Enhancing Computational Thinking Skills through Markerless Augmented Reality and GPS-Supported Learning in Computer Networking

Muhammad Dominique Mendoza[1,*], Olnes Yosefa Hutajulu[2], Wan Ahmad Jaafar Wan Yahaya[3], Sriadhi[1], Reni Rahmadani[1], Ressy Dwitias Sari[4], Eka Dodi Suryanto[2], and Elsa Sabrina[5]

[1]Information Technology and Computer Education Study Program, Universitas Negeri Medan, Indonesia
[2]Electrical Engineering Study Program of Universitas Negeri Medan, Indonesia
[3]Centre for Instructional Technology and Multimedia of Universiti Sains Malaysia, Malaysia
[4]Information Technology and Computer Education Study Program, Universitas Negeri Jakarta, Indonesia
[5]Department of Family Welfare Education, Faculty of Engineering, Universitas Negeri Medan, Medan, Indonesia
Email: aenaen@unimed.ac.id (M.D.M.); olnes.hutajulu@unimed.ac.id (O.Y.H.); wajwy@usm.my (W.A.J.W.Y.); sriadhi@unimed.ac.id (S.); renirahmadani@unimed.ac.id (R.R.); ressydwitiassari@unj.ac.id (R.D.S.); ekadodisuryanto@unimed.ac.id (E.D.S.); elsasabrina@unimed.ac.id (E.S.)
*Corresponding author

Manuscript received May 6, 2025; revised June 3, 2025; accepted August 12, 2025; published February 5, 2026

Abstract—**This study aims to examine the influence of self-efficacy, engagement, motivation, and computational thinking skills on the utilization of Markerless Augmented Reality (MAR) and Global Positioning System (GPS) technologies in higher education. Technology enhances learning by expanding access and promoting equity among diverse student populations. In this context, MAR and GPS are employed to support more interactive and contextualized instruction, thereby stimulating student engagement and motivation. The study surveyed every one of the 128 undergraduates enrolled in the Informatics and Computer Technology Education program to understand their perceptions of incorporating technology into their coursework. Adopting a mixed-methods approach, the research combined quantitative and qualitative analyses through techniques such as Partial Least Squares Structural Equation Modeling (PLS-SEM) and Importance-Performance Map Analysis (IPMA). The analysis demonstrated that students' self-efficacy is a key predictor of their computational thinking abilities, perceived usefulness and ease of use of technology, and their overall attitudes toward digital tools. Additionally, high levels of engagement and motivation were found to be essential for successfully using these technologies in educational activities. Together, the findings emphasize the value of enhancing self-efficacy by employing accessible Mobile Augmented Reality (MAR) and GPS applications to support learning, which can enhance student engagement, support the achievement of academic goals, and strengthen computational thinking skills.**

Keywords—**Markerless augmented reality, students' engagement, motivation, self-efficacy, computational thinking skill**

I. Introduction

Technological innovations have driven major transformations in learning systems and methods, opening up opportunities for students from diverse backgrounds to access equitable educational experiences [1–3]. Although technology has significantly changed instruction and the use of educational resources, gaps in technology utilization remain evident among students across different academic disciplines and socioeconomic statuses [4, 5]. In this context, technologies such as Markerless Augmented Reality (MAR) and Global Positioning System (GPS) tracking offer solutions for creating interactive, contextualized, and collaborative learning media. These technologies enable students to engage more deeply in their learning experiences and simulate real-world scenarios that support better understanding and practical application.

In technology-enhanced learning, students' confidence in using digital tools plays a crucial role in shaping their level of engagement and learning outcomes. This aligns with Bandura's self-efficacy theory, which explains that individuals' belief in their ability to complete tasks influences their motivation, active participation, and academic achievement. Students who feel capable of operating technologies such as MAR and GPS are more likely to engage enthusiastically in learning activities and demonstrate improved performance.

On the other hand, the effectiveness of technology in supporting learning is also influenced by how information is presented. Cognitive Load Theory, introduced by Sweller, emphasizes the importance of managing learners' cognitive load to avoid overwhelming their mental processing capacity. When technology is designed to be intuitive and contextually relevant—such as in the use of MAR and GPS—information can be processed more efficiently, enabling students to understand concepts more deeply without experiencing cognitive overload. This approach fosters a more focused, relevant, and meaningful learning experience.

Through the MAR and GPS technologies' existing approaches, student engagement, conceptual understanding, and real-world application skills can be significantly enhanced. Implementing MAR and GPS in learning media represents an effective, innovative step because it combines visual, spatial, and interactive elements to create a richer, more meaningful learning experience. This technology benefits diverse educational fields by enabling more authentic, adaptive, and situational learning. MAR and GPS hold great potential for improving student learning by delivering experiences that feel more real, engaging, and relevant [6–8]. These technologies effectively support student involvement in the learning process, even when faced with limitations of space, time, or resources. Learning becomes far more interactive and contextualized when MAR- and GPS-based media can simulate complex real-world scenarios [9]. Merging interactive capabilities with location-aware features plays a pivotal role in strengthening students' understanding of the subject matter, thereby fostering richer, contextually relevant and more impactful educational experiences.

Furthermore, MAR and GPS can be leveraged to boost the effectiveness of experiential learning programs by sharpening students' practical and collaborative skills across various disciplines. They also help students bridge theory and practice in real-world contexts—critical for solidifying conceptual understanding and developing applicable competencies. As such, MAR and GPS serve as valuable tools in education, engineering, tourism, and related fields, offering an innovative framework for integrating location-based learning and real-world interaction.

MAR and GPS-based tools can likewise be harnessed to cultivate computational thinking by embedding learning within authentic, real-world contexts [10, 11]. These technologies enhance students' proficiency and disposition toward computational thinking—abilities that are essential for creative problem solving and high achievement in technology-intensive professional settings. Cognitive improvements in location-based learning can be facilitated through the integration of MAR and GPS [12]. To better prepare students for twenty-first-century challenges, it is essential to understand the complex interplay among critical thinking skills, technology adaptation, and contextual interaction [13, 14]. MAR and GPS effectively foster the development of both critical and creative thinking by providing authentic, location-based learning experiences [15]. They offer an objective, contextualized, and comprehensive instructional approach, rendering them valuable across both academic and industry settings.

Consequently, the study formulates several research questions, chief among them: In what ways does integrating Markerless Augmented Reality (MAR) and Global Positioning System (GPS) technologies influence students' engagement levels and the depth of their conceptual understanding? And in what ways can this technology-driven engagement influence students' critical thinking abilities and computational thinking skills? These questions will be synthesized into a conceptual model designed to inform and enrich instructors' teaching strategies, enabling them to create more interactive, contextualized, and application-oriented learning experiences. Fig. 1 illustrates the proposed pathways that were examined in this study.

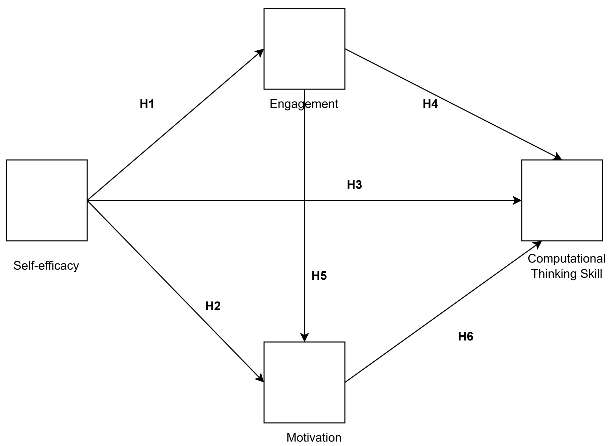

Fig. 1. Hypothesis development.

Drawing on the conceptual framework in Fig. 1, this study examines the following hypothesis:

1) H1: Self-efficacy serves as a significant antecedent to student engagement. Evidence suggests that learners with stronger academic self-efficacy display higher levels of engagement in their studies [16].
2) H2: Self-efficacy positively influences students' motivation. Basileo *et al.* [17] demonstrated, that self-efficacy exhibits a strong, statistically significant relationship with both autonomous and controlled forms of academic motivation.
3) H3: Self-efficacy supports the development of computational thinking abilities. Research shows a strong positive correlation between learners' self-efficacy beliefs and their performance on computational thinking tasks; in other words, greater confidence in one's learning capacity is associated with stronger computational thinking skills [18].
4) H4: Student engagement significantly predicts computational thinking skill. In an "unplugged" coding activity, Li *et al.* [19] confirmed that engagement variables (cognitive, emotional, behavioral) serve as strong predictors of students' computational thinking performance.
5) H5: Engagement is associated with increased motivation. Empirical studies show that high levels of student engagement are closely associated with learners' motivation to learn [20].
6) H6: Motivation acts as a significant predictor of computational thinking proficiency. For instance, Kaur and Chalal [21] observed in their study of primary school students learning Scratch programming that higher levels of motivation consistently forecasted improvements in computational thinking. In other words, learners who are more motivated tend to make greater gains in their computational thinking skills.

II. Literature Review

A. Self-Efficacy

Self-efficacy describes the connection between an individual's belief in their own competence and the proficiency with which they execute a particular task [22–24]. A student's belief in their own talents has a substantial impact on their will to learn, which is why efficacy is so important in the classroom, ultimately leading to successful academic outcomes. Direct experience and the subsequent modification of that experience are central to the experiential learning paradigm [25]. Self-efficacy serves as the driving force behind motivation. Confidence in one's own abilities profoundly influences motivation and academic achievement, underscoring the centrality of self-efficacy throughout the educational journey [26].

Self-efficacy develops through several pathways, with prior experiences—often termed mastery experiences—serving as the most influential. Other contributors include verbal encouragement from others, learning through observation, and the influence of different emotional and social states [27]. In discussing self-efficacy, two separate kinds of achievement goals are brought up. Two types of these objectives are performance achievement goals and mastery achievement goals [28].

In contrast, those with performance objectives aim to evade negative outcomes by showcasing their competency in the subject matter [29]. In essence, individuals with mastery goals are generally more inclined to seek solutions and embrace challenges within their area of focus [30], while those aiming for performance objectives often place a premium on providing enough proof to lessen the impact of unfavorable results [31]. Examining how people adopt digital tools and strengthen their confidence in using them offers valuable insights for this literature review [32]. It is beneficial to examine the impacts of markerless augmented reality and GPS, evaluate their implications, and explore approaches for determining best practices in future deployments.

B. Engagement

The notion of engagement and its effect on learning is crucial for comprehending the significance of student involvement in higher education [33]. Engagement can be classified into three distinct categories [34]. Academic and social engagements fall under behavioral engagement, while emotional and cognitive components include goals for motivation, self-regulation of learning to understand and master difficult concepts and abilities, metacognition, the execution of strategies for learning, strategic thinking, and studying. Attitudes, passions, and principles are associated with positive and negative interactions [35].

