Online Learning in Educational Research
Volume 4, Issue 2, 185-198.
e_ISSN: 2798-2351
https://www.journal.foundae.com/index.php/oler/index
DOI: 10.58524/oler.v4i2.501

Harnessing Digital Skills For Academic Success: Unveiling The Power of Learning Motivation in Computational Thinking and Tech Integration

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Article Info

Article history:

Received: October 8, 2024
Revised: November 28, 2024
Accepted: December 11, 2024
Published: December 20, 2024

Keywords:

Computational Thinking;
Learning Motivation;
Student Performance;
Technology Integration.

Abstract

The workforce's demand for critical thinking and innovation highlights the need to improve students' problem-solving skills, thus encouraging educational institutions to adopt technology-based strategies for an engaging learning environment. Previous studies have explored the relationship between learning motivation and academic outcomes and the role of technology and web-based media in improving problem-solving skills. However, limited research has comprehensively examined the interaction between computational thinking, technology integration, learning motivation, and student performance. This study aims to examine how Computational Thinking (CT) and Technology Integration (TI) influence Learning Motivation (LM) and Student Performance (SP), providing insights into optimizing digital skills for academic success in the digital age. Data were collected from 426 respondents' university students in Indonesia randomly. A questionnaire with a 5-point Likert scale consisting of several variables such as Computational Thinking, Technology Integration, Learning Motivation, and Student Performance were used in this study. Then, the data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to check the measurement and assessment model. The results showed that CT and TI positively and significantly impacted LM and SP. In addition, LM serves as an important mediator, strengthening the influence of CT and IT on academic outcomes. Specifically, technology integration has a greater impact on LM than CT, while LM significantly improves SP. This study presents a detailed framework for educators to enhance learning experiences by integrating digital skills and fostering student motivation. The findings offer practical implications for developing effective educational strategies that meet the changing demands of the digital age. Future research is recommended to investigate the long-term effects of CT and IT in various educational environments.

To cite this article: Rauf, A., Fakhri, M. M., Fathahillah, F., Surianto, D. F., Baso, F., Arifiyanti, F, & Amukune, S. (2024). Fostering academic success through computational thinking and technology integration: The mediating role of learning motivation. *Online Learning in Educational Research, 4*(2), 185-198. https://doi.org/10.58524/oler.v4i2.501

INTRODUCTION

Problem-solving is a fundamental skill that supports various educational approaches and is crucial for student success across different disciplines. It encompasses cognitive processes such as problem identification, information analysis, and solution generation (Alfares, 2021). In education, especially in STEM fields, problem-solving goes beyond academic exercises. It is an essential competency that equips students to face real-world challenges, such as developing effective

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problem-solving skills among college students (Şahin, 2021). Integrating technological knowledge into the higher education curriculum promotes sustainable development by equipping students with problem-solving skills to address real-world challenges through technology (Alshammari et al., 2023). Additionally, cultivating problem-solving abilities is increasingly seen as a vital element of 21st-century education, aimed at preparing learners with the skills needed in a rapidly evolving world (M. Albay, 2020).

The need to enhance students' problem-solving abilities is emphasized by the changing demands of the workforce, which increasingly prioritizes critical thinking and innovative solutions (Sun, 2021). As a result, educational institutions are encouraged to implement instructional strategies that cultivate these skills, incorporating technology to create engaging learning environments (Furtasan Ali Yusuf et al., 2023). This shift is justified by evidence showing that students involved in problem-based learning tend to have higher motivation and improved academic performance (Atma et al., 2021). The post-COVID-19 era has also underscored the importance of adaptive learning strategies that maintain student engagement and motivation in remote or hybrid learning environments (Fadila et al., 2022).

A comprehensive plan is proposed to integrate computational thinking into the curriculum and technology-enhanced learning environments. This strategy is designed to develop students' problem-solving skills and learning motivation (Setiawan et al., 2023). By utilizing digital tools and resources, educators can create interactive learning experiences that engage students and promote collaborative problem-solving (Turgut & Ocak, 2017). Additionally, it is essential to train teachers in innovative instructional methods to ensure they can effectively guide these learning experiences (Seechaliao, 2017).

