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Effects of learning methods and self-motivation on students' computational thinking skills

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Abstrak

Penelitian ini bertujuan untuk menganalisis (1) pengaruh langsung metode pembelajaran terhadap kemampuan berpikir komputasional, (2) pengaruh langsung motivasi diri terhadap kemampuan berpikir komputasional, dan (3) peran motivasi diri sebagai mediator antara metode pembelajaran dan kemampuan berpikir komputasional pada siswa Kelas X MPLB SMK Negeri 6 Surakarta. Penelitian kuantitatif ini menggunakan analisis statistik dengan pendekatan metode Partial Least Squares-Structural Equation Modeling (PLS-SEM) menggunakan SmartPLS. Sampel dalam penelitian ini berjumlah 85 siswa. Hasil penelitian menunjukkan bahwa (1) metode pembelajaran berpengaruh positif dan signifikan terhadap kemampuan berpikir komputasional (p-value: 0.000, β: 0.693, t-statistics: 15.211). (2) Motivasi diri juga memberikan pengaruh positif dan signifikan (p-value: 0.000, β: 0.581, t-statistics: 6.073). Temuan lain mengungkapkan adanya (3) pengaruh tidak langsung metode pembelajaran terhadap kemampuan berpikir komputasional melalui motivasi diri (p-value: 0.000, β: 0.451, t-statistics: 5.668). Hasil ini menunjukkan bahwa metode pembelajaran yang baik dapat meningkatkan motivasi siswa, yang pada akhirnya mendorong peningkatan kemampuan berpikir komputasional. Penelitian ini memberikan implikasi penting bagi pendidik dalam merancang metode pembelajaran yang efektif dan memotivasi siswa.

Kata kunci: analisis statistik; implikasi; kuantitatif; mediator; SmartPLS

Abstract

This study aimed to analyze: (1) the direct effect of learning methods on computational thinking skills, (2) the direct effect of self-motivation on computational thinking skills, and (3) the mediating role of self-motivation between learning methods and computational thinking skills among Grade X Office Administration and Business Services (OABS) students at SMK Negeri 6 Surakarta. Methods: This quantitative research employed statistical analysis using Partial Least Squares-Structural Equation Modeling (PLS-SEM) with SmartPLS software. The sample comprised 85 students selected through stratified random sampling. Data were collected using validated 4-point Likert scale questionnaires and analyzed through

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both outer and inner model assessments. Results: The findings revealed that: (1) learning methods demonstrated a positive and significant effect on computational thinking skills ($p = 0.000$, $\beta = 0.693$, $t = 15.211$); (2) self-motivation exhibited a positive and significant effect on computational thinking skills ($p = 0.000$, $\beta = 0.581$, $t = 6.073$); and (3) self-motivation significantly mediated the relationship between learning methods and computational thinking skills ($p = 0.000$, $\beta = 0.451$, $t = 5.668$). Conclusion: These results indicate that effective learning methods enhance student motivation, which subsequently improves computational thinking skills. The study provides important implications for educators in designing effective and motivating instructional approaches that foster 21st-century computational competencies.

Keywords: implications; mediator; SmartPLS; statistical analysis; quantitative

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Introduction

Computational thinking represents one of the most critical skills amid rapid information technology development. Computational thinking refers to a thinking approach that encompasses the ability to solve problems using computational concepts and principles (Christi & Rajiman, 2023). This cognitive framework serves as an essential foundational skill for confronting life challenges and future complexities characterized by increasing competition and sophistication (Juldial & Haryadi, 2024). Computational thinking capabilities enable individuals to engage in critical and analytical reasoning, which are highly demanded across various professional domains. Furthermore, computational thinking enhances problem-solving expertise that is effective, efficient, and optimal, forming the foundation for creative, critical, and independent solution development (Fauji et al., 2023). The significance of computational thinking as a cognitive process encompasses computer application development and problem-solving facilitation across diverse disciplines, including science, mathematics, and humanities (Megawati et al., 2023).