Using strategies that cater to each student's unique learning style is considered to improve the learning process in higher education [36]. Engagement among students plays a significant role in influencing retention rates. However, there exists a discrepancy between research and what is perceived as challenges in implementing feasible solutions to address this discrepancy [37]. This involves concentrating on the behaviors of students and faculty, the outcomes that are sought, and the comparable results among institutions to assist higher education administration in formulating effective strategies for implementation and achieving favorable results [38]. In contrast, students who engage in active learning actively seek ways to interact with others about the material at hand [39]. These outcomes are supported by discussion, critical reasoning, collaboration, and meaningful learning experiences. Empirical studies indicate that students who play an active role in their education typically display greater intrinsic motivation, higher engagement, enhanced self-esteem, and an increased sense of competence [40].

C. Motivation

Finding markers of learning performance that take motivation into consideration is vital. Research indicates that learners' motivation is a strong determinant of their academic achievement [41]. Motivation can be understood as the psychological framework that enables a person to initiate a task and persist until its completion [42]. The drive to learn, enhanced by recognizing the value of the material, plays a crucial role and influences an individual's learning process [43]. Social interaction, amusement, social standing, affectionate socialising, relaxation, portability, instant gratification, acquisition, and efficient use of time are some of the fundamental incentives that drive the technologies we use today. Due to the social nature of the situations in which students learn in higher education, the concepts of community, collaboration, and interaction must permeate all aspects of educational practice [44–46]. Building close relationships with students is essential for improving their motivation, academic motivation, and achievement [47].

D. Computational Thinking Skill

Computational thinking leverages concepts from computing to enhance individuals' abilities in problem-solving, critical reasoning and creative thought [48]. The ability to "think like a machine" and tackle complex problems is a vital twenty-first–century competency [49]. Computational thinking encompasses a wide range of problem-solving strategies applicable to many disciplines and situations, not limited to programming or coding [50]. Accordingly, numerous educational institutions have incorporated computational thinking into their curricula to ready students for emerging career paths and ongoing technological change.

Users' belief that computational tools simplify problem solving and enhance their CT skills can be understood as perceived value, which in turn influences their readiness to adopt and use CT platforms and tools [51]. Likewise, perceived ease of use describes a person's subjective assessment of how simple and convenient a computational thinking tool is to operate. People tend to gravitate toward technologies they find intuitive, and these perceptions strongly influence their willingness to engage with such tools [52]. Fundamentally, the aim of using these tools and platforms is to develop one's computational thinking skills. This purpose acts as a primary motivator for individuals to adopt computational thinking technologies, thereby enhancing their proficiency in the field.

The evaluation process for using Markerless Augmented Reality (MAR) and Global Positioning System (GPS) technology begins with defining clear learning objectives, followed by identifying the components involved in the location-based, interactive learning experience. This strategy mirrors the decomposition and abstraction stages of computational thinking: by breaking complex problems into smaller, manageable units, students can better grasp how the interconnected components operate in real-world contexts.

A synthesis of the reviewed literature suggests that self-efficacy plays a foundational role in influencing students' engagement and motivation, particularly within technology-integrated learning environments. Students with higher self-efficacy tend to demonstrate greater perseverance and confidence in navigating digital learning tools, which positively affects their motivational drive. Engagement and motivation, in turn, act as complementary forces that promote the acquisition of computational thinking (CT) skills. When students are both motivated and actively engaged, they are more likely to approach CT-related tasks with deeper cognitive investment and problem-solving abilities. These four constructs are conceptually interconnected and form an integrated framework that determines how effectively students utilize and benefit from emerging educational technologies such as Markerless Augmented Reality (MAR) and Global Positioning System (GPS).

In MAR- and GPS-based learning, solutions are rendered more concrete and relevant to everyday scenarios, and instructional plans are continuously evaluated during their design phase [53]. This mirrors the generalization stage of computational thinking, in which broadly applicable solutions are formulated and tested across multiple situations. Leveraging MAR and GPS to address complex, context-rich learning challenges is particularly effective because these technologies merge visual and spatial data to create immersive, application-driven experiences—an essential aspect of developing students' computational thinking skills. By integrating information from diverse sources (e.g., geographic coordinates, interactive visual overlays), MAR and GPS deliver a holistic learning environment.

III. Materials and Methods

A. *Design of the Study*

To gain a holistic examination of how the variables under investigation interact, the present research utilises a mixed-methodology that synthesises quantitative measurements with qualitative insights. This dual strategy affords a richer, more nuanced understanding of the complex relationships being studied. Prior to data collection, participants had prior exposure to the MAR and GPS technologies through a custom Android-based Augmented Reality application. The population consisted of all students in the 2020–2021 cohort of the Computer and Informatics Engineering Education program a public university in Indonesia and all 128 students (from classes A, B, and C) were included, i.e. a census of the cohort [54] were surveyed using a six-point Likert scale via Google Forms. In this study, a census of the cohort approach was employed, meaning that data were collected from the entire population of students within a specific academic group [55]. All individuals enrolled in the targeted cohort—specifically, 128 undergraduate students from the Informatics and Computer Technology Education program—were invited to participate. Using this approach allows the study to capture data from the entire target population, thus removing sampling bias and yielding a thorough depiction of participants' characteristics, perceptions, and experiences with technology integration in learning. By canvassing the entire cohort, the research also facilitates more accurate generalizations about how these students engage with educational technologies.

An innovative learning media has been developed by the research team through the use of MAR technology and GPS. During this phase of development, the Unity platform served as the primary foundation for integrating these technological features. The learning application was developed using Unity and integrated with advanced Application Programming Interfaces (APIs) such as Niantic Lightship, Wayfarer, and Geospatial Browser, enabling the incorporation of interactive and geolocation-based learning components. This technology enables students to navigate and explore the campus environment while participating in engaging and immersive learning experiences, as illustrated in Fig. 2.

Once all 3D elements were successfully developed and the API was seamlessly integrated with the Niantic Lightship, the subsequent stage involved scanning six designated locations within the campus environment. The selected points were deliberately identified as key sites for students to engage with Augmented Reality (AR)-enhanced learning beyond the traditional classroom setting. Each of these locations is crafted to enable students to engage with a variety of interactive games and puzzles, aimed at improving their collaborative abilities in understanding and applying computer networking concepts. Furthermore, the six locations function as distinct learning points while being integrally linked through a seamless location-based learning system. Students are required to collaborate effectively to complete tasks at each designated location, culminating in a set of practice questions designed to assess their understanding as shown from Fig. 3.

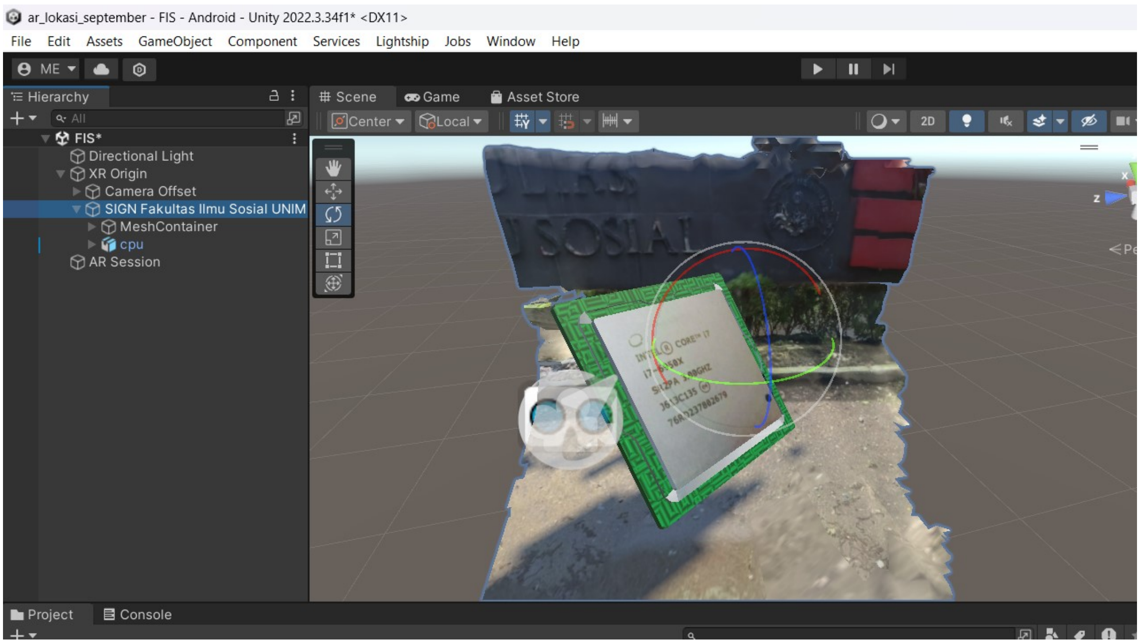

Fig. 2. Learning media development with unity.

The site scan procedure is designed to enrich students' learning experiences and deepen their theoretical understanding by integrating hands-on elements, collaboration and problem solving—key components of computer networking education. Moreover, this implementation marks a notable advance in the use of markerless augmented reality and GPS technologies to create more interactive, dynamic location-based learning experiences. The finished learning media resulting from this implementation is presented in Fig. 4.

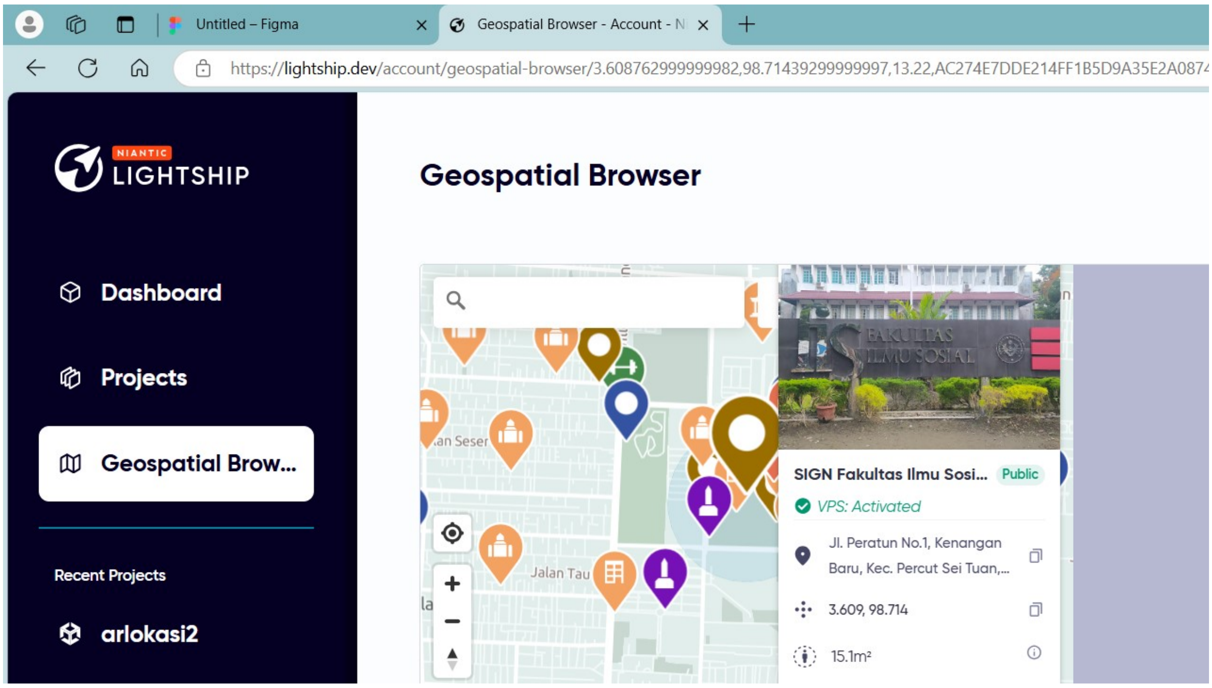

Fig. 3. GPS scan results obtained from six specific locations within the campus area.

