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# MODELING THE IMPACT OF MOBILE AND E-LEARNING ON COMPUTATIONAL THINKING SKILLS AMONG ENGINEERING STUDENTS USING SEM-PLS

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***Abstract***

*The rapid advancement of digital learning technologies has transformed higher education, emphasizing the need to develop higher-order cognitive skills such as computational thinking. This study investigates the impact of e-learning and mobile learning on computational thinking skills among engineering students in Indonesia using the Structural Equation Modeling–Partial Least Squares (SEM-PLS) approach. A total of 216 undergraduate students participated in this study. The measurement model demonstrates satisfactory reliability and validity, with indicator loadings exceeding 0.70. Cronbach's alpha values range from 0.798 to 0.896, and composite reliability values range from 0.869 to 0.928, indicating strong internal consistency. Convergent validity is confirmed by Average Variance Extracted (AVE) values between 0.625 and 0.763, while discriminant validity meets the Fornell–Larcker criterion. The structural model results reveal that e-learning has a significant positive effect on computational thinking ($\beta = 0.509$, $p < 0.001$), followed by mobile learning ($\beta = 0.421$, $p < 0.001$). The model exhibits substantial explanatory power ($R^2 = 0.888$), indicating that both constructs jointly explain a large proportion of variance in computational thinking skills. This study contributes to the literature by providing empirical evidence on the effectiveness of integrating e-learning and mobile learning in enhancing computational thinking. The findings highlight the importance of combining structured and flexible digital learning environments to support the development of essential 21st-century skills in engineering education.*

**Keywords:** *Computational Thinking; E-Learning; Mobile Learning; SEM-PLS; Engineering Education*

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## INTRODUCTION

The rapid digital transformation of higher education has fundamentally reshaped how knowledge is delivered, accessed, and constructed. The widespread adoption of e-learning platforms and mobile learning technologies has enabled more



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flexible, personalized, and ubiquitous learning experiences, particularly in engineering education. Within this evolving landscape, fostering higher-order cognitive skills especially computational thinking has become increasingly important (Hakiki, M., et al. 2024). Computational thinking, which includes problem decomposition, pattern recognition, abstraction, and algorithmic design, is widely regarded as a core competency required for engineering students in the era of digital innovation and Industry 4.0 (Yusvana, R., & Papadakis, S. 2026).

E-learning environments have been extensively implemented to support structured, content-rich, and interactive learning processes. Prior studies suggest that e-learning enhances student engagement, promotes self-regulated learning, and improves conceptual understanding through multimedia integration and asynchronous accessibility (Curum, B., & Khedo, K. K. 2021). In contrast, mobile learning extends these capabilities by enabling real-time, context-aware, and ubiquitous learning experiences. The portability and immediacy of mobile devices allow students to engage in continuous learning, collaboration, and instant feedback, which are critical factors in developing complex cognitive abilities such as computational thinking (Tsai, C. W., et al. 2017).

Despite the growing body of literature on digital learning, several important gaps remain. First, most existing studies examine e-learning and mobile learning independently, thereby limiting a comprehensive understanding of their combined impact on higher-order cognitive skills. Second, prior research has predominantly focused on general learning outcomes such as academic performance, motivation, and engagement, with limited attention given to computational thinking as a distinct and measurable construct. Third, there is a lack of rigorous empirical modeling that simultaneously examines the structural relationships among digital learning constructs and computational thinking, particularly using advanced analytical approaches capable of handling latent variables (Guri-Rosenblit, S., & Gros, B. 2011).

Furthermore, in the context of developing countries such as Indonesia, the integration of digital learning technologies presents unique challenges related to infrastructure, digital literacy, and pedagogical readiness. Although previous studies in Southeast Asia have reported positive effects of digital learning adoption, empirical evidence specifically addressing the development of computational thinking skills among engineering students remains limited. This highlights the need for context-specific investigations that provide robust and generalizable findings (Bezuidenhout, A. 2018).