Although there is an expanding body of research on problem-solving and technology integration in education, a significant research gap persists concerning the specific mechanisms by which these elements interact to affect student motivation and performance. While some studies have examined the relationship between learning motivation and academic outcomes, empirical evidence directly connecting computational thinking and technology integration with enhanced problem-solving abilities and student engagement is still limited (Filgona et al., 2020). Park and Kwon illustrate how AI education improves students' problem-solving abilities, especially within the context of technology education (Park & Kwon, 2023). This study was reinforced by Setiawan et al. (2023)., who highlighted the important role of web-based learning media in transforming mathematics education while improving problem-solving skills. Moreover, previous research often lacks a comprehensive framework that integrates these factors into a cohesive model, leaving a gap in understanding how they collectively influence educational outcomes in the digital age. This study addresses this gap through an integrated approach, analyzing the direct and mediated relationships between these variables.

This study develops a set of hypotheses to explore the interrelationships between Computational Thinking (CT), Technology Integration (TI), Learning Motivation (LM), and Student Performance (SP). This study investigates the effect of Computational Thinking and technology integration on students' learning motivation and academic achievement. This study will also evaluate the role of learning motivation in improving academic performance and examine whether learning motivation can mediate the relationship between Computational Thinking and technology integration with student performance. With these objectives, this study is expected to provide deeper insights into optimizing digital skills and learning motivation to support academic success in the digital era.

In this study, the questions discussed are:

1. How does Computational Thinking affect Learning Motivation and Student Performance?
2. How does Technology Integration affect Learning Motivation and Student Performance?
3. How does Learning Motivation affect Student Performance?
4. Does Learning Motivation mediate the effect of Computational Thinking and Technology Integration on Student Performance?

METHOD

Figure 1 shows a flowchart illustrating the research steps in this study, from identifying variables to preparing conclusions and implications. This flowchart presents a systematic sequence of steps in the research process, ensuring each stage contributes to achieving the research objectives and generating meaningful findings.

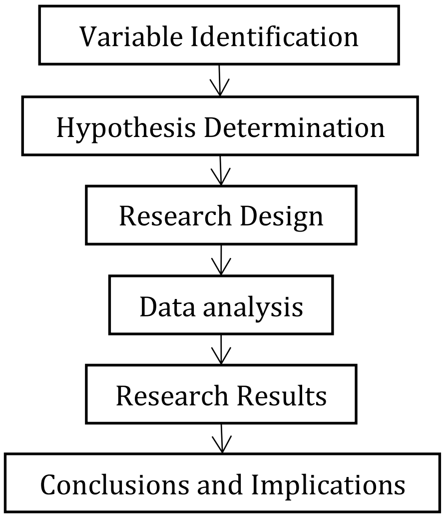

Figure 1. Research Flowchart

Figure 1 shows the stages of research, starting with the identification of variables, namely Computational Thinking (CT), Technology Integration (TI), Learning Motivation (LM), and Student Performance (SP). The next stage is determining hypotheses to test the relationship between variables and then designing quantitative research using the PLS-SEM model. Data were collected through questionnaires and analyzed using PLS-SEM, with hypothesis testing based on path coefficient, T-statistics, and P-values. The analysis results conclude and provide implications for developing technology-based learning strategies.

Research Approach and Design

This study used a quantitative approach with a cross-sectional design (Creswell, 2009). It was conducted to explore the relationship between Computational Thinking and Learning Motivation to Foster Growth Mindsets and its impact on Student Performance. This design makes it possible to collect data from a wider population in a relatively short period so that the results can provide a clear picture of the relationship between variables in the context of the research being conducted. (Agortey et al., 2023).

Population and Sample

The participants in this study were students engaged in technology-driven learning at different universities, with the sample being chosen through purposive sampling to ensure the active involvement of students in the technology-based learning process (Cabezas-González et al., 2021). The sample of this study amounted to 426 respondents. The sample size was determined based on the rule of thumb, considering the model's complexity and the number of indicators used in the study (Riley et al., 2020). This approach ensures that the sample size is sufficient for the analysis to be carried out so that the research results can be considered valid and generalized to a wider population (Snell et al., 2021).