After the location scanning process was completed, the research team continued with testing the quality of learning media using whitebox and blackbox testing methods. Whitebox testing was conducted to ensure the validity of internal logic and program code flow, while blackbox testing focused on verifying external functionality without examining the internal structure of the system. The results of these two testing methods show that the MAR and GPS technology-based learning media developed has met the technical feasibility criteria.

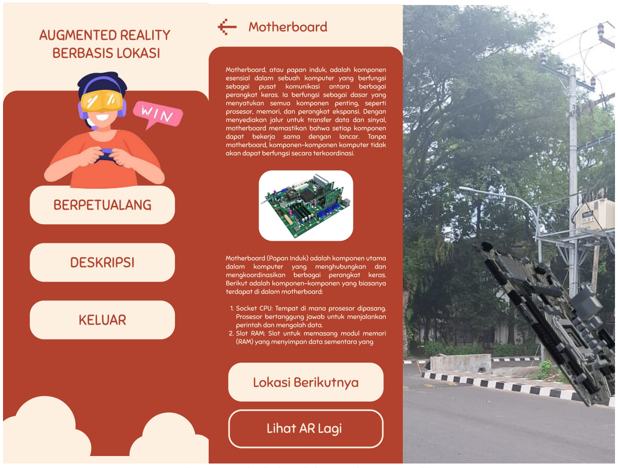

Fig. 4. Finished learning media.

This development is designed to cultivate a learning environment that is more dynamic and engaging than conventional classroom instruction. By incorporating augmented reality and GPS technologies, it expands opportunities for outdoor learning, yielding richer educational experiences and increased student engagement. This technology is anticipated to enhance students' conceptual understanding while also motivating them to engage with the material independently by interacting directly with their environment. The advancement of this media represents progress in technology-driven education, aligning with the global movement towards increasingly personalized, interactive, and location-aware learning experiences.

B. Sample

All 128 students were invited to complete the study instrument, and every participant provided a complete response. Consequently, the analysis included the entire cohort of 128 students. Given the small class size, the researchers adopted a census (saturated sampling) approach, gathering data from every student to ensure representativeness and enhance the reliability of the findings. Throughout data collection, the researchers maintained participant confidentiality and used the data solely for research purposes in line with ethical standards.

By recruiting only participants who had previously used the application, the study ensured that the data collected were directly pertinent to its central focus: students' perceptions of the application's impact. This approach is considered more reliable because the sample consists of individuals who have actually used the technology under investigation. Although participation was voluntary—open to anyone willing to complete the instrument—this method may slightly reduce the generalizability of the findings to populations beyond those who chose to participate.

C. Instrument

The research employed a survey as its principal data-collection instrument. Most of the measurement items were adapted from earlier studies to maintain relevance and comparability. The questionnaire served as the primary means of identifying the variables aligned with the study's objectives and was designed to accurately capture data on four key constructs: self-efficacy [56], engagement [57], motivation [58], and computational thinking skills [59]. The measurement items used in this study is presented in Table 1.

Each questionnaire item was scored on a six-point Likert-type scale, and the instrument comprised 17 questions spanning the four constructs of interest. The six-point scale deliberately omits a neutral midpoint, prompting respondents to lean toward agreement or disagreement. This design helps reduce central tendency bias and yields more decisive responses, which is crucial for accurately capturing perceptions and attitudes toward technology use. Factor loadings for each item were calculated using SmartPLS to evaluate the measurement model's precision. Convergent validity was assessed via the Average Variance Extracted (AVE) based on standardized loadings, while discriminant validity was evaluated using the Heterotrait–Monotrait (HTMT) ratio. Finally, internal consistency reliability for each construct was verified through Cronbach's Alpha and Composite Reliability, ensuring the robustness of the measurement scales.

Table 1. The test instruments

Variable	Instruments
Self-Efficacy	I can complete the activities I get in a lab class
	If I went to a place, I could figure out what is being shown about topics in
	I am often able to help my classmates with activities in the laboratory or in recitation.
	I get a sinking feeling when I think of trying to tackle difficult from activities problems.
Engagement	I actively participate in classroom discussions when using MAR and GPS technology.
	I show a high level of interest when using technology-based learning media.
	I enjoy the learning process when it involves MAR and GPS technology.
	I feel enthusiastic about using MAR and GPS technology for learning.
	I frequently interact with peers or instructors when engaging with MAR and GPS technology in learning activities.
Motivation	I am motivated to study more when using MAR and GPS technology.
	I feel driven to complete tasks that involve using this technology.
	I find the learning process more engaging with the use of technology.
	I feel confident when facing new challenges through technology-based learning.
Computational Thinking Skill	I can break down complex problems into smaller, manageable parts.
	I am able to identify patterns within problems to find solutions.
	I can develop logical step-by-step procedures to solve problems.
	I can use technology to help solve problems in a systematic way.

The analysis relied on Partial Least Squares Structural Equation Modeling (PLS-SEM), supplemented by Importance–Performance Map Analysis (IPMA), to evaluate the relationships among the model's constructs. IPMA goes beyond assessing path coefficients by also considering the average scores of latent variables, offering a more comprehensive view of how each predictor contributes to the desired outcomes.

D. Data Collection

Referring to Burns and Grove [60], it is crucial in reporting research findings to include the research context, participant characteristics, study scope, as well as data collection and analysis procedures. Additionally, a description of the research sample must also be provided. In this research, every engineering faculty student who was administered the questionnaire participated by fully completing and submitting the survey, ensuring complete response coverage from the target population. Participation was carried out through the completion of an online form accompanied by a survey link. Only respondents who accurately completed the questionnaire were included in the data tabulation process.

E. Data Validation

To conduct the SEM–PLS analysis, this study utilized SmartPLS version 3. The Partial Least Squares (PLS) method offers distinct advantages over traditional Ordinary Least Squares (OLS) regression by effectively managing common challenges such as limited sample sizes, missing data, deviations from normality, and multicollinearity. SmartPLS was employed to ensure precise measurement modeling and structural robustness. The analysis adhered to the two-step approach outlined by Anderson and Gerbing [61], which involves sequential assessment of the measurement model followed by evaluation of the structural model. In the initial phase, the measurement model was evaluated to ensure the suitability of both the constructs and the data collection procedures. Convergent validity was assessed by examining the Average Variance Extracted (AVE) and the standardized factor loadings of each item. Discriminant validity was determined using the heterotrait–monotrait (HTMT) ratio. Additionally, the internal consistency of each construct was confirmed through the calculation of Cronbach's Alpha and Composite Reliability (CR) coefficients.

In the second phase, the structural model was evaluated by testing the hypothesized relationships among the constructs using a bootstrapping procedure to determine their statistical significance. Table 2 presents the factor loadings for all measurement items, each of which exceeds the 0.60 threshold recommended by Hair *et al.* [62], thus reinforcing the validity of the construct measurements and confirming the robustness and appropriateness of the overall measurement model for further structural analysis.

Table 2. Outer loadings

Variable	Item	Outer Loading
Self-Efficacy	SE1	0.840
	SE2	0.880
	SE3	0.791
	SE4	0.827
Engagement	EN1	0.806
	EN2	0.826
	EN3	0.852
	EN4	0.841
Motivation	MT1	0.843
	MT2	0.837
	MT3	0.830
	MT4	0.758
Computational Thinking Skill	CTS1	0.736
	CTS2	0.834
	CTS3	0.841
	CTS4	0.784

Table 2 displays the outer loadings, representing the degree to which each indicator reliably measures its associated construct within the context of this study. In this case, reliability denotes the consistency. By employing an appropriate measurement model, this questionnaire can produce stable results under the same conditions and with similar participant profiles. Such consistency is crucial to ensure that conclusions drawn about the respondents can be generalized. Reliability testing confirms that the survey is well-constructed, especially in the context of higher education. Low reliability suggests that specific items fail to consistently capture the underlying construct, highlighting the potential need for revising the instrument or eliminating underperforming indicators. In the context of higher education research, maintaining methodological rigor is essential—especially when working with large respondent groups—as the findings carry significant weight for decision-makers, including institutional leaders and policymakers.

To determine the components for PLS bootstrapping, this study followed a widely recognized procedure commonly applied in Structural Equation Modeling (SEM). This method relies on repeated resampling techniques to estimate the stability and significance of model parameters. To evaluate the measurement quality of each construct, several key indicators were utilized, including standardized factor loadings, composite reliability, Cronbach's alpha, and Average Variance Extracted (AVE). These metrics were assessed in accordance with the methodological standards set forth by Hair *et al.* [63], As shown in Table 3, all values for composite reliability and Cronbach's alpha surpass the commonly accepted threshold of 0.70, indicating strong internal consistency across the measured constructs. This confirms that each latent construct's factor loadings satisfy the AVE standard (minimum 0.50) and that each construct's AVE value is greater than 0.60.

Table 3. Cronbach's alpha, composite reliability, average variance extracted

Variable	Cronbach Alpha	Composite Reliability	AVE > 0.5
Self-Efficacy	0.855	0.902	0.698
Engagement	0.890	0.919	0.695
Motivation	0.836	0.890	0.669
Computational Thinking Skill	0.811	0.876	0.640

Each construct in this study achieved an Average Variance Extracted (AVE) above 0.50. According to Hair *et al.* [63], the minimum acceptable AVE is 0.50, and all scores in Table 3 meet this criterion: Self-Efficacy at 0.698, Engagement at 0.695, Motivation at 0.669, and Computational Thinking Skill at 0.640. The Cronbach's alpha scores for each construct demonstrate strong internal reliability, with values of 0.855 for Self-Efficacy, 0.890 for Engagement, 0.836 for Motivation, and 0.811 for Computational Thinking Skill. In addition, Composite Reliability values ranged from 0.876 to 0.919, further reinforcing the internal consistency of the measurement instrument. Discriminant validity was evaluated through the Heterotrait–Monotrait (HTMT) ratio of correlations, and all values were found to be below the recommended threshold of 0.90, as outlined by Hair *et al.* [63], thereby confirming clear distinction among the constructs. The detailed results of the HTMT analysis are presented in Table 4.