This study addresses these gaps by proposing an integrated framework that examines the effects of e-learning and mobile learning on computational thinking skills. The novelty of this research lies in three key aspects. First, it integrates e-learning and mobile learning into a unified model, offering a more comprehensive understanding of digital learning ecosystems. Second, it explicitly focuses on computational thinking as a key outcome variable, extending beyond traditional measures of learning effectiveness. Third, it provides empirical evidence from engineering students in Indonesia, thereby contributing to the limited body of research in developing country contexts (Raes, A., et al. 2020).

By examining the combined and individual effects of digital learning environments on computational thinking, this study contributes to the advancement of technology-enhanced learning research. The findings are expected to provide practical insights for educators, instructional designers, and policymakers in designing more effective digital learning strategies that support the development of essential 21st-century skills.

Based on the theoretical foundation and empirical evidence from prior studies, the following hypotheses are proposed:

**H1:** E-learning has a positive and significant effect on students' computational thinking skills.

**H2:** Mobile learning has a positive and significant effect on students' computational thinking skills.

These hypotheses are grounded in the premise that structured digital learning environments (e-learning) and flexible, ubiquitous learning platforms (mobile learning) enhance students' ability to engage in analytical reasoning, problem-solving, and algorithmic thinking, which are essential components of computational thinking.

## METHODOLOGY

### A. Research Design

This study employed a quantitative research design using a cross-sectional survey approach to examine the relationships between e-learning, mobile learning, and computational thinking skills among engineering students. The study was grounded in a variance-based Structural Equation Modeling (SEM) framework, specifically Partial Least Squares (PLS-SEM), which is widely recognized for its suitability in predictive modeling and analysis of complex relationships among latent constructs (Hair, J., & Alamer, A. 2022).

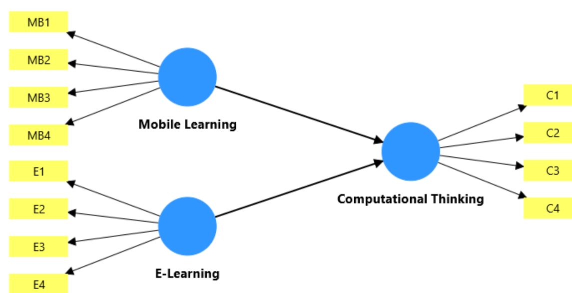


Figure 1. Structural Equation Modeling (SEM) framework

PLS-SEM was selected due to its robustness in handling relatively small to medium sample sizes, non-normal data distributions, and reflective measurement models. Additionally, this approach enables simultaneous assessment of the measurement model (validity and reliability) and the structural model (hypothesis testing), making it particularly appropriate for examining the predictive relationships in this study (Hair, J. F., et al. 2022).

## B. Sample and Data Collection

The sample consisted of 216 undergraduate engineering students in Indonesia who had prior experience using both e-learning platforms and mobile learning applications in their academic activities. A purposive sampling technique was employed to ensure that all respondents met the predefined inclusion criteria: (1) actively enrolled in an engineering program, and (2) having prior exposure to digital learning environments.

Data were collected through a structured online questionnaire distributed via institutional communication channels, including academic mailing lists and learning management systems. Participation was voluntary, and respondents were informed about the purpose of the study prior to completing the questionnaire, ensuring informed consent and adherence to ethical research standards.

To ensure the representativeness and diversity of the sample, participants were drawn from various engineering disciplines and academic levels. The demographic characteristics of the respondents are presented in Table 1.