Variable and Measures

This study includes four main variables consisting of independent variables, such as Computational Thinking, which is measured through five items (CT1 to CT4) and Technology Integration, which has four items (TI1, TI2, TI3 and TI5); mediating variables such as Learning Motivation which is measured through four items (LM1, LM2, LM4, and LM5); and dependent variables such as Student Performance, which is measured through four items (SP1 to SP4). Table I explains each variable in this study with specific operational definitions.

Table 1. Definition of variables

No.	Variable	Definition
1	Computational Thinking (CT)	Diverse problem-solving skills are crucial for interacting effectively with computing technologies and processes (Denning & Tedre, 2019).
2	Technology Integration (TI)	Integration of technology resources and technology-based practices into the daily routine of teaching and learning (Syawallina & Suganda, 2023).
3	Learning Motivation (LM)	Intrinsic motivations, emotions, and desires drive students to engage in certain actions, especially in the context of language learning (Nong, 2023).
4	Student Performance (SP)	Various methods, including exams and assignments, are crucial for assessing whether students have achieved their educational goals (Maryansyah & Danim, 2024).

Data collection technique

The data collection technique involved distributing questionnaires. In this study, the questionnaire utilized a 5-point Likert scale, where 1 represented "strongly disagree," 2 represented "disagree," 3 represented "neutral," 4 represented "agree," and 5 represented "strongly agree." Each question was designed to assess the indicators of the variables under investigation (Saregar et al., 2024).

Data Analysis

The gathered data will be analyzed using the Partial Least Squares Structural Equation Modeling (PLS-SEM) method, as it can estimate relationships between complex latent variables, is appropriate for small sample sizes, and does not require the assumption of data normality (Varma, 2019). Data analysis was conducted with the help of SmartPLS software through two main stages: outer model and inner model analysis (Aulia Khoirunnisa & Usman, 2024).

Outer Model

At the outer model stage, it plays an important role in assessing the validity and reliability of measurements of latent constructs (Wang, 2023). The outer model test is also known as the measurement mode (Nurdin & Abidin, 2023). The outer model explains the relationship between latent constructs (latent variables) and measured indicators (observed variables). The outer model discussion includes convergent validity and construct reliability (Prihandoko et al., 2024).

Convergent validity measures how well indicators correlate with each other when measuring a construct. Several key metrics are used to evaluate convergent validity: Outer Loading and Average Variance Extracted (AVE) (Lian et al., 2022). The accepted outer loading value is above 0.70, which indicates that the indicator contributes significantly to the latent construct (Mohd Dzin & Lay, 2021). An acceptable AVE value is ≥ 0.50, indicating that more than 50% of the indicator variance is explained by the construct (Alghamdi, 2020). Meanwhile, construct reliability refers to the internal consistency of indicators in measuring latent constructs (Albra et al., 2023). This ensures that the indicators consistently reflect the same constructs across models (Leguina, 2015). Two main metrics are used to assess construct reliability in PLS-SEM: Composite Reliability (CR) and Rho_A (Díaz-Fúnez et al., 2024). Accepted CR and Rho_A values are ≥ 0.70, indicating adequate internal consistency (Zhou & Wang, 2022). Then, discriminant validity in PLS-SEM measures the extent to which the constructs in the model are significantly different from each other (Kumar et al., 2023). Discriminant validity is evaluated through the Heterotrait-Monotrait Ratio (HTMT), where an acceptable HTMT value is below 0.85 or 0.90, indicating that the constructs in the model are truly distinct from one another (Bachmid & Noval, 2023).

Inner Model

The inner model stage is an important element that focuses on the relationship between latent variables in a model (Sarstedt et al., 2021). The inner model examines the interactions and mutual influences between latent constructs, which usually describe a study's independent, mediator, and dependent variables.

The model's predictive ability is assessed through R Square (R^2). R^2 values range between 0 and 1, with higher values indicating that the model explains most of the variance of the dependent variable (Ozili, 2022). Hypothesis testing is done by analysing Path Coefficients, T-statistics, and P-values (Rabaa'i et al., 2021). Significant Path Coefficients usually have T-Statistics values above 1.96 at the 5% significance level, and the P-values received are less than 0.05, which indicates that the relationship between variables does not occur by chance and is statistically significant (Muttaqin et al., 2023).