Validity testing was performed to confirm that the measurement model developed in SmartPLS effectively captures the relationships between latent constructs and their corresponding indicators, thereby improving the accuracy and relevance of the study's results. An instrument with strong validity ensures that students' experiences, perceptions, and behaviors are represented with fidelity, providing a sound foundation for meaningful interpretation and generalization. This testing is essential to ensure that the survey questions genuinely measure the intended research objectives. Without validity testing, there is a heightened risk of measuring irrelevant factors, which could lead to inaccurate conclusions about the target population.

Table 4. Heterotrait-Monotrait (HTMT) ratio of correlations

Variable	CTS	EN	MT	SE
CTS	-	-	-	-
EN	0.867	-	-	-
MT	0.641	0.699	-	-
SE	0.851	0.832	0.594	-

Validity focuses on the accuracy of measuring the intended constructs, while reliability ensures the consistency of latent variable measurement. By rigorously applying tests for validity and reliability, researchers ensure that the data collected from students is both accurate and dependable. This process is essential for reinforcing the credibility of the study's findings. In the realm of higher education research, generating valid and reliable evidence forms the cornerstone for making well-founded conclusions and informing data-driven decisions that can shape educational policy and practice.

Following the confirmation of the instrument's validity and reliability, additional analysis was performed to assess the explanatory strength of the structural model by examining the R^2 (R Square) values. The R^2 statistic reflects the proportion of variance in the dependent variables that can be accounted for by the independent variables in the mode [63]. The results of this analysis are presented in Table 5.

Table 5. Results of the *R* Square analysis

Variable	R Square
Computational Thinking Skill	0.619
Engagement	0.529
Motivation	0.383

As presented in Table 5, the R^2 value for Computational Thinking Skill is 0.619, indicating that the independent variables in the model account for 61.9% of its variance. For Engagement, the R^2 is 0.529, signifying that 52.9% of the variation in student engagement is explained by its associated predictors. Meanwhile, the R^2 for Motivation stands at 0.383, reflecting that 38.3% of the variance in student motivation can be attributed to the independent variables included in the model. Collectively, these R^2 values suggest that the structural model demonstrates moderate to substantial explanatory power in accounting for the variance in the core dependent constructs.

Overall, the measurement model demonstrated satisfactory levels of validity and reliability, while the structural model exhibited adequate explanatory power based on the R Square values. These results validate the model's effectiveness in representing the interrelationships among self-efficacy, engagement, motivation, and computational thinking skills. This provides a robust empirical basis for conducting hypothesis testing and offers a solid framework for interpreting the study's findings with greater confidence.

F. Data Analysis

This study utilized SmartPLS version 3 as the primary analytical tool. Traditional Ordinary Least Squares (OLS) regression is often limited by issues such as small sample sizes, non-normal data distributions, missing values, and multicollinearity. To overcome these limitations, the study adopted the Partial Least Squares (PLS) approach, which is better suited for complex models and exploratory research contexts. The validation process commenced with an evaluation of the measurement model, following the procedural guidelines outlined by Anderson and Gerbing [61], ensuring a systematic assessment of construct reliability and validity before proceeding to structural model analysis. Subsequently, a bootstrapping procedure with 5,000 samples was conducted to test the strength of the relationships between constructs. The bootstrapping analysis for hypothesis testing was carried out using SmartPLS.

Additionally, the study incorporated Importance-Performance Map Analysis (IPMA) to assess the relative effectiveness of each construct within the model. This technique adds practical depth to the Partial Least Squares Structural Equation Modeling (PLS-SEM) results by simultaneously evaluating both the importance (impact) and performance (average scores) of the constructs. Consequently, the analysis highlights which constructs are critical in influencing outcomes yet underperforming, thereby guiding targeted interventions and improvements in future implementations.

IV. RESULT AND DISCUSSION

The results of the SmartPLS analysis, detailed in Table 4 and illustrated in Fig. 5, summarize the path coefficients for all proposed hypotheses. Regarding Hypothesis 1, the analysis reveals that self-efficacy exerts a strong, positive, and statistically significant influence on student engagement (β = 0.727, ρ = 0.000). This indicates that learners who possess greater confidence in their capabilities are more likely to actively participate in the learning process. This finding aligns with Zhao *et al*. [64], who reported that students with elevated self-efficacy levels tend to be more engaged in technology-mediated learning environments. Consistent results were also observed in the work of Zhao and Cao [65], which demonstrated that self-efficacy is a significant predictor of behavioral engagement in online learning contexts.

The analysis of Hypothesis 2 reveals that self-efficacy has a positive and statistically significant impact on student motivation (β = 0.155, ρ = 0.000). This suggests that learners who exhibit greater confidence in their academic abilities are more likely to demonstrate heightened motivation toward their studies. This result aligns with the findings of Lin *et al.* [66], who reported that academic self-efficacy serves as a significant predictor of learning motivation, particularly within blended learning environments. Similarly, Hayat *et al.* [67] emphasized that self-efficacy influences motivation by enhancing students' metacognitive self-regulation and affective processes, leading to greater learning persistence. Moreover, recent research by Alhadabi and Karpinski [68] affirm that self-efficacy is a robust predictor of both intrinsic motivation and academic engagement, particularly within technology-mediated learning environments. Their findings highlight the pivotal role of self-belief in fostering deeper motivation and sustained involvement in digitally enhanced educational settings.

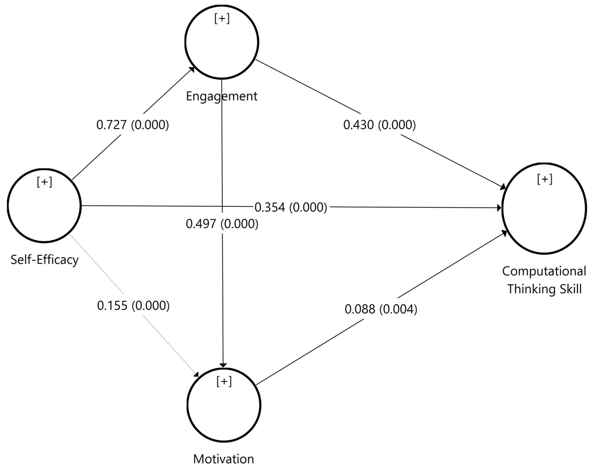

Fig. 5. Hypothesis path.

The analysis of Hypothesis 3 demonstrates that self-efficacy exerts a positive and statistically significant influence on students' computational thinking skills, with a path coefficient of β = 0.354 and ρ = 0.000. This suggests that students who exhibit greater confidence in their abilities are more likely to perform well in tasks requiring computational thinking. This outcome aligns with the findings of Kvaššayová *et al.* [69], who observed that students with high self-efficacy in programming tasks show marked improvements in their computational thinking performance.

The results for Hypothesis 4 indicate that student engagement has a positive and statistically significant effect on computational thinking skills, with a path coefficient of β = 0.430 and ρ = 0.000. This finding suggests that active involvement in the learning process contributes meaningfully to the development of computational thinking abilities. It is in line with the study by Li *et al.* [70], which demonstrated that engagement—particularly when supported by Markerless Augmented Reality (MAR) and GPS technologies—can significantly enhance computational thinking. These technologies promote interactive, context-rich learning environments that facilitate deeper comprehension and more effective application of computational concepts.

Furthermore, the analysis of Hypothesis 5 reveals that engagement exerts a positive and statistically significant impact on motivation, with a path coefficient of β = 0.497 and ρ = 0.000. This result suggests that students who actively participate in the learning process—particularly when facilitated by MAR and GPS technologies—tend to exhibit higher levels of motivation. The immersive and contextually rich learning environments enabled by these technologies foster greater enthusiasm and drive among students, encouraging them to engage more deeply with the learning content.

Moreover, Hypothesis 6 demonstrates that motivation contributes positively and meaningfully to the development of computational thinking skills, as reflected by a path coefficient of $\beta = 0.088$ and a significance level of $\rho = 0.002$. This finding indicates that students with higher levels of motivation are more likely to enhance their computational thinking abilities, highlighting the important role of motivational factors in fostering cognitive skill development. Motivated students are more active in applying computational concepts, which ultimately improves their ability to solve problems logically and systematically. These findings are consistent with Gümüş *et al.* [71], who demonstrated that motivated students are more likely to develop computational thinking competencies through increased effort and persistence in problem-solving tasks. Although the effect size ($\beta = 0.088$) is relatively small, it remains statistically significant, suggesting that while motivation contributes to computational thinking skills, its practical impact is more modest compared to other factors such as self-efficacy and engagement. This may imply that motivation alone may not strongly drive computational thinking development unless supported by other variables, such as confidence in using technology or active participation in learning activities. Therefore, strategies that simultaneously address students' motivation and engagement behaviors are likely to yield greater effectiveness in fostering the development of computational thinking skills.

Self-efficacy emerged as a significant determinant of students' motivation, engagement, and computational thinking skills. The results indicate that learners with elevated self-efficacy are more inclined to participate actively in the learning process due to their heightened motivation. Their confidence in handling technological tools positively shapes their perception of usability, which subsequently enhances their level of engagement. As students become more engaged, they interact more frequently and meaningfully with technology, thereby facilitating deeper comprehension of complex concepts within computational thinking instruction.

The study further demonstrated that motivation serves as a key driver in fostering students' engagement with technology-enhanced learning environments. Learners who exhibit high levels of motivation are more inclined to take an active role in educational activities and to adopt technology as a meaningful tool in their learning process. This finding is consistent with prior research, which suggests that strong motivational factors contribute to greater engagement, ultimately supporting the advancement of computational thinking skills. Students who are intrinsically motivated to explore and apply technology in their learning are more likely to attain superior outcomes in cultivating their computational thinking competencies.

In addition, elevated levels of student engagement are strongly associated with enhanced computational thinking skills. Learners who actively participate in technology-integrated educational activities tend to demonstrate greater proficiency in applying computational thinking to address problem-solving tasks. Frequent interaction with digital tools, combined with the use of more effective learning strategies, contributes to the development of students' critical reasoning and analytical capabilities. Therefore, student engagement not only boosts motivation but also enriches their computational thinking skills.

Overall, the findings of this study highlight the pivotal role of self-efficacy, motivation, and engagement in fostering students' computational thinking skills. Accordingly, it is essential for educational institutions and instructors to implement instructional strategies and design learning environments that actively cultivate students' confidence in their abilities, stimulate intrinsic motivation, and promote sustained engagement with technology. Such efforts are key to enhancing students' capacity to develop and apply computational thinking in diverse learning contexts.