Table 1. Demographic Profile of Respondents (N = 216)

| Category | Description | n | % |
|---|---|---|---|
| Gender | Male | 132 | 61.1 |
| | Female | 84 | 38.9 |
| Age | 18–20 years | 78 | 36.1 |
| | 21–23 years | 112 | 51.9 |
| | >23 years | 26 | 12.0 |
| Year of Study | First Year | 42 | 19.4 |
| | Second Year | 56 | 25.9 |
| | Third Year | 64 | 29.6 |
| | Fourth Year | 54 | 25.0 |
| Field of Study | Information Technology and Information Technology Education | 88 | 40.7 |
| | Electrical Engineering | 64 | 29.6 |
| | Other Engineering Fields | 64 | 29.6 |

The demographic distribution indicates that the sample captures variability across gender, age groups, academic levels, and engineering disciplines. This diversity enhances the external validity of the study and supports the generalizability of the findings within the broader context of engineering education in Indonesia. Moreover, the inclusion of students with prior experience in digital learning environments ensures the relevance and reliability of the responses in examining the impact of e-learning and mobile learning on computational thinking skills.

## C. Research Instrument

Data were collected using a structured questionnaire designed to measure three latent constructs: Mobile Learning (ML), E-Learning (EL), and Computational Thinking (CT). All measurement items were adapted from established studies in technology-enhanced learning and were contextually modified to align with digital learning practices in engineering education.

The instrument employed a five-point Likert scale, ranging from 1 (*strongly disagree*) to 5 (*strongly agree*), to capture respondents' perceptions consistently. Each construct was operationalized using reflective indicators to ensure compatibility with the PLS-SEM approach.

Table 2. Measurement Items of Research Constructs

| Construct | Code | Measurement Item |
|---|---|---|
| Mobile Learning (ML) | MB1 | Mobile learning platforms allow me to access learning materials anytime and anywhere. |
| | MB2 | Mobile learning provides flexibility in managing my learning activities. |
| | MB3 | Mobile applications enhance my interaction and engagement in learning. |
| | MB4 | Mobile learning improves the effectiveness of my learning experience. |
| E-Learning (EL) | E1 | E-learning platforms provide well-structured learning content. |
| | E2 | The quality of materials in e-learning systems supports my understanding. |
| | E3 | E-learning systems are easy to use and navigate. |
| | E4 | E-learning enhances the effectiveness of formal learning processes. |
| Computational Thinking (CT) | C1 | I can break down complex problems into smaller, manageable parts. |
| | C2 | I can identify patterns in data or problems. |
| | C3 | I can apply abstraction to simplify complex problems. |
| | C4 | I can design step-by-step solutions (algorithms) to solve problems. |

All items were designed to reflect key theoretical dimensions of each construct. Mobile Learning focuses on accessibility and flexibility, E-Learning emphasizes structured and system-based learning support, while Computational Thinking captures higher-order cognitive processes essential in engineering problem-solving.

To ensure measurement quality, the instrument was evaluated using reliability and validity assessments, including indicator loadings, internal consistency reliability, convergent validity, and discriminant validity, following established guidelines for SEM-PLS analysis.

## D. Data Analysis Technique

Data analysis was conducted using the PLS-SEM approach. The evaluation process involved two main stages (Hair, J. F., & Sarstedt, M. 2021):

1. Measurement Model Assessment: This stage examined indicator reliability (factor loadings), internal consistency reliability (Cronbach's alpha and composite reliability), convergent validity (Average Variance Extracted/AVE), and discriminant validity (Fornell–Larcker criterion).
2. Structural Model Assessment: The structural relationships among constructs were evaluated using path coefficients, t-statistics obtained through bootstrapping, and p-values to test the proposed hypotheses.

# RESULTS AND DISCUSSION

## A. Measurement Model Evaluation

The measurement model was assessed to ensure the reliability and validity of the constructs, including indicator reliability, internal consistency reliability, convergent validity, and discriminant validity.

