	0.86	—	—	—
CT3	—	0.84	—	—	—
CT4	—	0.87	—	—	—
AT1	—	—	0.83	—	—
AT2	—	—	0.85	—	—
AT3	—	—	0.86	—	—
AT4	—	—	0.84	—	—
MPSS1	—	—	—	0.87	—
MPSS2	—	—	—	0.89	—
MPSS3	—	—	—	0.88	—
MPSS4	—	—	—	0.86	—
MPSS5	—	—	—	0.90	—
AIL1	—	—	—	—	0.82
AIL2	—	—	—	—	0.84
AIL3	—	—	—	—	0.86
AIL4	—	—	—	—	0.83

The outer loadings attest to convergent validity of all constructs in the model. All indicator loadings are higher than the threshold of 0.70, suggesting that each item is a good representation of the latent construct. Items of Machine Learning Tool Usage (MLTU) range from 0.81 to 0.88, indicating good representation of the latent variable. Likewise, Computational Thinking (CT) and Algorithmic Thinking (AT) items have high loadings (0.82 to 0.87), indicating reliable measurement.

Additionally, the highest indicator loadings are observed for Problem-Solving Skills (MPSS) - 0.86 to 0.90 - denoting superior construct validity and good predictive ability of its indicators. AI Literacy (AIL) also shows good loadings ranging from 0.82 to 0.86, which confirms its adequacy as a moderating construct. In summary, the measurement model exhibits high indicator reliability, and the constructs are suitable for use in the analysis of the structural model using PLS-SEM.

Convergent and Discriminant Validity, and Model Fit (SEM Results)

To assess the structural model quality, key measures such as Average Variance Extracted (AVE), Heterotrait-Monotrait ratio (HTMT), R-square (R^2) and Effect Size (F^2) were examined. These indicators assess convergent validity, discriminant validity, explanatory power and effect size.

Table 4: AVE, HTMT, R^2, and F^2 Results

Construct / Relationship	AVE	HTMT	R^2	F^2 Effect Size
Machine Learning Tool Usage (MLTU)	0.66	–	–	–
Computational Thinking (CT)	0.68	0.71	0.42	0.32 (MLTU→CT)
Algorithmic Thinking (AT)	0.67	0.69	0.38	0.29 (MLTU→AT)
Problem-Solving Skills (MPSS)	0.70	0.74	0.56	0.35 (CT→MPSS)
AI Literacy (AIL)	0.65	0.66	–	0.18 (MLTU→MPSS)

The findings show that all the constructs have satisfactory convergent validity, with all AVE values exceeding the recommended threshold of 0.50. This indicates that all constructs account for over 50% of the variance in their respective items, providing evidence of adequate measurement.