This study further underscores the influential role of self-efficacy in shaping students' perceptions of technology use, particularly within the domain of computational thinking. The findings indicate that students with higher levels of self-efficacy are more inclined to perceive technology as a valuable asset in their learning journey, which, in turn, fosters greater engagement and more frequent use of technological tools. This aligns with prior research showing that individual confidence significantly affects how learners assess the utility of technology in educational settings. In essence, students who believe in their technological competence are more receptive to adopting and integrating digital tools into their learning, thereby supporting the development of their computational thinking skills.

Moreover, this study reinforces the strong connection between motivation and the development of computational thinking skills. The findings reveal that students' intrinsic motivation to engage with technology significantly enhances their capacity for logical reasoning and complex problem-solving—core elements of computational thinking. When learners are genuinely motivated, they are more likely to adopt technology as a tool to support and deepen their cognitive skills, particularly in problem-solving contexts. This supports the view that intrinsic motivation, shaped in part by self-efficacy, plays a crucial role in enhancing students' comprehension and application of technology-integrated learning concepts. Additionally, the study confirms that engagement exerts a significant influence on the advancement of computational thinking. Students who participated more actively in technology-driven learning environments—particularly through the integration of AR and GPS tools in network systems programming—exhibited stronger computational thinking capabilities, highlighting the importance of immersive and interactive learning experiences. This engagement is closely related to the intuitive and user-friendly nature of the technology, which helps students interact more deeply with the learning material. Technological tools that are specifically designed to enhance student engagement can play a vital role in facilitating the comprehension of abstract concepts. At the same time, they support the development of critical and systematic thinking skills, enabling students to approach problems with greater analytical depth and structured reasoning. The results of the hypothesis testing are summarized in Table 6.

In conclusion, the results of this study underscore the critical need to cultivate a learning environment that actively promotes students' self-efficacy, motivation, and engagement in the use of technology. Such an environment is particularly essential in technology-rich educational settings, where these factors collectively contribute to the effective development of computational thinking skills. Supporting these psychological and behavioral dimensions can significantly enhance students' ability to engage meaningfully with complex technological content. Educational institutions and technology developers should focus on designing accessible, intuitive, and student-centered technologies to improve student engagement and learning outcomes.

Table 6. Hypothesis result

Hypothesis	*β*	*ρ*	T-values	Result
H1. Self-Efficacy → Engagement	0.727	0.000	36.182	Supported
H2. Self-Efficacy → Motivation	0.155	0.000	3.835	Supported
H3. Self-Efficacy → Computational Thinking Skill	0.354	0.000	8.871	Supported
H4. Engagement → Computational Thinking Skill	0.430	0.000	10.99	Supported
H5. Engagement → Motivation	0.497	0.000	13.09	Supported
H6. Motivation → Computational Thinking Skill	0.430	0.002	3.069	Supported

The PLS-SEM analysis, combined with Importance–Performance Map Analysis (IPMA), was employed to investigate the influence of self-efficacy, engagement, motivation, and computational thinking skills on students' use of technology in learning environments. While PLS-SEM assesses the strength and significance of relationships among constructs, IPMA adds a practical dimension by identifying which variables are most important yet underperforming, thereby guiding targeted improvements. Table 7 presents the standardized total effects, representing the importance of each construct, alongside the standardized latent variable scores, which indicate their respective performance levels.

Table 7. Importance-Performance Map Analysis (IPMA) result

Variable	Computational Thinking Skill	Performance	Important (Total Effect)
Self-Efficacy	0.713	76.028	0.713
SE1	0.209	73.855	
SE2	0.234	75.249	
SE3	0.195	80.727	
SE4	0.214	74.602	
Engagement	0.474	72.041	0.474
EN1	0.109	68.003	
EN2	0.112	72.585	
EN3	0.116	71.738	
EN4	0.112	75.324	
Motivation	0.088	67.309	0.088
MT1	0.031	72.062	
MT2	0.029	72.56	
MT3	0.024	63.446	
MT4	0.024	56.449	

In the IPMA, performance scores are reported on a standardized scale from 0 to 100, with higher values representing stronger perceived performance of the respective constructs. This scale facilitates the identification of areas where improvements are needed by highlighting constructs that are highly important yet exhibit relatively lower performance levels [72]. Table 7 presents the total effects and corresponding performance scores for the key variables examined in the study—namely, self-efficacy, engagement, and motivation—and their influence on the development of computational thinking skills. These values provide insight into both the relative importance and perceived effectiveness of each construct, enabling a more nuanced interpretation of their roles within the technology-integrated learning context. The results of the IPMA provide further insight into the factors influencing computational thinking skills within technology-enhanced learning environments. The findings highlight that self-efficacy exerts the strongest influence on the development of computational thinking skills among the variables examined [73]. This underscores the pivotal role of students' confidence in their own abilities as a foundation for enhancing their capacity to think logically, solve problems, and engage effectively with technology-based learning environments (total effect = 0.713; performance = 76.028), confirming its pivotal role in students' learning outcomes. Among the self-efficacy sub-indicators, SE3 (confidence in operating technological tools) demonstrated the highest performance score (80.727), while SE1 (confidence in understanding and applying basic technological concepts) showed the lowest (73.855). The relatively lower performance in SE1 suggests that some students still experience difficulties in mastering fundamental technological knowledge, which could potentially hinder their computational thinking development. This finding is consistent with previous research that underscores the critical role of self-efficacy in promoting cognitive engagement and enhancing students' problem-solving capabilities [74, 75]. Elevated self-belief has been shown to empower learners to approach complex tasks with greater persistence and strategic thinking, both of which are essential for developing computational thinking skills.

To improve SE1, several instructional strategies should be considered. Scaffolding techniques, including step-by-step guided instruction, allow learners to build confidence gradually while advancing through increasingly complex computational tasks [75]. Furthermore, integrating real-world problem-based learning can contextualize abstract concepts, thereby enhancing both comprehension and confidence. Peer mentoring and collaborative learning activities may foster supportive social interactions that strengthen students' self-efficacy through vicarious experiences and shared problem-solving [76]. In addition, formative assessments with immediate, constructive feedback can guide students in recognizing their strengths and areas for improvement, contributing positively to self-regulated learning. Moreover, the use of Augmented Reality (AR) and GPS-based technologies, as applied in this study, can be further optimized to deliver adaptive, interactive tutorials that reinforce students' understanding of foundational technological concepts.

In terms of engagement, the IPMA results reveal a moderate but significant total effect (0.474; performance = 72.041). Sub-indicator EN4 (enthusiasm in using technology for learning) scored the highest (75.324), while EN1 (active participation in class discussions) recorded the lowest performance (68.003). The relatively low score in EN1 suggests that students may benefit from pedagogical models that encourage more active and participatory learning environments. The flipped classroom model, along with problem-based and team-based learning approaches, has been shown to increase engagement by promoting student autonomy and peer interaction [77]. Gamification and interactive learning systems may also enhance engagement by increasing motivation, persistence, and collaborative behaviors (EN2 and EN3) [78].

Motivation, while exhibiting the weakest total effect on computational thinking skills (0.088; performance = 67.309), remains a critical factor to address. Notably, MT4 (confidence in facing new technological challenges) recorded the lowest performance score (56.449), indicating that many students experience anxiety or lack confidence when confronted with unfamiliar tasks—a pattern consistent with prior findings on self-confidence and growth mindset [79]. Several external factors may explain the low MT4 performance, including complex course design, limited instructional support, and inadequate access to user-friendly technologies. These factors can heighten anxiety when encountering new technological demands. To mitigate this, instructional designs should provide sufficient scaffolding, technical support, and intuitive learning technologies to foster confidence and reduce anxiety. Moreover, targeted interventions such as resilience training, counseling, and explicit coping strategies may help strengthen MT4. Aligning learning materials with students' interests and career aspirations can enhance intrinsic motivation (MT1, MT2), while short-term goal setting, positive reinforcement, and gamified rewards may further sustain engagement and persistence.

Overall, the IPMA results suggest that while self-efficacy remains the most influential factor, targeted improvements in both engagement and motivation sub-indicators—especially SE1, EN1, and MT4—are essential for optimizing computational thinking skill development. A holistic, student-centered instructional approach that integrates scaffolding, interactive technology, real-world problem solving, peer collaboration, and motivation-enhancing strategies can serve as a comprehensive framework for improving computational thinking skills in technology-mediated learning contexts.

IPMA are used to examine how self-efficacy, engagement, motivation, and computational thinking skills influence the use of technology in learning. Table 7 displays the importance and performance metrics for each construct, as derived from the IPMA results. These values offer a comprehensive view of which constructs are most influential in predicting outcomes and how effectively each is currently performing, thereby guiding priorities for instructional improvement and strategic intervention Importance values were calculated using standardized total effects, while performance values were obtained from rescaled latent variable scores on a 0–100 scale.

Then, Importance values reflect the total effects (standardized) of each construct on computational thinking skills, while performance values represent the rescaled latent variable scores (0–100 scale) obtained from SmartPLS. These results provide strategic insight for prioritizing interventions: efforts should continue to maintain high self-efficacy, while greater attention should be devoted to enhancing engagement and especially motivation to optimize students' computational thinking development.

Fig. 6 illustrates the Importance-Performance Map, with indicators plotted based on their standardized total effects. The X-axis reflects the importance of each construct, measured by its total effect on the outcome variable, while the Y-axis indicates performance levels, presented on a standardized scale from 0 to 100. This visual representation helps identify high-impact constructs that may require targeted improvement to enhance overall learning outcomes. Quadrant divisions reflect combinations of high/low importance and high/low performance, helping to prioritize improvement areas. Fig. 6 shows that self-efficacy is the most critical and highest-performing construct in supporting computational thinking skills, with a standardized total effect of approximately 0.71 and a performance score near 78. Engagement falls in the middle—its effect is substantial (≈ 0.47) but its performance (≈ 72) leaves room for improvement—while motivation exhibits the weakest influence (≈ 0.09) and the lowest performance (≈ 67).

