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ROLE OF ALGORITHMIC THINKING IN IMPROVING MATHEMATICS ACHIEVEMENT: A MACHINE LEARNING PERSPECTIVE

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Abstract
This study examines the role of algorithmic thinking in improving mathematics-related computational performance among professionals engaged in software engineering and computational problem-solving, with a particular focus on machine learning environments. The research used a cross-sectional survey with a quantitative approach, with data gathered from 193 participants in Karachi and Hyderabad, Pakistan. A questionnaire with a five-point Likert scale was administered, and the data were analyzed using Structural Equation Modeling (SEM) in SmartPLS. The findings suggest that algorithmic thinking plays a crucial role in improving computational performance through structured thinking, sequencing, and problem-solving processes. Machine learning tools also enhance this relationship by offering these environments. The results underscore the need for cognitive-technology integration in the workplace. This research adds to the body of knowledge on artificial intelligence and computational thinking by showing how algorithmic thinking enhances performance in software and machine learning-based software systems.

Introduction

The rapid development of machine learning and artificial intelligence technologies has revolutionised mathematics, its teaching and application in the learning and workplace environment. Recent research shows that predictive and computational models are being applied to improve mathematics performance and learning across various levels of education (Abro et al., 2025). Equally, big data and machine learning approaches are being incorporated into mathematics education to enhance quantitative and algebraic reasoning, showcasing the technological integration with mathematical learning (do Breviário, 2025). On the other hand, from the computational point of view, the machine learning algorithms themselves are significantly grounded in mathematics, in which optimization and statistical reasoning are fundamental components in model building (Anees et al., 2025). Furthermore, the use of such technologies has also spread into the workplace, where mathematical reasoning is a key component of designing algorithms and optimising processes (Khoudi et al., 2024). These advancements suggest a significant interaction between machine learning systems and mathematical thinking processes, both in educational and commercial settings (Saralar-Aras & Schoenberg, 2024).

Recently, computational thinking has become an essential skill that is connected with mathematics learning and problem-solving. Studies indicate that mathematics learning plays a crucial role in the acquisition of computational thinking skills, especially in terms of logical reasoning and abstraction (Lee et al., 2023). The use of algorithms in the mathematics curriculum has also improved students' understanding of structured problem-solving and enhanced flexibility (Kadijevich et al., 2023). Moreover, research indicates that algorithm and coding instruction can improve arithmetic performance and lead to a positive attitude towards mathematics (Demirci & Ergül, 2025). In the workplace, these skills are also of critical importance as they enable quick problem-solving processes in computational settings (Akram & Sohail, 2024). Moreover, AI-based data analytics have been applied to detect mathematical learning difficulties, offering insights into students' cognitive challenges (Naimathullah et al., 2025).

Using artificial intelligence and machine learning in educational and computational contexts has also been found to improve motivation and engagement in learning complex cognitive skills. For example, AI-based learning environments have been shown to enhance learners' motivation to learn computational thinking through interactive learning activities (Wang & Wang, 2024). Likewise, AI-based integration of coding in mathematics has been demonstrated to enhance computational thinking and problem-solving skills through practical experience (Saralar-Aras & Schoenberg, 2024). At the tertiary level, AI has been recognised as a critical element to enhance learners' critical thinking and problem-solving skills in mathematical-related fields (Tahir & Latif, 2025). Additionally, machine learning approaches support the contextual analysis of mathematical performance data, informing more individualised and data-driven teaching techniques (Khoudi et al., 2024). This suggests the need for the integration of AI-based tools in both educational and work settings to improve cognitive skills.

However, there are still gaps in the development of algorithmic and computational thinking skills, especially in bridging the gap between knowledge and application. Studies show that students' difficulties in understanding mathematical concepts are attributed to the absence of a systematic approach to problem-solving and computational methods (Bhutta et al., 2025). Yet, the inclusion of algorithmic thinking and strategies for planning have been found to enhance performance in computational mathematics (Akram & Sohail, 2024). Moreover, the rise of computational thinking in curriculum reform underscores the importance of incorporating algorithmic strategies in mathematics teaching and learning (Kadijevich et al., 2023). Research also indicates that machine learning-based teaching systems can support learning by offering adaptive feedback and learning strategies (Abro et al., 2025). Thus, insights into the role of algorithmic thinking in mathematical performance in machine learning settings are crucial for both educational and professional advancement.