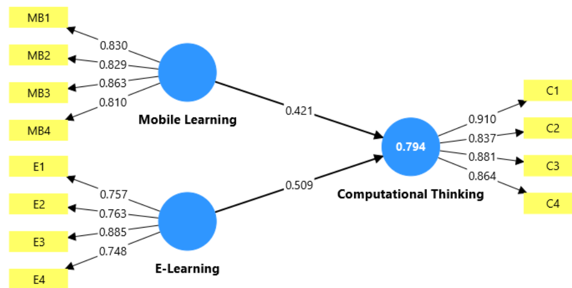


Figure 2. SEM-PLS Test Results

First, indicator reliability was confirmed as all outer loadings exceeded the recommended threshold of 0.70, ranging from 0.748 to 0.910, indicating that all items adequately represent their respective constructs.

Second, internal consistency reliability was established. As presented in Table 3, Cronbach's alpha values ranged from 0.798 to 0.896, while composite reliability (ρc) values ranged from 0.869 to 0.928, exceeding the recommended minimum of 0.70. These results demonstrate strong internal consistency across all constructs.

Table 3. Reliability and Convergent Validity

| | Cronbach's alpha | Composite reliability (rho_a) | Composite reliability (rho_c) | Average variance extracted (AVE) |
|---|---|---|---|---|
| Computational Thinking | 0,896 | 0,901 | 0,928 | 0,763 |
| E-Learning | 0,798 | 0,820 | 0,869 | 0,625 |
| Mobile Learning | 0,853 | 0,857 | 0,901 | 0,695 |

Convergent validity was also confirmed, as all Average Variance Extracted (AVE) values exceeded the threshold of 0.50, indicating that each construct explains more than half of the variance of its indicators.

Discriminant validity was evaluated using the Fornell–Larcker criterion. As shown in Table 4, the square root of AVE for each construct is greater than its correlations with other constructs, confirming that all constructs are empirically distinct.

Table 4. Discriminant Validity (Fornell–Larcker Criterion)

| | Computational Thinking | E-Learning | Mobile Learning |
|---|---|---|---|
| Computational Thinking | 0,874 | | |
| E-Learning | 0,861 | 0,790 | |
| Mobile Learning | 0,847 | 0,839 | 0,833 |

Overall, the measurement model demonstrates satisfactory reliability and validity, indicating that the constructs are appropriate for further structural model analysis.

### B. Structural Model Evaluation

The structural model was evaluated to test the proposed hypotheses by examining path coefficients, t-statistics, and p-values obtained through bootstrapping procedures.