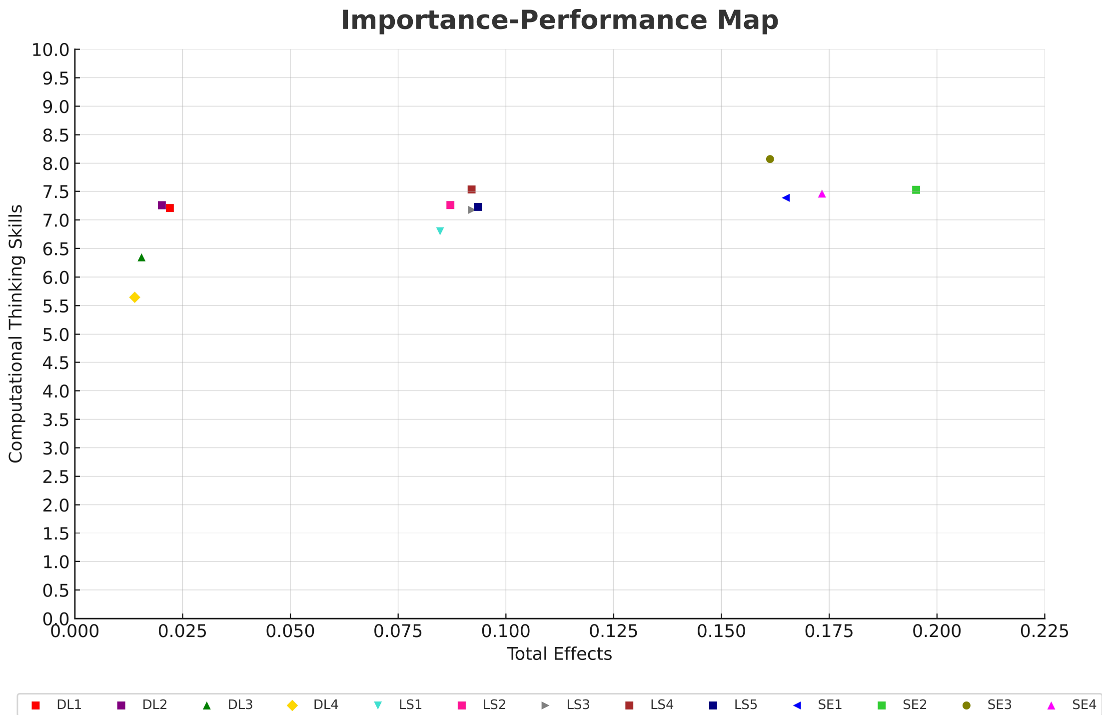

Fig. 6. Importance-Performance Map indicators standardized total effects.

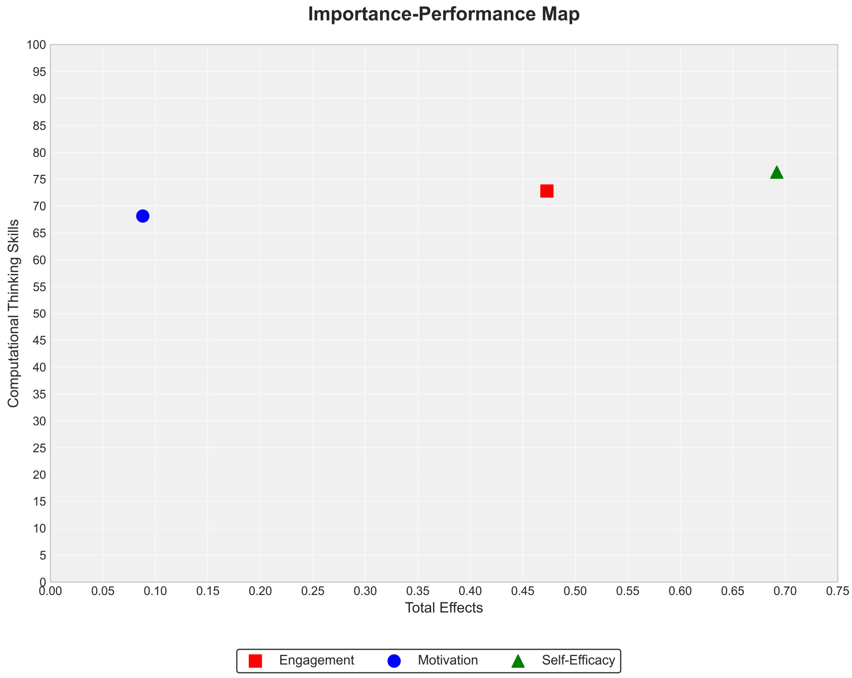

Fig. 7. Importance-Performance Map constructs standardized total effects.

Fig. 7 Importance-Performance Map constructs standardized total effects. Constructs are positioned across quadrants based on their total effects (importance) and performance levels. Self-efficacy constructs cluster in the high-importance/high-performance quadrant, while motivation constructs, particularly MT4, fall in the low-performance quadrant. Based on the Fig. 7 breaks down the performance of each latent indicator: all four self-efficacy indicators (SE1–SE4) occupy the top-right quadrant, confirming students' confidence as both consistent and important; the engagement indicators (EN1–EN5) are scattered in the mid-range area, signaling a need to boost their performance to match their relevance; and the motivation indicators (MT1–MT4) cluster in the bottom-left quadrant—especially MT4 with a performance score of around 56—indicating that motivational aspects require more intensive intervention to contribute optimally to the development of computational thinking skills.

The findings of this study demonstrate that self-efficacy plays a pivotal role in shaping students' computational thinking skills, emphasizing the critical need to cultivate confidence in the use of technology. Learners who possess greater confidence in their technological capabilities are more inclined to incorporate digital tools into their educational activities, thereby strengthening their computational thinking. This underscores the value of pedagogical strategies that actively promote self-efficacy—such as targeted training programs, hands-on workshops, or mentorship initiatives focused on building technical proficiency. Enhancing students' belief in their ability to use technology effectively not only empowers them to engage more fully with learning tools but also facilitates deeper cognitive development in computational thinking.

However, it is essential to recognize that while self-efficacy significantly influences students' computational thinking, its effectiveness can be further amplified when paired with a strong perception of technology's usefulness. Even students with high levels of confidence may underutilize digital tools if they do not clearly perceive their educational value. Therefore, it is imperative for educators to integrate technologies that are not only user-friendly and accessible but also clearly aligned with academic goals and learning outcomes. By explicitly demonstrating the practical benefits of technology within instructional settings, educators can enhance students' perceived usefulness of these tools. This, in turn, supports the development of more robust computational thinking skills and fosters deeper engagement with the learning process.

The IPMA results indicate that the development of computational thinking skills is predominantly influenced by self-efficacy and engagement, while motivation plays a comparatively lesser role. Students' belief in their technological competence, coupled with their active participation in learning experiences supported by MAR and GPS technologies, are identified as the most impactful contributors. Based on these insights, educational interventions should prioritize enhancing self-efficacy through focused training programs, user-friendly technological interfaces, and hands-on practice with digital tools. Simultaneously, learning activities should be designed to promote engagement by incorporating collaborative, context-rich tasks that make technology use meaningful and immersive. Given motivation's lower performance, educators should additionally highlight the tangible benefits of MAR and GPS technologies—such as real-world problem-solving advantages and quick, successful experiences—to build intrinsic interest and maximize the impact on students' computational thinking development. This likely reflects the relatively limited influence exerted by perceived usefulness.

Overall, the advancement of self-efficacy, the perception of technology's usefulness, and the cultivation of computational thinking skills should be understood as mutually reinforcing components within the learning process. Educational interventions that address all three elements in a coordinated manner have the potential to significantly elevate student engagement, promote more effective and meaningful use of technology, and lead to improved academic performance. As a result, educational institutions and decision-makers in the education sector must prioritize the development of integrated strategies that embed these interconnected elements into all technology-supported learning programs. Such holistic approaches are vital to maximizing the educational benefits of digital tools and fostering deeper, more meaningful student learning experiences.

In summary, this study's findings highlight that self-efficacy, engagement, and motivation function collectively to support the development of students' computational thinking skills within technology-enhanced learning environments. Self-efficacy plays a pivotal role, exerting both direct and indirect effects—students who are confident in their technological capabilities are more inclined to participate actively in learning tasks and maintain high levels of motivation. Engagement serves as a mediating factor, bridging self-efficacy and computational thinking by fostering sustained involvement and deeper cognitive interaction with the learning content. Motivation, although contributing with a smaller effect size, reinforces students' persistence and willingness to apply computational concepts. The integrated interaction among these constructs emphasizes the importance of fostering not only cognitive competence but also affective and behavioral factors to optimize computational thinking outcomes.

Building on these insights, the following practical recommendations may help optimize the development of computational thinking by addressing the specific needs identified in self-efficacy, engagement, and motivation. To strengthen self-efficacy, learning designs should include scaffolded instruction, real-world problem-solving tasks, and continuous formative feedback to build students' confidence in handling technological challenges. Instructors should promote active engagement through collaborative learning, gamification elements, and interactive technologies that facilitate student-centered exploration. Moreover, targeted interventions such as resilience training, counseling, and goal-setting activities may help enhance motivation, particularly in addressing low-performing sub-indicators such as MT4. For technology developers, designing intuitive and user-friendly applications that reduce cognitive load can further support students' confidence and motivation, leading to improved computational thinking development.

While this study offers valuable insights into the interplay between self-efficacy, engagement, motivation, and computational thinking within technology-enhanced learning environments, several limitations warrant consideration. First, reliance on self-reported data introduces the possibility of bias stemming from students' subjective perceptions, which may not fully reflect actual behaviors or competencies. Second, the research was conducted within a single academic cohort from a specific program, potentially limiting the applicability of the findings to broader educational contexts or different fields of study. Third, the cross-sectional design of the study constrains the ability to draw causal conclusions about the relationships among variables. To address these limitations, future studies should consider employing longitudinal or experimental methodologies to track changes over time and provide stronger evidence of causal relationships. Additionally, further studies may explore how instructional design elements, cultural differences, or technological accessibility affect these relationships in diverse educational contexts.

V. Conclusion

This study highlights the interconnected roles of self-efficacy, engagement, motivation, and computational thinking in optimizing the use of Markerless Augmented Reality (MAR) and GPS technologies in higher education. Students with stronger self-efficacy are more likely to engage with and benefit from technology-enhanced learning, while engagement and motivation serve as key pathways for developing computational thinking skills. Instead of treating these constructs as separate entities, the findings suggest a dynamic relationship in which confidence, curiosity, and sustained interaction with technology reinforce one another. These psychological and behavioral factors collectively support deeper learning and stronger academic outcomes.

To support this, educational institutions should focus on cultivating students' confidence and motivation by integrating intuitive, meaningful, and enjoyable learning experiences. When students perceive MAR and GPS as useful and accessible, their willingness to explore and apply technology in real-world problem-solving increases—thereby strengthening computational thinking and improving learning achievement.