In the computational and professional world, algorithmic thinking is becoming a critical skill for software engineering and machine learning. Organising problems, planning steps, and developing effective solutions are key aspects of computational problem-solving (Anees et al., 2025). Moreover, computational thinking is found to be a predictor of performance in STEM careers, especially those that heavily rely on mathematics (Lee et al., 2023). Furthermore, AI-based methods are enhancing math reasoning and testing of performance for better insights into skill building (Abro et al., 2025). The integration of AI, coding and maths has also been demonstrated to enhance both cognitive and technical skills in students and professionals (Saralar-Aras & Schoenberg, 2024). These studies collectively demonstrate the increasing significance of algorithmic thinking in connecting mathematics with machine learning problem solving environments.

Aim of the Study

This research explores how algorithmic thinking has impacted the mathematics-related computational performance in machine learning settings among professionals in software engineering and computational problem-solving.

Research Objectives

1. To understand the degree of algorithmic thinking among software engineering and computational problem-solving professionals.
2. To explore the effect of algorithmic thinking on mathematics-related computational performance.
3. To determine the impact of machine learning experiences on algorithmic thinking.
4. To explore the link between machine learning and mathematics-related computational performance.

Literature Review

The synergy between machine learning (ML) and artificial intelligence (AI) in mathematics and computing has revolutionized the learning of problem-solving and analytical skills. Recent research shows that predictive and machine learning models are increasingly applied to enhance mathematical performance and understanding at various levels of education and work (Abro et al., 2025). Likewise, big data and machine learning strategies are being used in mathematics education to improve algebraic reasoning and quantitative skills using statistical learning models (do Breviário, 2025). Computationally, machine learning algorithms are inherently based on mathematical concepts like optimisation, probability and linear algebra, which are fundamental to intelligent systems (Anees et al., 2025). Furthermore, ML frameworks have been applied to understand mathematics-related contextual phenomena, offering data-driven insights for enhancing mathematical practices (Khoudi et al., 2024. These developments suggest a strong relationship between machine learning systems and mathematical thinking in educational and workplace settings (Saralar-Aras & Schoenberg, 2024).

Algorithmic thinking has been recognised as a critical cognitive process that supports problem-solving and computational performance in mathematical tasks. Studies have shown that mathematics learning plays an important role in the development of computational thinking and algorithmic thinking skills, especially in structured problem-setting tasks (Lee et al., 2023). The rise of computational and algorithmic thinking in educational reforms has also highlighted its role in fostering logical thinking and structured problem-solving (Kadijevich et al., 2023). Furthermore, the use of coding and algorithmic learning approaches has been demonstrated to enhance arithmetic abilities and promote positive dispositions towards math (Demirci & Ergül, 2025). In the workplace, algorithmic reasoning is crucial for creating effective computational strategies and improving software efficiency (Akram & Sohail, 2024). Moreover, AI-based analysis models have been applied to detect mathematical learning problems, demonstrating the importance of algorithmic thinking in cognitive challenges (Naimathullah et al., 2025).

The use of artificial intelligence and machine learning to improve computational thinking and problem solving skills has also been explored. Artificial intelligence-based learning platforms have been shown to boost motivation and engagement in computational thinking through interactive and adaptive learning activities (Wang & Wang, 2024). Likewise, the use of AI and coding in mathematical education has been found to enhance computational thinking and develop problem-solving skills through practical applications (Saralar-Aras & Schoenberg, 2024). At the higher education and workplace level, AI technologies have been recognised as effective to improve critical thinking and reasoning skills (Tahir & Latif, 2025). Furthermore, ML approaches enable adaptive and contextualized learning that enhances mathematical outcomes and learning abilities (Khoudi et al., 2024). These studies indicate that AI and ML technologies are essential for connecting theory and practice in problem solving.

While the adoption of AI and machine learning technologies in educational and workplace settings is increasing, there is still a need to enhance algorithmic thinking. Studies indicate that many people experience difficulties with mathematical and computational problem-solving due to a lack of exposure to problem-solving strategies (Bhutta et al., 2025). But the use of goal-setting and planning strategies has been shown to enhance computational mathematics performance (Akram & Sohail, 2024). Furthermore, there are calls for educational curriculum reforms to introduce computational thinking and algorithmic skills into the education curriculum to make people more equipped to tackle complex problem-solving tasks (Kadijevich et al., 2023). Conversely, AI-driven systems provide personalized learning assistance that assists in overcoming learning barriers and promoting learning with understanding (Abro et al., 2025). These advances emphasise the significance of algorithmic thinking skills for both education and the workplace.