Contemporary educational contexts require competent human resources as valuable assets for developing millennial generations prepared for emerging challenges, ensuring young people become more prepared and competitive in facing increasingly complex and dynamic global challenges (Rezky et al., 2019). The development of computational thinking has become an integral component of school curricula worldwide. This integration relates to calls for computational thinking to be considered a "21st Century" competency, valuable for all students as a transferable process for problem-solving and building understanding of human behavior and systems (Falloon, 2024). Computational thinking skills are essential for developing new competencies and capabilities in educational contexts due to technological advancement (Alonso-García et al., 2024). However, field evidence indicates that current computational thinking capabilities remain inadequate, as demonstrated by numerous prospective teacher students exhibiting low success expectations and high anxiety toward computational thinking (Barkela et al., 2024).

The challenge of developing student computational thinking abilities involves analyzing requirements for developing innovative approaches to computational thinking in the information age and outlining the necessity for innovative education and instruction (Xiaohong et al., 2021). While efforts to integrate computational thinking into education exist, numerous barriers continue to hinder deep understanding among adolescents and young people. Student acceptance of computational thinking presents educational challenges due to multiple factors requiring attention in computational thinking development. Learning methods represent one factor influencing computational thinking skills (Mueller et al., 2017). Mueller emphasized the importance of using assessment system approaches to measure computational thinking abilities, involving assessment as learning, assessment of learning, and assessment for learning. This approach helps teachers understand and enhance student computational thinking abilities effectively. Additionally, self-motivation serves as another factor influencing computational thinking, as Yusup et al. (2023) explained that students with strong computational thinking skills tend to demonstrate higher motivation in problem-solving and knowledge development.

Based on preliminary study results through questionnaires distributed to OABS students at SMK Negeri 6 Surakarta, conclusions indicated that computational thinking abilities among OABS competency students at SMK Negeri 6 Surakarta remain suboptimal, though computational thinking represents an alternative for problem-solving. Factors suspected to influence computational thinking abilities among Grade X OABS students at SMK Negeri 6 Surakarta include learning methods and self-motivation.

Self-motivation demonstrates connections to computational thinking, as research by Bers et al. (2014) revealed that intrinsic motivation in children, such as student curiosity and satisfaction in completing challenges, can strengthen computational thinking development. Self-motivation is important because it functions as a driver for achieving positive outcomes. Individuals engage in activities due to internal motivation. High learning motivation enables individuals to achieve optimal results (Rahman, 2022). Self-motivation was selected as a mediator in examining learning method effects on computational thinking abilities, based on research by Copriady (2015) investigating self-motivation as effective mediation between ICT implementation in teaching and ICT application in learning. Research by McDonough and Crocker (2007) also demonstrated that self-motivation can mediate relationships between psychological needs and affective and behavioral outcomes. These studies, combined with connections between self-motivation effects and computational thinking, as well as relationships between self-motivation and learning methods, strengthen the proposition that self-motivation provides both direct effects and effective mediation roles in research.

This research offers novelty compared to previous studies by not only analyzing direct relationships or effects of learning methods and self-motivation on computational thinking abilities, but also examining indirect effects of learning methods on computational thinking abilities through self-motivation as a mediating variable. Based on this background, this research aims to answer primary questions: (1) whether learning methods influence computational thinking abilities among Grade X OABS students at SMK Negeri 6 Surakarta, (2) whether self-motivation influences computational thinking abilities among Grade X OABS students at SMK Negeri 6 Surakarta, and (3) whether learning methods influence computational thinking abilities through self-motivation as a mediating variable. By addressing these questions, this research is expected to provide valuable knowledge for principals, teachers, students, and secondary education policymakers.

Research Methods

This research was conducted at SMK Negeri 6 Surakarta with research approval according to research permit response letter Number 000.9.2/201, implemented through six stages: preparation, implementation (data collection and analysis), research report compilation, examination, and revision. The research period extended from August 2024 to May 2025. This study employed a quantitative approach with survey methods to examine learning method and self-motivation effects on computational thinking abilities among Grade X OABS students at SMK Negeri 6 Surakarta. The research population comprised 108 students representing all Grade X OABS students at SMK Negeri 6 Surakarta, with a sample of 85 students calculated using the Slovin formula.