Enhancing students' belief in their own abilities can lead to increased motivation, which subsequently promotes more active engagement with MAR and GPS technologies. Consistent interaction with these tools contributes to the advancement of computational thinking abilities and supports the broader integration of technology into the learning process. When educational technologies are designed to be intuitive and engaging, their frequent use becomes more likely, thereby improving learners' capacity for analytical and problem-solving tasks. Additionally, when students recognize the practical value of such technologies, it further reinforces their computational thinking development and contributes to improved academic outcomes.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Muhammad Dominique Mendoza contributed to the conceptualization, methodology, supervision, project administration, and was actively involved in writing both the original draft and the review and editing stages. Olnes Yosefa Hutajulu was responsible for software development, formal analysis, validation, visualization, and also participated in the review and editing of the manuscript. Wan Ahmad Jaafar Wan Yahaya provided contributions in conceptualization, resources, supervision, as well as reviewing and editing the manuscript. Sriadhi contributed through funding acquisition, project administration, supervision, and reviewing and editing. Reni Rahmadani was engaged in data curation and investigation, alongside writing the original draft and reviewing and editing the manuscript. Ressy Dwitias Sari contributed to investigation, data curation, and reviewing and editing. Eka Dodi Suryanto was responsible for software development, formal analysis, validation, and visualization. Elsa Sabrina participated in investigation and visualization, as well as writing the original draft and engaging in the review and editing of the manuscript. All authors have read and approved the final version of the manuscript.

ACKNOWLEDGMENT

The researchers would like to express their sincere appreciation to the Directorate of Research, Technology, and Community Service (DRTPM) for their invaluable support and funding, which made this study possible. Their contribution has been instrumental in advancing our research and achieving its objectives.

REFERENCES

[1] G. Hassan, "Technology and the transformation of educational practices: A future perspective," *Int. J. Econ. Bus. Account. Agric. Manag. Sharia Adm. IJEBAS*, vol. 3, no. 1, pp. 1596–1603, 2023.

[2] A. Alam and A. Mohanty, "Educational technology: Exploring the convergence of technology and pedagogy through mobility, interactivity, AI, and learning tools," *Cogent Eng.*, vol. 10, no. 2, 2283282, Dec. 2023. doi: 10.1080/23311916.2023.2283282

[3] P. S. Aithal and A. K. Maiya, "Innovations in higher education industry–Shaping the future," *Int. J. Case Stud. Bus. IT Educ. IJCSBE*, vol. 7, no. 4, pp. 283–311, 2023.

[4] O. T. Akintayo, C. A. Eden, O. O. Ayeni, and N. C. Onyebuchi, "Evaluating the impact of educational technology on learning outcomes in the higher education sector: A systematic review," *Int. J. Manag. Entrep. Res.*, vol. 6, no. 5, pp. 1395–1422, 2024.

[5] M. Anwar, T. Taali, H. Hidayat, and E. Sabrina, "Exploring trait thinking in predicting students' Higher-Order Thinking Skills (HOTS) using ANFIS: A study on electronics engineering education students," *TEM J.*, vol. 13, no. 4, 3103, 2024.

[6] H. T. Zimmerman, S. M. Land, L. Faimon, and Y.-C. Chiu, "Mobile augmented reality supporting families' immersive collaborative learning: Learning-on-the-move for place-based geoscience sense-making," *Int. J. Comput.-Support. Collab. Learn.*, vol. 18, no. 2, pp. 291–322, Jun. 2023. doi: 10.1007/s11412-023-09399-9

[7] M. Anwar, Y. Rahmawati, N. Yuniarti, H. Hidayat, and E. Sabrina, "Leveraging augmented reality to cultivate higher-order thinking skills and enhance students' academic performance," *Int. J. Inf. Educ. Technol.*, vol. 14, no. 10, 2024.

[8] D. Frialdo, M. Anwar, Y. H. Refdinal, E. Sabrina, and H. Hidayat, "Enhancing network systems programming learning through augmented reality: A study on student engagement and understanding," *Int. J. Inf. Educ. Technol.*, vol. 15, no. 4, 2025.

[9] M. Manna, "Contextualizing mobile augmented reality for the Italian language teaching and learning: A study on teachers' values and purposes in action," *Proy. Investig.*, 2024.

[10] J. Cao, K.-Y. Lam, L.-H. Lee, X. Liu, P. Hui, and X. Su, "Mobile augmented reality: User interfaces, frameworks, and intelligence," *ACM Comput. Surv.*, vol. 55, no. 9, pp. 1–36, Sep. 2023. doi: 10.1145/3557999

[11] A. Hamidi, "Advancing computational thinking education: Insights from systems thinking applications," *Hum. Syst. Manag.*, vol. 44, no. 1, pp. 157–172, Jan. 2025. doi: 10.3233/HSM-240024

[12] A. García-Requejo, M. C. Pérez-Rubio, J. M. Villadangos, and Á. Hernández, "Activity monitoring and location sensory system for people with mild cognitive impairments," *IEEE Sens. J.*, vol. 23, no. 5, pp. 5448–5458, 2023.

[13] N. S. Alharbi, "Exploring the perspectives of cross-cultural instructors on integrating 21st century skills into EFL university courses," *Frontiers in Education*, Frontiers Media SA, 2024.

[14] R. A. Rahimi and G. S. Oh, "Rethinking the role of educators in the 21st century: Navigating globalization, technology, and pandemics," *J. Mark. Anal.*, vol. 12, no. 2, pp. 182–197, Jun. 2024. doi: 10.1057/s41270-024-00303-4

[15] Y. M. Park, "A GPS-enabled portable air pollution sensor and web-mapping technologies for field-based learning in health geography," *J. Geogr. High. Educ.*, vol. 46, no. 2, pp. 241–261, Apr. 2022. doi: 10.1080/03098265.2021.1900083

[16] Y. Wang and W. Zhang, "The relationship between college students' learning engagement and academic self-efficacy: A moderated mediation model," *Front. Psychol.*, vol. 15, 1425172, 2024.

[17] L. D. Basileo, B. Otto, M. Lyons, N. Vannini, and M. D. Toth, "The role of self-efficacy, motivation, and perceived support of students' basic psychological needs in academic achievement," *Frontiers in Education*, Frontiers Media SA, 2024.

[18] X. Shang, Z. Jiang, F.-K. Chiang, Y. Zhang, and D. Zhu, "Effects of robotics STEM camps on rural elementary students' self-efficacy and computational thinking," *Educ. Technol. Res. Dev.*, vol. 71, no. 3, pp. 1135–1160, Jun. 2023. doi: 10.1007/s11423-023-10191-7

[19] Q. Li, Q. Jiang, J.-C. Liang, W. Xiong, and W. Zhao, "Engagement predicts computational thinking skills in unplugged activity: Analysis of gender differences," *Think. Ski. Creat.*, vol. 52, 101537, 2024.

[20] Y. Liu, S. Ma, and Y. Chen, "The impacts of learning motivation, emotional engagement and psychological capital on academic performance in a blended learning university course," *Front. Psychol.*, vol. 15, 1357936, 2024.

[21] A. Kaur and K. K. Chahal, "Exploring personality and learning motivation influences on students' computational thinking skills in introductory programming courses," *J. Sci. Educ. Technol.*, vol. 32, no. 6, pp. 778–792, Dec. 2023. doi: 10.1007/s10956-023-10052-1

[22] J. Moneva and S. M. Tribunalo, "Students' level of self-confidence and performance tasks," *Asia Pac. J. Acad. Res. Soc. Sci.*, vol. 5, no. 1, pp. 42–48, 2020.

[23] M. S. Hussain, S. A. Khan, and M. C. Bidar, "Self-efficacy of teachers: A review of the literature," *Multi-Discip. Res. J.*, vol. 10, no. 1, pp. 110–116, 2022.

[24] D. Schunk and M. Dibenedetto, "Self-efficacy and human motivation," *Advances in Motivation Science*, vol. 8, pp. 153–179, Elsevier, 2020.

[25] T. H. Morris, "Experiential learning—A systematic review and revision of Kolb's model," *Interact. Learn. Environ.*, vol. 28, no. 8, pp. 1064–1077, Nov. 2020. doi: 10.1080/10494820.2019.1570279

[26] S. Graham, "Self-efficacy and language learning—What it is and what it isn't," *Lang. Learn. J.*, vol. 50, no. 2, pp. 186–207, Mar. 2022. doi: 10.1080/09571736.2022.2045679

[27] K. Bhati and T. Sethy, "Self-efficacy: Theory to educational practice," *Int. J. Indian Psychol.*, vol. 10, no. 1, pp. 1123–1128, 2022.

[28] A. Alhadabi and A. C. Karpinski, "Grit, self-efficacy, achievement orientation goals, and academic performance in University students," *Int. J. Adolesc. Youth*, vol. 25, no. 1, pp. 519–535, Dec. 2020. doi: 10.1080/02673843.2019.1679202

[29] L. Wirthwein and R. Steinmayr, "Performance-approach goals: the operationalization makes the difference," *Eur. J. Psychol. Educ.*, vol. 36, no. 4, pp. 1199–1220, Dec. 2021. doi: 10.1007/s10212-020-00520-2

[30] P. Berrone, H. E. Rousseau, J. E. Ricart, E. Brito, and A. Giuliodori, "How can research contribute to the implementation of sustainable development goals? An interpretive review of SDG literature in management," *Int. J. Manag. Rev.*, vol. 25, no. 2, pp. 318–339, Apr. 2023. doi: 10.1111/ijmr.12331

[31] R. Goodman and D. Burton, "What is the nature of the achievement gap, why does it persist and are government goals sufficient to create social justice in the education system?" *Contemporary Issues in Primary Education*, Routledge, 2022.

[32] H. Farley, "Promoting self-efficacy in patients with chronic disease beyond traditional education: A literature review," *Nurs. Open*, vol. 7, no. 1, pp. 30–41, Jan. 2020. doi: 10.1002/nop2.382

[33] Z. Y. Wong and G. A. D. Liem, "Student engagement: Current state of the construct, conceptual refinement, and future research directions," *Educ. Psychol. Rev.*, vol. 34, no. 1, pp. 107–138, Mar. 2022. doi: 10.1007/s10648-021-09628-3

[34] S. M. Kelders, L. E. Van Zyl, and G. D. Ludden, "The concept and components of engagement in different domains applied to eHealth: A systematic scoping review," *Front. Psychol.*, vol. 11, 2020.

[35] E. Nusantari, A. Abdul, I. Damopolii, A. S. R. Alghafri, and B. S. Bakkar, "Combination of discovery learning and metacognitive knowledge strategy to enhance students' critical thinking skills," *Eur. J. Educ. Res.*, vol. 10, no. 4, pp. 1781–1791, 2021.

[36] A. Brown, J. Lawrence, M. Basson, and P. Redmond, "A conceptual framework to enhance student online learning and engagement in higher education," *High. Educ. Res. Dev.*, vol. 41, no. 2, pp. 284–299, 2022.

[37] N. Pearson, P.-J. Naylor, M. C. Ashe, M. Fernandez, S. L. Yoong, and L. Wolfenden, "Guidance for conducting feasibility and pilot studies for implementation trials," *Pilot Feasibility Stud.*, vol. 6, no. 1, 167, Dec. 2020. doi: 10.1186/s40814-020-00634-w

[38] H. E. Fitzgerald, K. Bruns, S. T. Sonka, A. Furco, and L. Swanson, "The centrality of engagement in higher education," *J. High. Educ. Outreach Engagem.*, vol. 20, no. 1, pp. 223–244, 2016.