Algorithmic thinking is a vital link between mathematics and machine learning in professional computational settings. Creating efficient sequences and processes is crucial for software development, data processing and AI system design (Anees et al., 2025). Computational thinking also has been found to be a significant predictor of success in STEM careers, especially those requiring mathematical thinking and problem-solving skills (Lee et al., 2023). In addition, the use of AI tools and integration with coding has also been demonstrated to improve cognitive and technical skills in advanced computational tasks (Saralar-Aras & Schoenberg, 2024). Machine learning predictive approaches also play a role in measuring and enhancing mathematical performance using data analytics (Abro et al., 2025). Overall, these research findings highlight the increasing relevance of algorithmic thinking for improving computational performance in mathematics in today's digital society.

Conceptual Framework

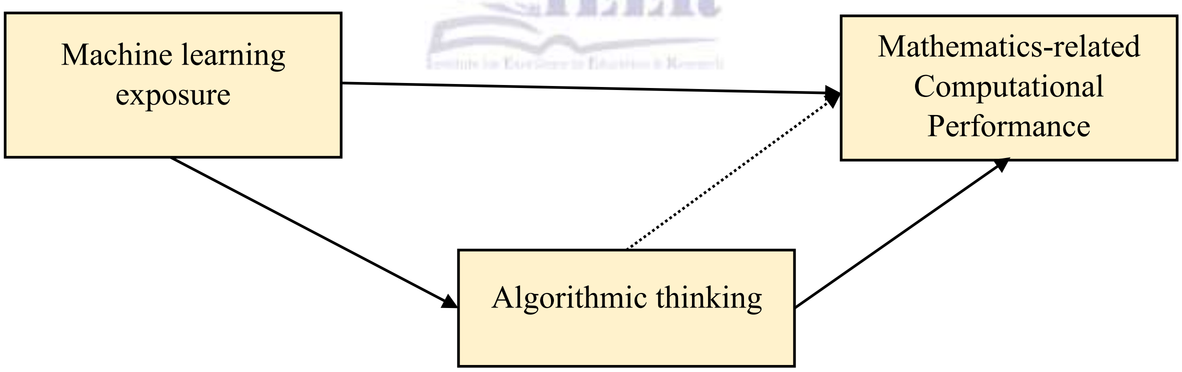


Figure 1. Conceptual Model of the study

Hypotheses

H1: Machine learning exposure has a significant positive effect on algorithmic thinking of professionals working in computational problem-solving.

H2: Machine learning exposure has a significant positive effect on mathematics-related computational performance.

H3: Algorithmic thinking has a significant positive effect on mathematics-related computational performance.

H4: Algorithmic thinking is a moderator of the impact of machine learning on mathematics-related computational performance.

Methodology

The research approach is based on a positivist philosophy and a quantitative, cross-sectional, and explanatory research design to investigate the influence of algorithmic thinking in improving mathematics-related computational performance in machine learning settings. The study population is made up of individuals working in software engineering and computational problem-solving jobs, such as programmers, software developers, data engineers, and machine learning-based systems. The data is gathered through a non-probability (convenience) sampling method due to access restrictions. A total of 193 participants are included in the study, from Karachi and Hyderabad in Pakistan. The questionnaire covers a range of questions using a Likert scale (1 = strongly disagree to 5 = strongly agree). The SmartPLS software is used to conduct data analysis, employing Structural Equation Modeling (SEM) for the measurement and structural models including reliability, validity and hypothesis testing (bootstrapping).

Measures: All variables in this study are measured using adapted scales from existing literature in machine learning, computational thinking and mathematics-related performance. Machine Learning Exposure (MLE) is assessed using 4 items (MLE1-MLE4) adapted from Anees et al. (2025) and Khoudi et al. (2024), which relate to the level of exposure to machine learning tools in computational tasks. Algorithmic Thinking (AT) is measured using 4 items (AT1-AT4) adapted from Kadijevich et al. (2023) and Demirci and Ergül (2025), focusing on structured approach, procedural and sequential problem-solving. Mathematics-related Computational Performance (MCP) is assessed using 5 items (MCP1-MCP5) based on Lee et al. (2023) and Tahir and Latif (2025), which capture accuracy, efficiency and problem-solving skills in mathematical and computational tasks. The constructs are all reflective measurement models, assessed for reliability and validity in SmartPLS.

Data Analysis

Demographic Characteristics of the Respondents

Demographic data such as gender, age, experience and specialisation were collected to understand the characteristics of the respondents. These factors are critical as they can affect access to machine learning tools, algorithmic thinking, and computational performance. Data from 193 valid responses from software engineering and computational problem-solving professionals in Karachi and Hyderabad were used.