The sampling technique employed probability sampling through stratified random sampling to enhance representation of each population stratum. The population was initially divided into three homogeneous strata based on specific characteristics. Stratification criteria were based on class origin, specifically Grade X OABS classes at SMK Negeri 6 Surakarta consisting of three classes (OABS 1, OABS 2, OABS 3). The population was divided into these three strata based on class origin, assuming that learning characteristics and student motivation could differ between classes. Following division, samples were proportionally selected using the Slovin formula from each stratum: 28 students from Grade X OABS 1, 28 students from Grade X OABS 2, and 29 students from Grade X OABS 3, ensuring balanced representation of each group in research data.

Data collection employed researcher-developed questionnaires distributed through Google Forms to targeted students and respondents. Data confidentiality was ensured through aggregate presentation without identifying names or personal identities, strictly for academic purposes without third-party distribution. The selected questionnaire type was closed-ended using a 4-point Likert scale (strongly agree, agree, disagree, strongly disagree), allowing respondents to select answers according to their conditions. The 4-point Likert scale selection, adapted from Sugiyono (2016), was based on considerations to avoid neutral responses (central tendency bias), encouraging respondents to choose positive or negative tendencies more decisively while facilitating data analysis by reducing unnecessary variance.

Prior to research implementation, pilot testing was conducted to measure research validity and reliability for indicators and items developed by researchers. Pilot testing involved 30 Grade X OABS students at SMK Negeri 6 Surakarta, proving valid and reliable for learning method, self-motivation, and computational thinking variables. The learning method variable comprised 5 statements covering 5 indicators: material understanding, student engagement, teacher-student interaction, student independence, and group cooperation. The motivation variable included 5 statements with indicators encompassing: desire and aspiration for success, learning need motivation, future hopes and aspirations, and self-appreciation or reinforcement. The computational thinking variable consisted of 5 statements with specific dimensions including: creativity, algorithmic thinking, critical thinking, problem-solving, and pattern recognition.

This research employed Partial Least Squares-Structural Equation Modeling (PLS-SEM) data analysis techniques using SmartPLS software. PLS-SEM method selection enabled testing direct and indirect relationship effects between research variables. Instrument validity and reliability assessment was conducted through outer model analysis, encompassing convergent validity, discriminant validity, and reliability tests. Hypothesis testing was performed through inner model analysis to determine direct effects of learning methods and self-motivation on computational thinking abilities, as well as indirect effects of learning methods on computational thinking abilities through self-motivation as a mediating variable.

Results and Discussion

Results

Outer Model Assessment

As presented in Table 1, convergent validity analysis results demonstrated that all research variables learning methods, self-motivation, and computational thinking possessed indicators meeting established criteria. The learning method variable comprised 5 indicators with loading factor values ranging from 0.719 to 0.817 and an Average Variance Extracted (AVE) value of 0.620, indicating that 62% of indicator variance could be explained by the primary construct. The self-motivation variable also consisted of 5 indicators with excellent loading factor values ranging from 0.835 to 0.886 and an AVE value of 0.744, meaning 74% of indicator variance could be explained by the primary construct, demonstrating very strong convergent validity. Meanwhile, the computational thinking variable exhibited loading factors between 0.737 and 0.882 with an AVE of 0.663, showing that 66% of indicator variance could be explained by the primary construct. All loading values exceeded the 0.500 threshold, indicating that these three variables possessed adequate convergent validity and were suitable for use as measurement instruments in this research.

The Heterotrait-Monotrait (HTMT) analysis results shown in Table 2 revealed that all inter-variable relationships in this research fell below the 0.90 threshold, indicating that despite relatively strong correlations between variables, each could still be distinguished as different constructs. HTMT values between computational thinking and learning methods were 0.876, between computational thinking and self-motivation were 0.894, and between learning methods and self-motivation were 0.872. These three values demonstrated relatively high correlations but remained within acceptable limits, ensuring all variables met discriminant validity requirements and could be considered as independent constructs.