The framework presented in Figure 2 explores the interrelationships between Computational Thinking, Technology Integration, Learning Motivation, and Student Performance. The model specifically proposes that Learning Motivation plays a direct and mediating role in influencing these relationships. Each hypothesis is marked to highlight the proposed relationships within the framework.

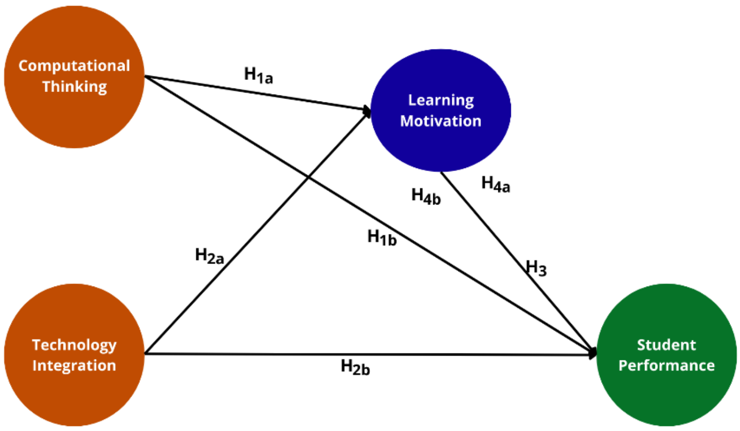

Figure 2. Proposed Model in This Study

Hypothesis:

H_1: Computational Thinking has a significant positive influence on Learning Motivation and Student Performance.

- H_{1a}: Computational Thinking has a significant positive influence on Learning Motivation.
- H_{1b}: Computational Thinking has a significant positive effect on Student Performance.

H_2: Technology Integration has a significant positive influence on Learning Motivation and Student Performance.

- H_{2a}: Technology Integration has a significant positive influence on Learning Motivation.
- H_{2b}: Technology Integration has a significant positive influence on Student Performance.

H_3: Learning Motivation has a significant positive influence on Student Performance.

H_4: Learning Motivation mediates the effect of Computational Thinking and Technology Integration on Student Performance.

- H_{4a}: Learning Motivation mediates the effect of Computational Thinking on Student Performance.
- H_{4b}: Learning Motivation mediates the effect of Technology Integration on Student Performance.

RESULTS AND DISCUSSION

Demographic Analysis

The total number of participants in this study was 426. Most were female (56.8%) compared to male participants (43.2%). Most respondents were 19 years old (45.1%), followed by those aged 18 years (23.9%) and 20 years (21.4%). A significant proportion of respondents were in their third semester (70.7%) compared to those in their first semester (22.8%). The class of 2022 made up the largest group (70.7%), surpassing the class of 2023 (22.8%). Most respondents came from STEM majors (70.2%), compared to those from non-STEM majors (29.8%). Regarding digital technology skills, most respondents rated their skills at the "Moderate" level (62.2%), compared to "Proficient" (17.1%) and "Very Proficient" (15.7%).

Outer Model

Convergent Validity and Construct Reliability

Table 2 displays the evaluation results for several latent constructs in the PLS-SEM model, including Computational Thinking (CT), Technology Integration (TI), Learning Motivation (LM), and Student Performance (SP). Each construct is represented by several indicators that are analyzed based on outer loading, rho_A value, Composite Reliability (CR), and Average Variance Extracted (AVE).

Table 2. Outer Loading, Rho_A, Composite Reliability (CR), and Average Variance Extracted (AVE)

Construct and Items	Outer Loading	Rho_A	Composite Reliability (CR)	Average Variance Extracted (AVE)
Computational Thinking (CT)				
CT1	0.812	0.850	0.895	0.682
CT2	0.815			
CT3	0.831			
CT4	0.844			
Technology Integration (TI)				
TI1	0.843	0.896	0.925	0.755
TI2	0.905			
TI3	0.867			
TI5	0.860			
Learning Motivation (LM)				
LM1	0.882	0.899	0.929	0.767
LM2	0.875			
LM4	0.867			
LM5	0.878			
Student Performance (SP)				
SP1	0.808	0.807	0.866	0.618
SP2	0.816			
SP3	0.726			
SP4	0.791			