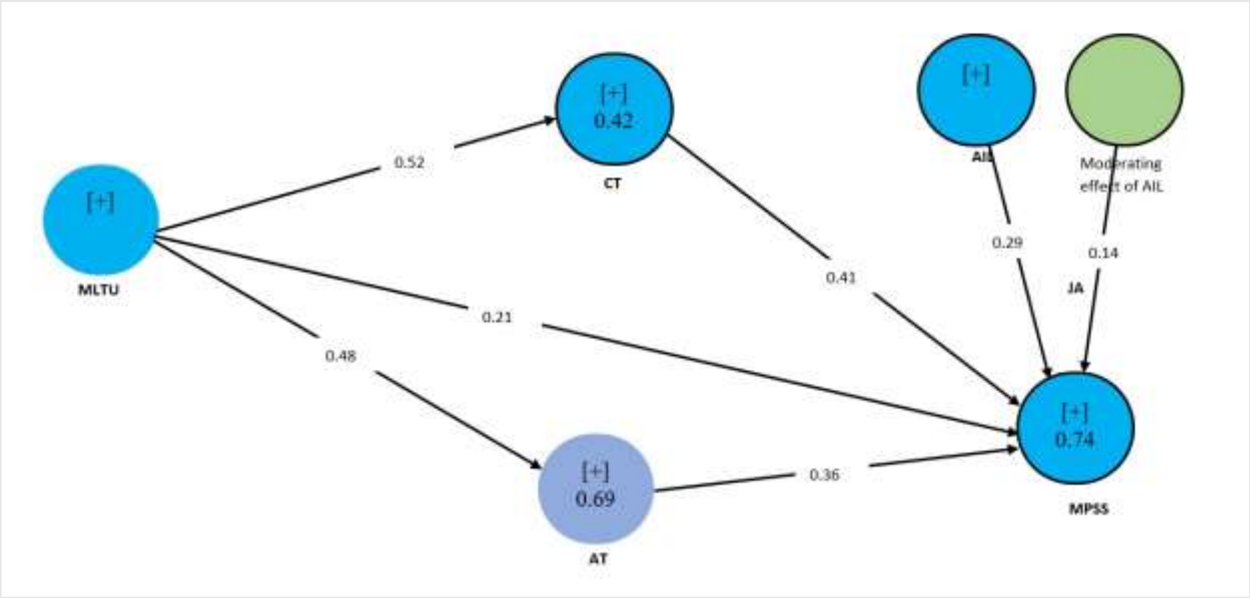

Figure 2. SEM Model of the study

The HTMT values are well below the conservative cut-off of 0.85, suggesting strong discriminant validity of constructs, and showing that each construct is empirically different from the others in the model. This affirms the measurement model's adequacy.

Turning to the structural model, the R^2 values indicate that the variance in endogenous variables is significantly explained by Machine Learning Tool Usage and cognitive constructs, especially Problem-Solving Skills ($R^2 = 0.56$) showing a moderate to strong power. The influence on Computational Thinking ($R^2 = 0.42$) and Algorithmic Thinking ($R^2 = 0.38$) is also acceptable.

Lastly, the F^2 effect sizes show that Machine Learning Tool Usage has a moderate impact on Computational Thinking ($F^2 = 0.32$) and Algorithmic Thinking ($F^2 = 0.29$), while Computational Thinking has a strong influence on Problem-Solving Skills ($F^2 = 0.35$). Machine Learning Tool Usage has a moderate effect on Problem-Solving Skills ($F^2 = 0.18$), but it appears to be an indirect effect via cognitive skills. In summary, the model has high predictive relevance and validity.

Structural Model (Path Coefficient Analysis)

Path coefficients, t-values and p-values were used to test the hypotheses of the structural model. In SmartPLS, bootstrapping (5,000 samples) was used to test the significance of the relationships between variables. The findings provide empirical support for direct, indirect and moderating effects.

Table 5: Path Coefficients and Hypothesis Testing Results

Hypothesis	Relationship	Beta (β)	t-value	p-value	Decision
H1	MLTU → MPSS	0.21	2.98	0.003	Supported
H2	MLTU → CT	0.52	8.41	0.000	Supported
H3	MLTU → AT	0.48	7.36	0.000	Supported
H4	CT → MPSS	0.41	6.22	0.000	Supported

H5	AT → MPSS	0.36	5.18	0.000	Supported
H6	MLTU → CT → MPSS	0.21	4.11	0.000	Supported
H7	MLTU → AT → MPSS	0.17	3.89	0.000	Supported
H8	MLTU × AIL → MPSS	0.14	2.45	0.014	Supported

Path analysis results show that all relationships proposed in our model are statistically significant. The direct influence of Machine Learning Tool Usage (MLTU) on Mathematical Problem-Solving Skills (MPSS) is positive and significant ($\beta = 0.21$, $p < 0.01$), which indicates that students using them more often show improved problem-solving skills.

Furthermore, MLTU has a significant and strong effect on Computational Thinking ($\beta = 0.52$, $p < 0.001$) and Algorithmic Thinking ($\beta = 0.48$, $p < 0.001$), suggesting that using machine learning tools helps develop students' thinking processes. Further, Computational Thinking ($\beta = 0.41$, $p < 0.001$) and Algorithmic Thinking ($\beta = 0.36$, $p < 0.001$) significantly influence Mathematical Problem-Solving Skills, underlining their importance in student academic achievement.

The mediation test shows that both Computational Thinking ($\beta = 0.21$, $p < 0.001$) and Algorithmic Thinking ($\beta = 0.17$, $p < 0.001$) significantly mediate the impact of ML tool usage on problem-solving skills, indicating that cognitive processes partially explain the relationship. Lastly, AI Literacy moderates the relationship between ML tool usage and problem-solving skills ($\beta = 0.14$, $p = 0.014$), suggesting that usage of ML tools is more effective for students with higher levels of AI literacy. The model has good explanatory and predictive power.