Table 1
Loading Factor and Average Variance Extracted (AVE) Values

Variable	Item	Loading	AVE	
Learning Methods	MP1	0.813	0.620	Valid
	MP4	0.817		
	MP7	0.785		
	MP12	0.801		
	MP14	0.719		
Self-Motivation	MD3	0.860	0.744	Valid
	MD4	0.880		
	MD8	0.886		
	MD11	0.835		
	MD12	0.849		
Computational	BP2	0.858	0.663	Valid
Thinking	BP4	0.882		
	BP7	0.774		
	BP10	0.737		
	BP13	0.812		

Source: Data processed with SmartPLS (2025)

Table 2
Heterotrait-Monotrait (HTMT) Values

Variable	BP	MP	MD
BP	-		
MP	0.876		
MD	0.894	0.872	-

Source: Data processed with SmartPLS (2025)

Based on Table 3, the Fornell-Larcker criterion test used to evaluate discriminant validity showed that all research variables met discriminant validity criteria because the square root of AVE for each variable was higher than its correlations with other variables. The square root of AVE for computational thinking (0.814) exceeded its correlations with learning methods (0.758) and self-motivation (0.804), demonstrating that this variable could explain its indicators better than relationships with other constructs. Similarly, the learning method variable possessed a square root of AVE of 0.788, higher than its correlations with computational thinking (0.758) and self-motivation (0.775), indicating good discriminant validity. The same pattern appeared for self-motivation, with a square root of AVE of 0.862, greater than its correlations with computational thinking (0.804) and learning methods (0.775). Consequently, these three variables could be considered as validly different and non-overlapping constructs.

Table 3
Fornell-Lacker Criterion Values

Variable	BP	MP	MD
BP	0.814		
MP	0.758	0.788	
MD	0.804	0.775	0.862

Source: Data processed with SmartPLS (2025)

Table 4
Cross Loading

	MP	MD	BP
MP1	0.813	0.617	0.627
MP2	0.817	0.612	0.532
MP3	0.785	0.550	0.525
MP4	0.801	0.639	0.655
MP5	0.719	0.620	0.625
MD1	0.573	0.860	0.619
MD2	0.744	0.880	0.600
MD3	0.736	0.886	0.771
MD4	0.655	0.835	0.788
MD5	0.611	0.849	0.662
BP1	0.648	0.624	0.858
BP2	0.627	0.649	0.882
BP3	0.537	0.663	0.774
BP4	0.584	0.689	0.737
BP5	0.680	0.641	0.812

Source: Data processed with SmartPLS (2025)

As demonstrated in Table 4, cross-loading analysis results indicated that all indicators from the three variables learning methods, self-motivation, and computational thinking exhibited highest loading values on their respective construct variables compared to other variables, confirming discriminant validity fulfillment. Learning Method indicators (MP1 through MP5) showed highest loadings on the learning method variable; for example, MP1 demonstrated a loading value of 0.813 on learning methods, substantially higher than on self-motivation (0.617) and computational thinking (0.627), indicating these indicators better represented the learning method construct. Similarly, Self-Motivation indicators (MD1 through MD5) exhibited highest loadings on self-motivation, such as MD1 with a loading value of 0.860 on self-motivation compared to learning methods (0.573) and computational thinking (0.619), demonstrating that these indicators consistently reflected the self-motivation variable. The same pattern occurred for Computational Thinking indicators (BP1 through BP5), which displayed highest loadings on computational thinking, such as BP1 with a loading value of 0.858 on its own construct, higher than learning methods (0.648) and self-motivation (0.624). Consequently, each indicator maintained stronger relationships with its original variable compared to other variables, ensuring good discriminant validity for all three variables.