Table 2 shows that Computational Thinking (CT) has a significant contribution with an outer loading above 0.812, a rho_A value of 0.850, CR 0.895, and AVE 0.682, indicating good internal consistency and convergent validity. Technology Integration (TI) showed high outer loadings between 0.843 and 0.905, with a rho_A value of 0.896, CR 0.925, and AVE 0.755, indicating strong internal consistency and solid convergent validity. Learning Motivation (LM) contributed strongly with an outer loading of 0.867 to 0.882, supported by a rho_A value of 0.899, CR 0.929, and AVE 0.767, indicating strong internal consistency and excellent convergent validity. Student Performance (SP) had outer loadings varying from 0.726 to 0.816, with rho_A values of 0.807, CR 0.866, and AVE 0.618, which still supported adequate internal consistency and convergent validity.

Discriminant Validity

Table 3 shows the results of the Heterotrait-Monotrait Ratio (HTMT) test used to evaluate the discriminant validity among several latent constructs in the PLS-SEM model. The constructs analyzed include Computational Thinking (CT), Technology Integration (TI), Learning Motivation (LM), and Student Performance (SP).

Table 3. Heterotrait-Monotrait Rasio

	CT	TI	LM	SP
CT				
TI	0.804			
LM	0.737	0.835		
SP	0.738	0.800	0.899	

Based on Table 3, the construct pairs CT-IT (0.804), CT-LM (0.737), CT-SP (0.738), IT-SP (0.800), and IT-LM (0.835) have HTMT values that are below 0.85, indicating that the discriminant validity between these constructs is good. This means that each construct is sufficiently different from the others, so there is no problem with discriminant validity. Meanwhile, the LM-SP pair has an HTMT value of 0.899, close to 0.90. Although this value is still within acceptable limits, it is close to the upper threshold for discriminant validity, which is considered good. This suggests that LM and SP have similarities, although they can still be considered distinct constructs.

Inner Model

R Square

Table 4 shows the R Square (R^2) values for the two latent variables in the model, namely Student Performance and Learning Motivation.

Table 4. Result of R^2 Value

Variable	R Square	Information
Student Performance	0.629	Moderate
Learning Motivation	0.594	Moderate

Based on Table 4, it can be interpreted that Student Performance has an R^2 value of 0.629, which indicates that this model can explain 62.9% of the variability in Student Performance. This indicates that the model has a fairly strong or moderate predictive ability for this variable. Meanwhile, Learning Motivation, with an R^2 value of 0.594, can explain 59.4% of the variability in Learning Motivation, which indicates that the model has a moderate or moderately high predictive ability for this variable.

Hypothesis Test

Table 5 displays the results of hypothesis testing in PLS-SEM analysis. This table illustrates the relationship between latent constructs based on Path Coefficients, T-statistics, P-values, and the final decision on whether the relationship is positive and significant. (Alianti et al., 2023).

Table 5. Hypothesis Test

	Hypothesis	Path Coef	T Statistics	P Values	Decision
H1a	CT -> LM	0.237	4.548	0.000	Positive and Significant
H1b	CT -> SP	0.119	2.136	0.033	Positive and Significant
H2a	TI -> LM	0.586	12.269	0.000	Positive and Significant
H2b	TI -> SP	0.189	2.886	0.004	Positive and Significant
H3	LM -> SP	0.552	8.803	0.000	Positive and Significant
H4a	CT -> LM -> SP	0.131	4.146	0.000	Positive and Significant
H4b	TI -> LM -> SP	0.323	6.629	0.000	Positive and Significant

Based on Table 5, Computational Thinking (CT) has a positive and significant influence on Learning Motivation (LM), where the path coefficient is 0.237 with T-Statistics 4.548 and P-Values 0.000 (H1a is accepted). Supported by recent research shows that CT-based modules are more effective in improving cognitive abilities and learning motivation than traditional scientific methods by increasing students' understanding and problem-solving (Fauzi et al., 2022). These results are consistent with existing literature suggesting that there is a need for standards in CT assessment to avoid variation in research results (Kang et al., 2023). The relevance of Kang et al., (2023) research to this study is that this study examine the relationship between these variables and identify factors that influence the effectiveness of CT implementation in learning while considering possible variations in research results caused by discrepancies in assessment methods. In addition, Başaran & İlter, (2023) also supports that inquiry-based teaching incorporating CT can improve students' motivation and learning experience. The strengths of this study lie in the inclusion of learning motivation as a variable, offering a more holistic understanding of how CT affects student engagement, in contrast to earlier research that primarily emphasized cognitive aspects (Mukasheva & Omirzakova, 2021). These findings are important as they suggest the integration of CT in the curriculum to enhance students' cognitive skills and motivation, which are essential for developing 21st-century competencies. Nonetheless, further research is needed to understand how CT affects learning motivation, including the role of teaching strategies such as project-based learning. Recommendations for future research include longitudinal studies of the impact of CT on student motivation and exploration of the role of technology in CT teaching to increase student engagement.