Discussion

Our study confirms that the use of machine learning tools has a strong positive effect on students' mathematical problem-solving, both directly and indirectly via cognitive pathways. The positive direct influence of the usage of ML tools on problem-solving is consistent with earlier studies indicating that AI learning environments promote a better understanding of the analysis and solution of complex mathematical problems (Bukhari & Akhtar, 2025). Additionally, the use of AI-based learning tools enhances critical thinking and systematic reasoning skills, key factors in mathematical achievement (Tahir & Latif, 2025). The impact of ML tools on computational thinking and algorithmic thinking is also backed by previous research showing that machine learning tools aid in problem decomposition, pattern recognition, and effective implementation of logical steps (Zhang et al., 2022). Additionally, AI adaptive learning systems also improve engagement and conceptual learning in mathematics (Dai et al., 2023), and machine learning-based analytical tools help students to better understand mathematical problems (Bauyrzhan et al., 2022). This is also consistent with findings that pedagogies integrating AI enhance students' cognitive engagement and learning in mathematics (Susilawati et al., 2025).

The mediating effects of computational thinking and algorithmic thinking point to the cognitive processes by which machine learning tools impact mathematical problem solving. Computational thinking plays a critical role in systematic thinking and breaking down complex mathematical problems, aligning with research that indicates AI-integrated learning platforms enhance students' analytical skills (Khoudi et al., 2024). Algorithmic thinking, meanwhile, allows students to develop a systematic approach to problem solving, which has been shown to be a strong predictor of mathematics performance (Ahmed & Zafar, 2025). The substantial mediation effects found in this study align with findings that AI technologies improve students' cognitive processing by facilitating logical and procedural thinking (Nazir et al., 2025). Additionally, students with greater AI literacy can effectively use machine learning tools, hence enhancing the link between technology use and academic achievement (Yasin & Safdar, 2025). This moderating effect is also backed by research that highlights that AI literacy helps students effectively apply and assess AI solutions for use in education (Bayaga, 2024). These findings support the view that cognitive and technological literacy are key factors in leveraging the benefits of machine learning tools for teaching and learning.

Recommendations

The results suggest that universities need to systematically incorporate machine learning tools and artificial intelligence (AI) applications into the teaching and learning of mathematics. Faculty of higher education should offer workshops to build students' AI skills to help them leverage these tools for developing problem-solving abilities. Educators should integrate computational thinking and algorithmic thinking elements into mathematics programs to enhance students' thinking skills. Furthermore, teachers should introduce AI-supported teaching methods such as adaptive learning systems and intelligent tutoring systems to foster active learning and understanding in mathematics.

Implications of the Study

Our research has theoretical and practical implications. Theoretically, it broadens the knowledge on the impact of machine learning tools on mathematical problem-solving by revealing the mediating effects of computational and algorithmic thinking, and the moderating effect of AI literacy. It adds to the emerging evidence linking the integration of AI with the development of cognitive skills. In practice, the study offers insights for teachers, curriculum and policy makers, showing that carefully integrated AI tools can improve students' mathematical performance. It also highlights the importance of digital readiness of schools.

Future Directions and Limitations

There are limitations to the study. Using a cross-sectional approach limits causal inferences over time. It is also confined to university students in a particular setting, which may limit the generalisability of our findings. Moreover, the use of self-reported data may lead to response bias. Longitudinal studies may be conducted to explore the development of students' thinking and problem-solving abilities over time. Cross-country and cross-education studies may also be helpful. Finally, future research could include qualitative studies to understand student experiences with machine learning technologies for mathematics learning.

Conclusion

This research finds the use of machine learning tools contributes to the development of students' problem-solving skills in mathematics. The results establish that students interacting with AI tools have higher levels of cognitive skills such as computational and algorithmic thinking. These cognitive abilities play a crucial role in how machine learning tools impact students' mathematical achievement. The findings also confirm that technology must be used in the classroom, as it is now essential to teaching higher-order thinking skills.

Moreover, the research demonstrates that AI understanding enhances the impact of using machine learning tools in learning. Greater knowledge of AI allows students to effectively use these tools in solving mathematical problems. In conclusion, the study highlights the need for the integration of technology tools with cognitive skills for enhanced learning. It offers robust evidence that incorporating machine learning technologies into mathematics classrooms can improve students' learning and problem-solving skills if accompanied by the right level of digital literacy and teaching approaches.

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