Table 5 presents Composite Reliability (CR) analysis results, showing that all research variables learning methods, self-motivation, and computational thinking demonstrated high reliability levels because Composite Reliability values exceeded the 0.70 threshold. The learning method variable exhibited a Composite Reliability value of 0.848, indicating strong inter-indicator correlation and robust internal consistency, making it dependable for research purposes. The self-motivation variable achieved an exceptionally high Composite Reliability value of 0.918, signifying that constituent indicators were highly consistent in measuring the construct, establishing it as a highly reliable measurement instrument. Meanwhile, the computational thinking variable's Composite Reliability value of 0.871 also demonstrated high internal consistency levels, indicating trustworthiness in measuring intended concepts. Consequently, all three variables possessed satisfactory measurement quality and could be reliably employed in research applications.

Table 5
Composite Reliability (CR) Values

Variable	*Composite Reliability*	Status
MP	0.848	Reliabel
MD	0.918	Reliabel
BP	0.871	Reliabel

Source: Data processed with SmartPLS (2025)

As shown in Table 6, reliability testing using Cronbach's Alpha values demonstrated that all research variables learning methods, self-motivation, and computational thinking exhibited satisfactory internal consistency because all values exceeded the 0.70 threshold. The Cronbach's Alpha value for learning methods was 0.847, indicating consistent inter-indicator correlation and research dependability. The self-motivation variable achieved the highest value at 0.914, signifying very strong reliability and indicator consistency in measuring self-motivation aspects, ensuring trustworthy and stable measurement results. Meanwhile, the computational thinking variable demonstrated a Cronbach's Alpha value of 0.871, also indicating high reliability and satisfactory indicator suitability in measuring computational thinking concepts. Therefore, all three variables possessed adequate dependability for various research analyses, ensuring consistent data capture across different respondents and strengthening internal research validity through accurate variable representation.

Table 6
Cronbach's alpha (α) Values

Variable	*Cronbach's alpha*	Status
MP	0.847	Reliabel
MD	0.914	Reliabel
BP	0.871	Reliabel

Source: Data processed with SmartPLS (2025)

Table 7 indicates that all Variance Inflation Factor (VIF) values fell within acceptable ranges between 1.000-2.506, well below the threshold of 5, signifying no multicollinearity problems in the conducted research. These favorable VIF values enabled continuation of research processes through hypothesis testing.

Table 7
VIF Result Values

	BP	MP	MD
BP			
MP	2.506		1.000
MD	2.506		

Source: Data processed with SmartPLS (2025)

Based on Table 8, R-square analysis results revealed that 61.6% of variance in computational thinking variables could be explained by learning method and self-motivation variables, while the remaining 38.4% was influenced by factors outside the research model. The R^2 value of 0.616 fell within the substantial category, indicating that this research model was sufficiently robust in explaining factors influencing computational thinking abilities. Meanwhile, the R^2 value for self-motivation was 0.601, meaning 60.1% of variance in self-motivation could be explained by learning method variables, demonstrating that learning methods played important roles in shaping student motivation. Similar to previous findings, this R^2 value also belonged to the substantial category, indicating that the model possessed high predictive strength in explaining factors influencing student self-motivation.

Table 8
R-Square (R^2) Result Values (Coefficient of Determination)

Variable	*R-Square (R^2)*	Description
BP	0.616	Substantial
MD	0.601	Substantial

Source: Data processed with SmartPLS (2025)

As presented in Table 9, f-square test results showed that the f^2 value for learning method effects on computational thinking was 0.061, categorized as weak, indicating that learning methods provided only small contributions to computational thinking variation. This suggested that other more dominant factors, such as learning environments or cognitive intelligence, might play greater roles in influencing computational thinking abilities. Conversely, the f^2 value of 1.506 demonstrated that learning methods exerted very strong effects on student self-motivation, supporting theories that innovative learning approaches such as project-based learning or gamification could enhance learning motivation. Meanwhile, the f^2 value for self-motivation effects on computational thinking of 0.351 was also categorized as strong, indicating that self-motivation played important roles in enhancing student computational thinking abilities, particularly through intrinsic factors such as curiosity, persistence, and learning desire. Additionally, the upsilon (υ) value of 0.774 showed that self-motivation possessed strong mediation roles in relationships between learning methods and computational thinking abilities, significantly exceeding the 0.14 threshold.