Computational Thinking (CT) also positively and significantly impacts Student Performance (SP), although the impact is weaker than H1a. The path coefficient value is 0.119 with T-Statistics 2.136 and P-Values 0.033 (H1b accepted). This is supported by recent research which reveals that self-directed programming experience improves student performance in various aspects of CT (Tsai et al., 2021). These findings align with Ching et al., (2018), who highlighted the importance of programming tasks in a collaborative curriculum to develop students' thinking skills. Liu et al., (2023) pointed out that learning engagement is essential for CT skill development. This study adds value by integrating performance metrics, providing a more in-depth understanding of the impact of CT on student outcomes, in line with the challenges of integrating CT into school curricula (Tedre et al., 2021). These findings have important implications for educational practice, particularly in STEM education, and support the view that CT is a foundational skill in various academic disciplines (Maharani et al., 2019). However, further research is needed to explore effective teaching strategies, such as project-based learning, and longitudinal and comparative studies are recommended to assess the long-term impact and best practices in integrating CT into the curriculum.

Technology Integration (TI) has a very strong and significant influence on Learning Motivation (LM), where the path coefficient is 0.586 with T-Statistics 12.269 and P-Values 0.000 (H2a accepted). This is supported by recent research that shows the role of technology in increasing student engagement and motivation (Boateng & Kalonde, 2024). This study highlights the SAMR model as a structured framework for effective technology integration, especially in creating interactive learning experiences that enhance intrinsic motivation. The findings align with research showing that active use of technology increases academic engagement (Alegre, 2023) and Pathan et al., (2024), who emphasized the important role of teacher motivation. The implications of these findings confirm the importance of technology in teaching strategies. It recommends further research on the most effective types of technology and their long-term impact through longitudinal and comparative studies across different educational contexts.

Technology Integration (TI) positively and significantly affects Student Performance (SP). However, its impact is weaker than its effect on LM, with a path coefficient of 0.189, a T-Statistics of 2.886, and P-Values of 0.004 (H2b accepted). Supported by recent research highlighting the effectiveness of technology in education. Alegre, (2023) found that applying technology can improve students' academic outcomes. Boateng & Kalonde, (2024) support these findings through the SAMR model used for technology integration. At the same time, Pathan et al., (2024) emphasized the importance of teacher motivation in this process. Integrating technology through educational games is gaining popularity in learning, as it provides a fun and interactive learning experience, helps students hone cognitive skills and problem-solving, and increases learning motivation. With challenging game elements, educational games create an engaging learning atmosphere and support student's academic success. These findings suggest that technology should be a core part of the curriculum, not just an additional tool. Future research is proposed to explore the most effective technologies, the impact of artificial intelligence and the importance of teacher training through longitudinal and comparative studies.

Learning Motivation (LM) has a strong and significant influence on Student Performance (SP), with a path coefficient of 0.552, a T-Statistics of 8.803, and P-Values of 0.000 (H3 accepted). Recent research shows the importance of motivation in improving academic outcomes. Piliang et al., (2019) found that students with high motivation tend to achieve better academic performance. This study stands out with its focus on specific subjects and quantitative methods, providing strong evidence of the relationship between motivation and performance (Puput Iswandyah Raysharie et al., 2023). The main implication is creating a motivating learning environment for academic success. Further research is proposed to explore motivational factors, the role of intrinsic vs. extrinsic motivation, and its long-term effects through longitudinal and comparative studies.