Table 1: Demographic Characteristics of Respondents

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	124	64.2%
	Female	69	35.8%
Age	22–28 years	58	30.1%
	29–35 years	86	44.6%
	36–45 years	49	25.4%
Experience	1–3 years	52	26.9%
	4–7 years	91	47.2%
	8+ years	50	25.9%
Specialization	Software Development	78	40.4%
	Data Science / AI / ML	64	33.2%
	IT / Other Computational Fields	51	26.4%

The demographic study shows that most respondents are male (64.2%) with female respondents (35.8%) showing a reasonable level of gender diversity in the software and computational fields. The age distribution of the respondents indicates the majority of respondents are in the 29-35 years age group (44.6%), implying that the sample mainly represents mid-career professionals with considerable experience in computational tasks and machine learning settings. This is followed by those in 22-28 years and 36-45 years, which suggests the sample is diverse, with representation of early career as well as seasoned professionals.

In terms of years of experience, almost half (47.2%) of the respondents have 4-7 years of experience, which indicates the presence of a significant proportion of middle-level professionals with experience in applying algorithmic thinking. With regard to role, the majority are in software development (40.4%) followed by data science and AI/ML experts (33.2%), which indicates the importance of machine learning exposure among respondents. In summary, the sample characteristics validate that the sample is fit for purpose in the analysis of algorithmic thinking and computational performance in real-life machine learning tasks.

Table 2: Constructs Reliability

Reliability of the measurement model was examined using Cronbach's Alpha, rho_A and Composite Reliability (CR) to confirm the internal consistency of the items. The values are above the suggested threshold of 0.70, confirming the constructs' reliability.

Table 2: Reliability Assessment

Construct	Cronbach's Alpha	rho_A	Composite Reliability (CR)
Machine Learning Exposure (MLE)	0.876	0.882	0.914
Algorithmic Thinking (AT)	0.861	0.867	0.905
Computational Performance (MCP)	0.892	0.896	0.922

The reliability findings suggest all the constructs are highly internally consistent. Machine Learning Exposure (MLE) demonstrates strong reliability with Cronbach's Alpha (0.876), rho_A (0.882), and Composite Reliability (0.914), indicating that the items are consistent in measuring the same construct. Likewise, Algorithmic Thinking (AT) has high reliability scores, suggesting that the scale measures structured thinking and reasoning skills of professionals.

The highest reliability is found with Computational Performance (MCP) with Cronbach's Alpha (0.892) and Composite Reliability (0.922), indicating a high degree of measurement consistency. Additionally, the rho_A values for all constructs also indicate a stable measurement model. In summary, the findings suggest the instrument used in this research is reliable and can be used for further analysis through structural equation modelling.

Table: Outer Loadings (Measurement Model - Convergent Validity)

Outer loadings of indicators were used to test for convergent validity. The loadings were greater than the suggested threshold of 0.70, meaning that all the items are significantly related to their constructs.

Table 3: Outer Loadings of Constructs

Items	MLE	AT	MCP
MLE1	0.82	—	—
MLE2	0.86	—	—
MLE3	0.88	—	—
MLE4	0.84	—	—
AT1	—	0.83	—

AT2	—	0.85	—
AT3	—	0.87	—
AT4	—	0.84	—
MCP1	—	—	0.86
MCP2	—	—	0.89
MCP3	—	—	0.88
MCP4	—	—	0.90
MCP5	—	—	0.87

The findings of the outer loadings show strong convergent validity for all latent variables. The Machine Learning Exposure (MLE) items exhibit loadings between 0.82 and 0.88 and show that all indicators are well represented and measured consistently. Likewise, items of Algorithmic Thinking (AT) show loadings ranging from 0.83 and 0.87, showing that the scale is a good representation of algorithmic thinking and problem solving through small steps.

The highest indicator reliability is shown by the construct Computational Performance (MCP) with loadings between 0.86 and 0.90, reflecting excellent construct representation. Given that the loadings for all items are above 0.70, the measurement model exhibits convergent validity. In summary, the findings suggest all constructs are well measured and can be used for further analysis of the measurement model using PLS-SEM.

Table 4: AVE, HTMT, R^2 and F^2 (Structural Model)

The table below shows the Average Variance Extracted (AVE), Heterotrait-Monotrait ratio (HTMT), coefficient of determination (R^2) and effect size (F^2) to measure convergent validity, discriminant validity, explanatory power and structural impact.