Table 9
f-Square (f^2) Result Values

Variable	*f-square (f^2)*	*upsilon (υ)*	Description
MP -> BP	0.061		Weak
MP -> MD	1.506		Strong
MD -> BP	0.351		Strong
MP -> MD -> BP		0.774	Strong

Source: Data processed with SmartPLS (2025)

Table 10 displays Q^2 values for predictive relevance assessment. Learning methods achieved $Q^2 = 0.272$, indicating predictive relevance and demonstrating that indicators within learning methods could adequately explain variance in the construct. Self-motivation exhibited $Q^2 = 0.300$, also showing predictive relevance and indicating that indicators within self-motivation could explain the variable satisfactorily. Computational thinking demonstrated $Q^2 = 0.391$, signifying higher predictive relevance compared to learning methods and self-motivation.

Table 10
Q^2 Result Values

Variable	*Q^2 Result*	Description
MP	0.272	Has Predictive Relevance
MD	0.300	Has Predictive Relevance
BP	0.391	Has Predictive Relevance

Source: Data processed with SmartPLS (2025)

As demonstrated in Table 11, all research hypotheses proved significant. The first hypothesis showed that learning methods significantly and positively influenced computational thinking abilities, with t-statistics of 15.211 and p-value below 0.05, explaining 69.3% of computational thinking variance. The 95% confidence interval indicated learning method effects ranged between 0.607 and 0.785, meaning improved learning methods corresponded to enhanced computational thinking abilities. The second hypothesis confirmed that self-motivation also significantly influenced computational thinking, with t-statistics of 6.073 and p-value of 0.000, explaining 58.1% of computational thinking ability variance. The confidence interval showed self-motivation effects ranged from 0.391 to 0.848. Meanwhile, the third hypothesis demonstrated that self-motivation significantly mediated learning method effects on computational thinking, with t-statistics of 5.668 and p-value of 0.000. Indirect effects of learning methods through self-motivation exhibited confidence intervals between 0.306 and 0.690, explaining 45.1% of computational thinking ability variance, confirming that self-motivation played important roles as a mediator.

Table 11
Final Results

Variable	β	*t statistics*	*p values*	*Confidence Interval (CI)*		*Significance*
				2.5%	97.5%	
MP => BP	0.243	2.272	0.023	0.607	0.785	Sig
MD => BP	0.581	6.073	0.000	0.391	0.848	Sig
MP => MD => BP	0.451	5.668	0.000	0.306	0.620	Sig

Source: Data processed with SmartPLS (2025)

Figure 1 illustrates the structural model results, displaying path coefficients and significance levels between constructs. The figure demonstrates the direct relationships between learning methods and computational thinking, self-motivation and computational thinking, as well as the mediating pathway through self-motivation.