Learning Motivation (LM) successfully mediates the effect of Computational Thinking (CT) on Student Performance (SP) with a positive and significant effect, with a path coefficient of 0.131, a T-Statistics of 4.146, and P-Values of 0.000 (H4a accepted). Supported by recent research found that high learning motivation strengthens computational thinking ability and improves students' academic performance (Taupik & Fitria, 2023). Motivation is important in optimizing the effectiveness of computational thinking, where motivated students are more active in problem-solving (Gong et al., 2020). The mediating role of motivation provides a deeper understanding of the interaction of these variables (Taupik & Fitria, 2023). It also shows that strategies to increase motivation should be a priority, especially in STEM education (Hsieh et al., 2022). Further research is recommended to examine the long-term effects of motivation through longitudinal and comparative studies across different educational contexts.

Learning Motivation also mediates the effect of Technology Integration (TI) on SP positively and significantly, the path coefficient is 0.323 with T-Statistics 6.629 and P-Values 0.000 (H4b accepted). Recent research supported that gamification with technology, such as Kahoot, can increase students' motivation and critical thinking skills (Petrusly et al., 2024). Research from Hsieh et al., (2022)also showed that learning motivation mediates the relationship between technology integration and student learning outcomes. By focusing on the mediating role of motivation, Petrusly et al., (2024) deepen the understanding of how these variables interact and emphasize the importance of strategies that enhance motivation to maximize the benefits of technology in education (Yanti & Nurhidayah, 2020). Further research should be conducted to explore the impact of technology on student motivation and performance through longitudinal and comparative studies.

Technology integration (TI) has a greater impact than Computational Thinking (CT) in improving student motivation and performance. Technology can increase student engagement and motivation by using interactive tools such as gamification and learning apps, creating a more engaging learning environment. While CT helps develop computational thinking skills, its impact on student performance is more limited without the support of technology. Technology provides a more flexible learning experience and instant feedback and improves students' cognitive and problem-solving skills, ultimately supporting their academic achievement.

The uniqueness of this study lies in its comprehensive approach to exploring the interaction between computational thinking, technology integration, learning motivation, and student performance. By analyzing these elements together, the study offers a more complete framework for educators to improve learning experiences (Emda, 2018). Additionally, the emphasis on creating a structured plan for integrating these components into educational practices is designed to provide practical insights that can be applied in various educational settings (Frameiliada et al., 2023).

However, this study makes a significant contribution to developing an understanding of the relationship between Computational Thinking (CT), Technology Integration (TI), Learning Motivation (LM) and Student Performance (SP). By establishing a framework that connects the four elements, this study offers new insights into optimising digital skills and learning motivation to support academic success in the digital age. In addition, this study also provides practical guidance for educators in enhancing the learning experience by integrating CT and IT. It emphasizes the importance of learning motivation in improving student performance.

LIMITATIONS

This study has several limitations. The sample was limited to university students in Indonesia, which may reduce generalizability to other contexts. The study focused solely on quantitative analysis, leaving qualitative insights unexplored. Additionally, external factors such as socio-economic conditions and institutional support were not considered, which may influence the results. Future studies should address these aspects for a more comprehensive understanding.

CONCLUSION

Computational Thinking (CT) and Technology Integration positively and significantly affect Learning Motivation and Student Performance. Learning motivation is essential in enhancing academic achievement and is a key mediator in the relationship between computational thinking, technology integration, and student performance.

This study specifically found that technology integration has a greater impact on learning motivation than computational thinking while learning motivation significantly improves academic achievement. The findings contribute to developing more effective educational strategies in the digital age by highlighting the importance of optimizing digital skills and learning motivation to achieve better academic achievement. This study also opens up opportunities for further studies, especially in understanding the long-term impact of technology and computational thinking integration in various educational contexts and how these factors can be maximized to improve educational outcomes in the future.

AUTHOR CONTRIBUTIONS

AR and MMF primarily conceptualized the study, formulated the methodology, carried out the formal analysis, and led the investigative work. They also provided the necessary resources. SS and MMF drafted the initial manuscript, which was reviewed and edited by SS, FF, DFS, FB, and MMF. AR and MMF were responsible for the visualization, and SS supervised the entire process. All authors have read and approved the final manuscript.

ACKNOWLEDGEMENT

We thank all participants and Makassar State University for their support. Special appreciation goes to the National Research and Innovation Agency (BRIN) for their insights. We also thank the reviewers for their valuable feedback, which helped improve this article.

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