[39] D. Lombardi *et al.*, "The curious construct of active learning," *Psychol. Sci. Public Interest*, vol. 22, no. 1, pp. 8–43, Apr. 2021. doi: 10.1177/1529100620973974

[40] M. Jones, J. E. Blanton, and R. E. Williams, "Science to practice: Does gamification enhance intrinsic motivation?" *Act. Learn. High. Educ.*, vol. 24, no. 3, pp. 273–289, Nov. 2023, doi: 10.1177/14697874211066882
[41] O. Kryshko, J. Fleischer, J. Waldeyer, J. Wirth, and D. Leutner, "Do motivational regulation strategies contribute to university students' academic success?" *Learn. Individ. Differ.*, vol. 82, 101912, 2020.
[42] A. Bakhtiar and A. F. Hadwin, "Motivation from a self-regulated learning perspective: Application to school psychology," *Can. J. Sch. Psychol.*, vol. 37, no. 1, pp. 93–116, 2022.
[43] M. Hosen, S. Ogbeibu, B. Giridharan, T.-H. Cham, W. M. Lim, and J. Paul, "Individual motivation and social media influence on student knowledge sharing and learning performance: Evidence from an emerging economy," *Comput. Educ.*, vol. 172, 104262, 2021.
[44] G. L. Matee, N. Motlohi, and P. Nkiwane, "Emerging perspectives and challenges for virtual collaborative learning in an institution of higher education: a case of Lesotho," *Interact. Technol. Smart Educ.*, vol. 20, no. 1, pp. 73–88, 2023.
[45] M. D. Mendoza, O. Y. Hutajulu, A. R. Lubis, R. Rahmadani, and T. T. A. Putri, "The influence of the use of social media in education on students' academic achievement," *J. Teknol. Pendidik.*, vol. 15, no. 2, 2022. (in Indonesian)
[46] E. Sabrina, "The effect of control focus, courage, and open-mindedness on academic performance: Implications for education and management," *Perspekt. Ilmu Pendidik.*, vol. 37, no. 2, pp. 111–118, 2023.
[47] K. Xie, V. W. Vongkulluksn, L. Lu, and S.-L. Cheng, "A person-centered approach to examining high-school students' motivation, engagement and academic performance," *Contemp. Educ. Psychol.*, vol. 62, 101877, 2020.
[48] X. P. Voon, S. L. Wong, L. H. Wong, M. N. M. Khambari, and S. I. S. S. Abdullah, "Developing computational thinking competencies through constructivist argumentation learning: A problem-solving perspective," *Int. J. Inf. Educ. Technol.*, 2022.
[49] D. Liu *et al.*, *Using Educational Robots to Enhance Learning,* Singapore: Springer Nature Singapore, 2024. doi: 10.1007/978-981-97-5826-5
[50] K. Woo and G. Falloon, "Problem solved, but how? An exploratory study into students' problem-solving processes in creative coding tasks," *Think. Ski. Creat.*, vol. 46, p 101193, 2022.
[51] V. Kite and S. Park, "What's Computational Thinking?: Secondary Science Teachers' Conceptualizations of Computational Thinking (CT) and Perceived Barriers to CT Integration," *J. Sci. Teach. Educ.*, vol. 34, no. 4, pp. 391–414, May 2023.
[52] O. Cohavi and S. Levy-Tzedek, "Young and old users prefer immersive virtual reality over a social robot for short-term cognitive training," *Int. J. Hum.-Comput. Stud.*, vol. 161, 102775, 2022.
[53] C. Sailer, "Enhancing knowledge, skills, and spatial reasoning through location-based mobile learning," PhD Thesis, ETH Zurich, 2020.
[54] M. M. Willie, "Population and target population in research methodology," *Gold. Ratio Soc. Sci. Educ.*, vol. 4, no. 1, pp. 75–79, 2024.
[55] E. Gorman, N. Bowden, J. Kokaua, B. McNeill, and P. J. Schluter, "A national multiple baseline cohort study of mental health conditions in early adolescence and subsequent educational outcomes in New Zealand," *Sci. Rep.*, vol. 13, no. 1, 11025, 2023.
[56] G. Kutuk, D. W. Putwain, L. K. Kaye, and B. Garrett, "The development and preliminary validation of a new measure of self-efficacy: Questionnaire of self-efficacy in learning a foreign language," *ITL - Int. J. Appl. Linguist.*, vol. 174, no. 2, pp. 230–262, Sep. 2023. doi: 10.1075/itl.21031.kut
[57] M. E. Hannum and C. T. Simons, "Development of the Engagement Questionnaire (EQ): A tool to measure panelist engagement during sensory and consumer evaluations," *Food Qual. Prefer.*, vol. 81, 103840, 2020.
[58] H. J. Hermans, "A questionnaire measure of achievement motivation.," *J. Appl. Psychol.*, vol. 54, no. 4, 353, 1970.
[59] K. M. Yusoff, N. S. Ashaari, T. S. M. T. Wook, and N. M. Ali, "Validation of the components and elements of computational thinking for teaching and learning programming using the fuzzy Delphi method," *Int. J. Adv. Comput. Sci. Appl.*, vol. 12, no. 1, 2021.
[60] R. W. Barnes, J. W. Grove, and N. H. Burns, "Experimental assessment of factors affecting transfer length," *Struct. J.*, vol. 100, no. 6, pp. 740–748, 2003.
[61] J. C. Anderson and D. W. Gerbing, "Structural equation modeling in practice: A review and recommended two-step approach.," *Psychol. Bull.*, vol. 103, no. 3, 411, 1988.
[62] J. F. Hair, M. Sarstedt, C. M. Ringle, and J. A. Mena, "An assessment of the use of partial least squares structural equation modeling in marketing research," *J. Acad. Mark. Sci.*, vol. 40, no. 3, pp. 414–433, May 2012. doi: 10.1007/s11747-011-0261-6
[63] J. Hair and A. Alamer, "Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example," *Res. Methods Appl. Linguist.*, vol. 1, no. 3, 100027, 2022.
[64] L. Zhao, X. Liu, and Y.-S. Su, "The differentiate effect of self-efficacy, motivation, and satisfaction on pre-service teacher students' learning achievement in a flipped classroom: A case of a modern educational technology course," *Sustainability*, vol. 13, no. 5, 2888, 2021.
[65] S. Zhao and C. Cao, "Exploring relationship among self-regulated learning, self-efficacy and engagement in blended collaborative context," *Sage Open*, vol. 13, no. 1, Jan. 2023. doi: 10.1177/21582440231157240
[66] S. Lin, C. Longobardi, and P. Bozzato, "The impact of academic self-efficacy on academic motivation: The mediating and moderating role of future orientation among Italian undergraduate students," in *Academic Self-efficacy in Education*, M. S. Khine and T. Nielsen, Eds., Singapore: Springer Singapore, 2022, pp. 191–209. doi: 10.1007/978-981-16-8240-7_12
[67] A. A. Hayat, K. Shateri, M. Amini, and N. Shokrpour, "Relationships between academic self-efficacy, learning-related emotions, and metacognitive learning strategies with academic performance in medical students: A structural equation model," *BMC Med. Educ.*, vol. 20, no. 1, 76, Dec. 2020. doi: 10.1186/s12909-020-01995-9
[68] A. Alhadabi and A. C. Karpinski, "Grit, self-efficacy, achievement orientation goals, and academic performance in University students," *Int. J. Adolesc. Youth*, vol. 25, no. 1, pp. 519–535, Dec. 2020. doi: 10.1080/02673843.2019.1679202
[69] N. Kvaššayová, M. Cápay, Š. Petrík, M. Bellayová, and E. Klimeková, "Experience with using BBC micro: Bit and perceived professional efficacy of informatics teachers," *Electronics*, vol. 11, no. 23, 3963, 2022.
[70] Q. Li, Q. Jiang, J.-C. Liang, W. Xiong, Y. Liang, and W. Zhao, "Effects of interactive unplugged programming activities on computational thinking skills and student engagement in elementary education," *Educ. Inf. Technol.*, vol. 28, no. 9, pp. 12293–12318, Sep. 2023. doi: 10.1007/s10639-023-11634-7
[71] M. M. Gümüş, V. Kukul, and Ö. Korkmaz, "Relationships between middle school students' digital literacy skills, computer programming self-efficacy, and computational thinking self-efficacy," *Inform. Educ.*, vol. 23, no. 3, pp. 571–592, 2024.
[72] M. Haverila, K. C. Haverila, and J. C. Twyford, "The influence of marital status on customer-centric measures in the context of a ski resort using the importance-performance map analysis (IPMA) framework," *Eur. J. Manag. Stud.*, vol. 28, no. 1, pp. 49–68, 2023.
[73] A. Amoozegar, M. Abdelmagid, and T. Anjum, "Course satisfaction and perceived learning among distance learners in Malaysian Research Universities: The impact of motivation, self-efficacy, self-regulated learning, and instructor immediacy behaviour," *Open Learn. J. Open Distance E-Learn.*, vol. 39, no. 4, pp. 387–413, Oct. 2024. doi: 10.1080/02680513.2022.2102417
[74] F.-K. Chiang, Y. Zhang, D. Zhu, X. Shang, and Z. Jiang, "The influence of online STEM education camps on students' self-efficacy, computational thinking, and task value," *J. Sci. Educ. Technol.*, vol. 31, no. 4, pp. 461–472, Aug. 2022. doi: 10.1007/s10956-022-09967-y
[75] J. Van De Pol, M. Volman, and J. Beishuizen, "Scaffolding in teacher–student interaction: A decade of research," *Educ. Psychol. Rev.*, vol. 22, no. 3, pp. 271–296, Sep. 2010. doi: 10.1007/s10648-010-9127-6
[76] C. Wang, J. Shen, and J. Chao, "Integrating computational thinking in stem education: A literature review," *Int. J. Sci. Math. Educ.*, vol. 20, no. 8, pp. 1949–1972, Dec. 2022. doi: 10.1007/s10763-021-10227-5
[77] S. Liu, C. Peng, and G. Srivastava, "What influences computational thinking? A theoretical and empirical study based on the influence of learning engagement on computational thinking in higher education," *Comput. Appl. Eng. Educ.*, vol. 31, no. 6, pp. 1690–1704, Nov. 2023. doi: 10.1002/cae.22669
[78] E. Alsadoon, A. Alkhawajah, and A. B. Suhaim, "Effects of a gamified learning environment on students' achievement, motivations, and satisfaction," *Heliyon*, vol. 8, no. 8, 2022.
[79] B. Zheng, C. Chang, C.-H. Lin, and Y. Zhang, "Self-efficacy, academic motivation, and self-regulation: How do they predict academic achievement for medical students?" *Med. Sci. Educ.*, vol. 31, no. 1, pp. 125–130, Feb. 2021. doi: 10.1007/s40670-020-01143-4