Figure 1
Final structural model results

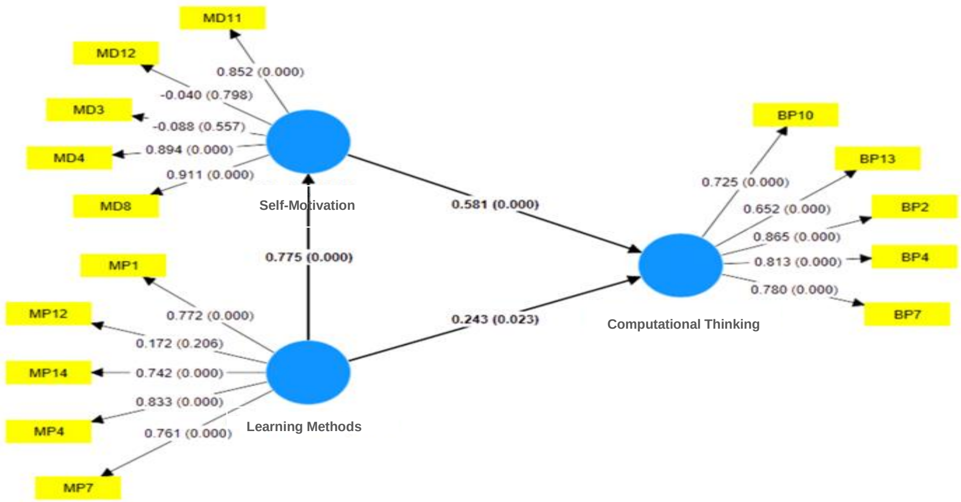

Table 12 presents model fit evaluation results. The Standardized Root Mean Square Residual (SRMR) values for both saturated and estimated models were 0.078, falling below the 0.08 threshold and within the 95% confidence interval (0.082-0.088), indicating good model fit between observed data and theoretical models. Additionally, the d_ULS (Difference of Unweighted Least Squares) value of 0.733 and d_G (Difference of Geodesic Distance) value of 0.318 for estimated models also fell below the upper bounds of 95% confidence intervals from bootstrapping results, specifically 0.805-0.939 for d_ULS and 0.424-0.485 for d_G. These results indicated no significant differences between models and empirical data, confirming structural model adequacy. Overall, evaluation results confirmed that research models met satisfactory fit criteria and were valid for further analysis and hypothesis testing.

Table 12
Model Fit and Quality Evaluation

Fit Index	Model	Original Sample (O)	Sample Mean (M)	95% CI	99% CI
SRMR	Saturated model	0.078	0.070	0.082	0.088
	Estimated model	0.078	0.070	0.082	0.088
d-ULS	Saturated model	0.733	0.593	0.805	0.939
	Estimated model	0.733	0.593	0.805	0.939
d-G	Saturated model	0.318	0.312	0.424	0.485
	Estimated model	0.318	0.312	0.424	0.485

Source: Data processed with SmartPLS (2025)

Discussion

Computational thinking represents a crucial aspect because it trains individuals to solve problems systematically, logically, and efficiently in the technology-driven digital era. Through computational thinking, students not only learn to understand technological operations but also develop analytical thinking patterns involving complex problem-solving. These skills are highly relevant not only for information technology fields but also beneficial in daily life and increasingly data- and technology-based work environments. Therefore, equipping students with computational thinking abilities helps them become adaptive, creative individuals prepared to face future challenges in Industry 4.0 and society.

This research focused on predicting and examining roles of two exogenous variables expected to provide significant effects on student skills in educational contexts, primarily computational thinking abilities. These two variables encompassed learning methods and self-motivation, selected based on various theoretical foundations and previous research results supporting their relevance in student thinking skill contexts.

For Hypothesis 1, research results demonstrated that learning methods significantly influenced computational thinking abilities among SMK Negeri 6 Surakarta students with a 24.3% contribution. These findings aligned with previous research by Mardiany et al. (2024) and Tedre and Denning (2016), which similarly showed positive relationships between learning methods and computational thinking abilities. Item analysis revealed that learning method variable indicators possessed loading factor values between 0.719 and 0.817, indicating that each indicator sufficiently supported research implementation. Learning Method indicator 4 (MP4), for example, demonstrated that classroom activities encouraging active student participation positively impacted computational thinking abilities. Studies by Grover and Pea (2018) and Kalelioglu et al. (2016) reinforced these results by emphasizing the importance of collaboration and student engagement. Learning Method indicators 1 (MP1) and 14 (MP14) reflected that material understanding and student comfort in learning significantly influenced computational thinking processes. Additionally, indicators such as Learning Method 7 (MP7) and 12 (MP12) showed the importance of effective communication and student independence in learning processes. Learning Method 14 (MP14) also confirmed that group work could enhance learning effectiveness. Overall, learning methods proved to provide significant and positive effects on computational thinking abilities (t statistics = 2.272, p value = 0.023), supported by indicator strength within the variable. These findings were reinforced by research by Angeli et al. (2016), demonstrating that learning methods represent key factors in developing student computational thinking abilities.