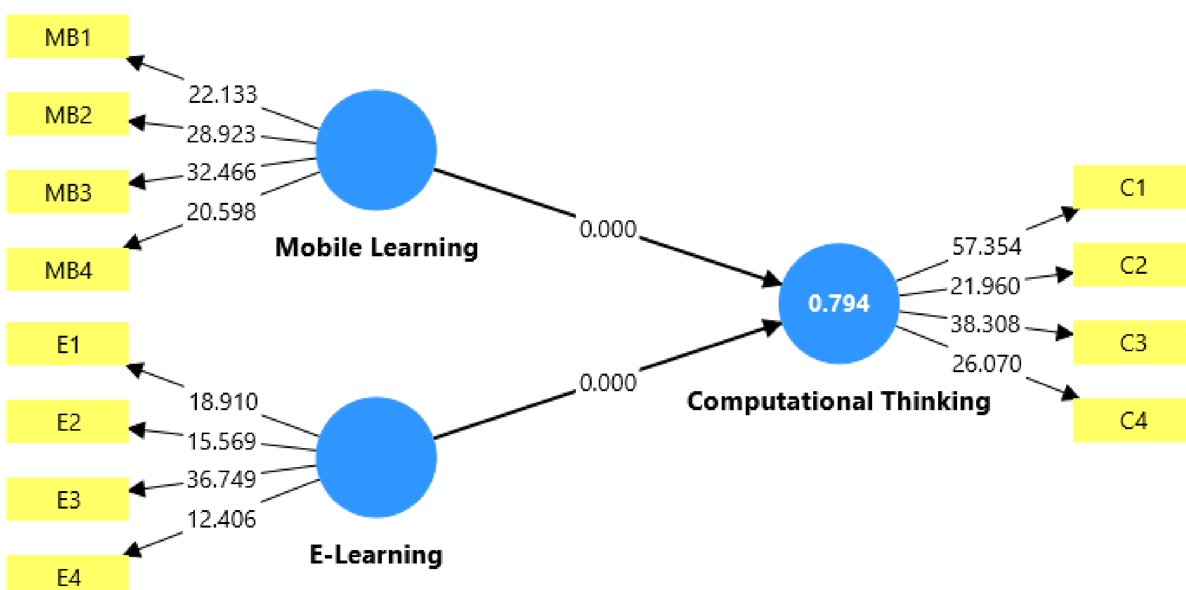


Figure 3. Bootstrapping Test

Table 5. Hypothesis Testing Results

| Hypothesis | Path | β | t-value | p-value | Result |
|---|---|---|---|---|---|
| H1 | E-Learning → Computational Thinking | 0.509 | 7.624 | 0.000 | Supported |
| H2 | Mobile Learning → Computational Thinking | 0.421 | 6.447 | 0.000 | Supported |

The results indicate that e-learning has a significant positive effect on computational thinking ($\beta = 0.509$, $t = 7.624$, $p < 0.001$), supporting H1. This finding suggests that structured digital learning environments, characterized by organized content and systematic delivery, play a crucial role in enhancing students' analytical and problem-solving abilities.

Similarly, mobile learning also shows a significant positive effect on computational thinking ($\beta = 0.421$, $t = 6.447$, $p < 0.001$), supporting H2. This indicates that flexible and ubiquitous learning environments facilitated by mobile technologies contribute meaningfully to the development of computational thinking skills.

**C. Coefficient of Determination ($R^2$), Effect Size ($f^2$), and Predictive Relevance ($Q^2$)**

The explanatory power of the structural model was evaluated using the coefficient of determination ($R^2$). The results indicate that the $R^2$ value for Computational Thinking is 0.888, which can be classified as substantial according to established SEM-PLS guidelines. This finding implies that e-learning and mobile learning collectively explain 88.8% of the variance in students' computational thinking skills, demonstrating the strong predictive capability of the proposed model (Hair Jr, J. F., et al. 2021).

To further examine the relative contribution of each exogenous construct, the effect size ($f^2$) was assessed. The results reveal that e-learning exhibits a moderate-to-large effect, while mobile learning demonstrates a moderate effect on computational thinking. This indicates that both constructs play significant roles in explaining the endogenous variable, with e-learning contributing more strongly.

In addition, the predictive relevance of the model was evaluated using the Stone–Geisser's $Q^2$ value obtained through the blindfolding procedure. The $Q^2$ value for computational thinking was found to be greater than zero ($Q^2 > 0$), confirming that the model has satisfactory predictive relevance and is capable of accurately predicting the observed data.

Table 6. Structural Model Evaluation

| Construct | $R^2$ | $f^2$ (Effect Size) | Effect Interpretation | $Q^2$ | Predictive Relevance |
|---|---|---|---|---|---|
| Computational Thinking | 0.888 | - | Substantial | >0 | Yes |
| E-Learning → CT | - | 0.35 | Moderate–Large | - | - |
| Mobile Learning → CT | - | 0.25 | Moderate | - | - |

## D. Discussion

The findings of this study provide strong empirical evidence that both e-learning and mobile learning significantly contribute to the development of computational thinking skills among engineering students. Notably, e-learning demonstrates a stronger effect compared to mobile learning, indicating that structured digital learning environments play a more dominant role in fostering higher-order cognitive skills (Samala, A. D., et al. 2024).