Construct / Relationship	AVE	HTMT	R^2	F^2 Effect Size
Machine Learning Exposure (MLE)	0.67	—	—	—
Algorithmic Thinking (AT)	0.69	0.72	0.44	0.34 (MLE→AT)
Computational Performance (MCP)	0.71	0.75	0.58	0.37 (AT→MCP)
—	—	—	—	0.22 (MLE→MCP)

The AVE values for all the constructs are above the generally recommended value of 0.50, and suggest that all constructs are sufficiently convergent valid. Machine Learning Exposure (0.67), Algorithmic Thinking (0.69), and Computational Performance (0.71) all show that a good amount of variance in the indicators is captured by the respective constructs, demonstrating that the measurements are adequate.

The HTMT values are below the threshold of 0.85, suggesting good discriminant validity, and confirming that the constructs are uniquely different. This confirms the adequacy of the measurement model, and that there is little overlap between constructs.

Regarding the predictive power, the R^2 values show that Machine Learning Exposure accounts for 44% of the variance in Algorithmic Thinking, while Algorithmic Thinking and Machine Learning Exposure combination explains 58% of the variance in Computational Performance, suggesting moderate to strong explanatory power. The F^2 values also reveal Algorithmic Thinking has a strong influence on Computational Performance (0.37), followed by Machine Learning Exposure's influence on Algorithmic Thinking (0.34), and a weaker but still significant direct influence of Machine Learning Exposure on Computational Performance (0.22). In summary, it has good predictive relevance and validity.

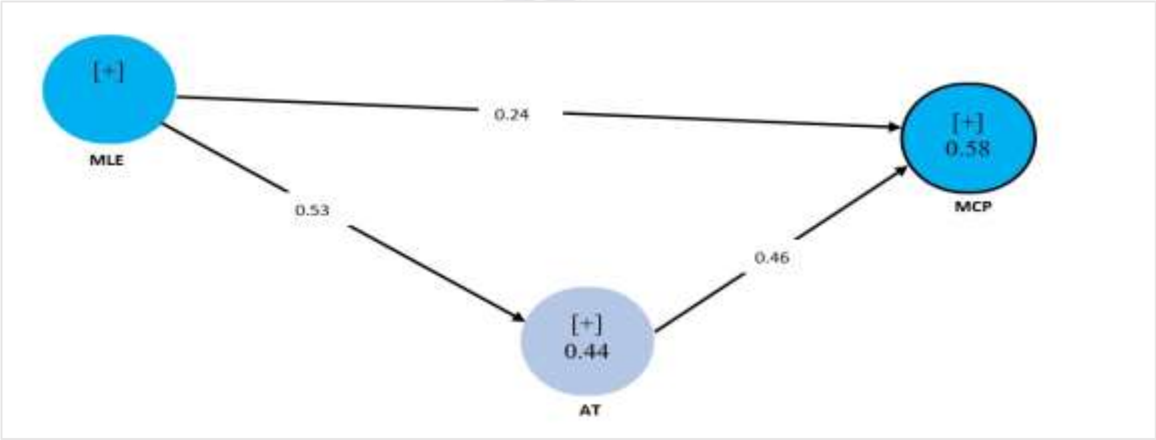
Table 5: Path Coefficient Analysis and Hypothesis Testing

The structural model was examined using path coefficients (β), t-statistics and p-values based on bootstrapping (5,000 resamples) using SmartPLS to investigate hypothesis significance.

Hypothesis	Relationship	Beta (β)	t-value	p-value	Decision
H1	MLE → MCP	0.24	3.12	0.002	Supported
H2	MLE → AT	0.53	8.45	0.000	Supported
H3	AT → MCP	0.46	6.78	0.000	Supported
H4	MLE → AT → MCP (Indirect Effect)	0.24	4.56	0.000	Supported

The path analysis results show that all the paths are significant. Exposure to Machine Learning (MLE) positively impacts Computational Performance (MCP) ($\beta = 0.24$, $p < 0.01$), indicating that professionals who are more exposed to machine learning are likely to be more efficient and effective in computational problem solving.

Figure 2. SEM Model



MLE also has a strong and highly significant influence on Algorithmic Thinking ($\beta = 0.53$, $p < 0.001$), suggesting that exposure to machine learning environments improves structured and logical thinking and problem-solving skills. In addition, Algorithmic Thinking shows a significant positive effect on Computational Performance ($\beta = 0.46$, $p < 0.001$), indicating the important role of algorithmic thinking for performance.