For Hypothesis 2, research results indicated that self-motivation significantly influenced computational thinking abilities among SMK Negeri 6 Surakarta students, with a 58.1% contribution, demonstrating the important role of this variable in supporting computational thinking ability development. Conducted tests proved significant relationships between self-motivation as exogenous variables and computational thinking abilities as endogenous variables. These findings aligned with previous research by Yusup et al. (2023), Supiarmo et al. (2021), and Ryan and Deci

(2020), stating that intrinsic motivation contributed to cognitive abilities, including computational thinking contexts. Items within self-motivation variables possessed loading factors ranging from 0.835 to 0.886, indicating strong contributions from each indicator. For example, Self-Motivation 3 (MD3) described strong student desires for success, Self-Motivation 4 (MD4) showed motivation due to educational importance, and Self-Motivation 8 (MD8) emphasized positive views toward academic achievement as motivation forms. Additionally, Self-Motivation items 11 (MD11) and 12 (MD12) confirmed that encouragement from teachers and peers, as well as pride in personal achievements, strengthened student motivation. These findings were supported by discoveries from Yeager et al. (2019), stating that growth mindset approaches could enhance student engagement. Overall, self-motivation variables demonstrated significant positive effects on computational thinking abilities (t statistics = 6.073, p value = 0.000), as all indicators provided strong contributions supporting self-motivation roles. Consequently, higher student self-motivation corresponded to enhanced computational thinking abilities.

For Hypothesis 3, this research examined whether learning methods possessed indirect effects on computational thinking abilities through self-motivation as mediators. Test results showed that despite non-significant direct effects of learning methods on computational thinking abilities (t statistics: 5.668, p value: 0.000, β: 0.451), indirect effect contributions reached 45.1% of total effects of 0.693. This meant self-motivation played important roles as partial mediators because portions of learning method effects on computational thinking abilities were channeled through self-motivation. These findings aligned with research by Tabas et al. (2024) and Prihanggara et al. (2024), demonstrating that learning methods influenced student self-motivation improvements by 30.5%. Previous research also supported that learning methods could trigger motivation, ultimately impacting computational thinking ability enhancement. When self-motivation increased, students tended to become more active, persistent, and interested in solving problems systematically. These results aligned with research by Copriady (2015) and McDonough and Crocker (2007), concluding that self-motivation effectively mediated learning method effects on computational thinking abilities. Therefore, self-motivation was believed capable of strengthening indirect relationships between learning methods and computational thinking abilities significantly.

Conclusion

This research demonstrated that learning methods and self-motivation exerted significant and positive effects on computational thinking abilities among Grade X OABS students at SMK Negeri 6 Surakarta. Implementing effective learning methods enhanced student computational thinking abilities, while high self-motivation also encouraged ability improvement. Additionally, findings revealed that learning methods indirectly influenced computational thinking abilities through self-motivation mediation roles, representing novel discoveries distinguishing this research from previous studies such as research by Yusup et al. (2023) and Mardiany et al. (2024), or other studies referenced in this research. This means that improved learning methods correspond to enhanced student self-motivation, ultimately improving computational thinking abilities. Nevertheless, this research possessed several limitations, including items with low loading factor values that did not fully support conducted analyses. Therefore, deeper instrument development was necessary, such as strengthening initial validity testing or revising suboptimal items. Additionally, f-square values for learning method effects on computational thinking abilities remained weak, suggesting the need for further research model development by adding relevant variables or strengthening instrument constructs to capture stronger and more meaningful effects. This research proved novelty through discovering indirect effects of learning methods on computational thinking abilities through self-motivation mediation. The study concluded that combinations of learning methods and self-motivation played important roles in enhancing computational thinking abilities. Implementing appropriate learning methods and improving student self-motivation could enhance student computational thinking abilities. The study's implications for educational practice suggest that vocational educators should focus on developing innovative learning methods that simultaneously enhance student self-motivation, as this dual approach proves most effective for developing computational thinking skills. Future research should explore additional factors contributing to computational thinking development and investigate the effectiveness of specific pedagogical interventions in different vocational education contexts.

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