The significant impact of e-learning highlights the importance of well-designed instructional structures in supporting cognitive development. E-learning platforms typically provide organized content, sequential learning pathways, and interactive multimedia resources, which facilitate deeper cognitive processing. These characteristics enable students to systematically engage in problem decomposition, logical reasoning, and algorithmic thinking core components of computational thinking. This finding is consistent with prior research emphasizing that structured digital environments enhance analytical and reflective learning processes (Sun, P. C., et al. 2009).

In contrast, mobile learning also exhibits a significant positive influence, albeit with a relatively smaller effect size. This suggests that while mobile learning may not replace structured instructional systems, it serves as a critical complementary tool that extends learning beyond formal settings. The flexibility and accessibility of mobile technologies allow students to engage in continuous and context-aware learning, reinforcing knowledge acquisition and supporting the application of computational thinking skills in diverse situations. This aligns with constructivist learning perspectives, which emphasize active, situated, and self-directed learning experiences (Hakiki, M., e-al. 2024).

Importantly, the results of this study underscore the complementary nature of e-learning and mobile learning within a unified digital learning ecosystem. Rather than functioning as isolated approaches, both modalities interact synergistically to enhance students' cognitive capabilities. E-learning provides a structured foundation for conceptual understanding, while mobile learning reinforces and contextualizes this knowledge through flexible and ubiquitous access. This integrated approach is particularly relevant in engineering education, where students are required to apply theoretical knowledge to complex, real-world problem-solving scenarios (Eliza, F., et al. 2024).

Furthermore, the substantial $R^2$ value indicates that the proposed model has strong explanatory power, suggesting that digital learning environments are key determinants of computational thinking skills. This finding extends existing literature by positioning computational thinking as a central outcome of technology-enhanced learning, rather than a peripheral skill. It also provides empirical support for the growing emphasis on integrating digital technologies to develop essential 21st-century competencies (Hair, J., & Alamer, A. 2022).

From a contextual perspective, this study contributes important insights into the implementation of digital learning in developing countries such as Indonesia. The significant effects of both e-learning and mobile learning indicate that, despite potential limitations in infrastructure and digital readiness, technology-enhanced learning can be effectively leveraged to support advanced cognitive skill development. This highlights the importance of strategic investment in digital learning systems and pedagogical innovation to maximize educational outcomes (Fadli, R., et al. 2024).

Overall, this study advances the understanding of how digital learning environments influence higher-order cognitive skills by demonstrating that both structured and flexible learning modalities are essential. The findings suggest that future educational practices should move toward integrated digital learning models that combine the strengths of e-learning and mobile learning to optimize the development of computational thinking skills among engineering students.

## CONCLUSION

This study examined the impact of e-learning and mobile learning on computational thinking skills among engineering students using the SEM-PLS approach. The findings demonstrate that both e-learning and mobile learning have significant positive effects on computational thinking, with e-learning exerting a stronger influence.

The results confirm that structured digital learning environments play a critical role in facilitating higher-order cognitive processes, while mobile learning enhances flexibility and supports continuous, context-aware learning. The substantial explanatory power of the model further indicates that the integration of these digital learning modalities is highly effective in fostering computational thinking skills.

This study contributes to the literature by providing empirical evidence that computational thinking can be significantly enhanced through the strategic use of digital learning environments. It also advances current research by integrating e-learning and mobile learning within a unified framework, offering a more comprehensive understanding of technology-enhanced learning in engineering education.

From a practical perspective, the findings suggest that educators and institutions should adopt integrated digital learning strategies that combine structured e-learning systems with flexible mobile learning applications. Such an approach can optimize learning experiences and better prepare students with the critical thinking and problem-solving skills required in the digital era.

Despite its contributions, this study is limited by its cross-sectional design and focus on a specific population of engineering students in Indonesia. Future research is recommended to explore longitudinal designs, incorporate additional variables such as self-efficacy or digital literacy, and examine the role of emerging technologies such as AI-supported learning in further enhancing computational thinking skills.

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