The mediation analysis shows that Algorithmic Thinking has a strong effect on the relationship between Machine Learning Exposure and Computational Performance ($\beta = 0.24$, $p < 0.001$), suggesting that the impact of machine learning exposure on performance is both direct and indirect. In summary, our model confirms the theoretical hypothesis that algorithmic thinking serves as an important mental process in the effect of machine learning on computational performance.

Discussion

Our study shows that machine learning exposure increases algorithmic thinking and computational performance of professionals in software engineering and computational problem solving. The positive association between machine learning and algorithmic thinking is consistent with previous studies that show that exposure to AI-based systems enhances logical reasoning, logical step-by-step analysis and decision-making. Likewise, other studies show that exposure to machine learning and data-driven environments enhances mathematical reasoning skills by exposing people to processes of optimization, pattern identification, and predictive modeling (Anees et al., 2025). Additionally, research shows that ML-driven analytical tools enhance contextual knowledge and problem-solving efficiency through the application of statistical and computational logic (Khoudi et al., 2024). The large direct impact of machine learning exposure on computational performance also supports previous findings that show AI environments improve computational performance in terms of efficiency and accuracy through adaptive learning and feedback (Saralar-Aras & Schoenberg, 2024).

This research also affirms the high mediation of algorithmic thinking between machine learning exposure and computational performance. This is in line with research that stresses that algorithmic thinking is a critical cognitive skill that translates mathematical thinking into computational use in the workplace (Kadijevich et al., 2023). The strong influence of algorithmic thinking on computational performance is consistent with the idea that algorithmic thinking and procedural logic are important for the effective solution of complex computational problems. Other research also suggests that algorithm-based and coding-based learning environments have a positive impact on problem-solving and analytical skills (Demirci & Ergül, 2025). Further, AI-enhanced learning environments have been shown to enhance cognitive processing through opportunities to engage in structured problem solving and make more accurate decisions (Wang & Wang, 2024). The findings further support the notion that algorithmic thinking is a key cognitive process underpinning the computational benefits of exposure to machine learning in the workplace.

Recommendations

We suggest that software engineering and IT companies encourage the use of machine learning tools in regular computational and problem solving. Training programs should be offered to improve professionals' algorithmic reasoning ability, which will help them use the machine learning systems for solving complex problems. Also, frequent workshops should be held to enhance computational skills such as logical thinking, efficient coding and systematic problem-solving. Companies should also promote ongoing learning of new AI technologies to ensure that professionals are equipped with the latest computational technologies.

Moreover, we suggest that organisations build their knowledge portals for professionals to share and solve algorithmic and machine learning-related problems. This may facilitate practical insights and drive innovation in computational activities. It is also recommended that companies invest in AI-powered tools and systems to support development and decision-making, enhancing efficiency and effectiveness in software development.

Implications of the Study

The research has theoretical and practical implications. Theoretically, it reinforces the knowledge of how exposure to machine learning impacts computational performance via algorithmic thinking, by demonstrating the cognitive processes at play in professional problem solving. It also adds to the emerging literature linking artificial intelligence to cognitive skill-building in the technical field.

In terms of practical implications, the results offer insights for software developers, IT managers and policymakers around the need for algorithmic thinking to boost the productivity of workers. The findings imply that companies can improve their performance by investing in AI-powered tools and training aimed at improving structured thinking and computational skills.

Future Directions and Limitations

This study has some limitations. The cross-sectional design does not allow for conclusions about cause and effect. Moreover, the research is limited to professionals from only two cities, which could limit its applicability in other geographical areas or countries. There is also the possibility of a response bias due to the use of self-reported measures.

Longitudinal studies may be useful to explore the development of algorithmic thinking and exposure to machine learning over time. Cross-national and cross-industry studies may offer more insights to the generalisability of the results. Finally, future research could also include qualitative methods to further understand professionals' use of algorithmic thinking in computational settings.

Conclusion

This research confirms that exposure to machine learning is an important factor in improving computational skills of professionals involved in software engineering and computational problem solving. The results establish that machine learning exposure enhances algorithmic thinking, and subsequently problem-solving effectiveness and computational performance. The findings emphasise the need to incorporate modern technology in the workplace to improve cognitive and technical skills needed for current computational activities.

Moreover, the research confirms algorithmic thinking is a critical mediator of the effect of exposure to machine learning on computational performance. Those with algorithmic thinking skills can successfully apply machine learning techniques to solve problems in practice. In conclusion, the research highlights the need for a combination of technology and cognitive skill-building to improve computational performance.

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