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When Learning Processes Fail Novices: Technology Acceptance Through Mediation-Moderation Analysis in High School AI-Coding Education

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Abstract: This study examines an expanded Technology Acceptance Model (TAM) to evaluate the implementation of an AI and coding curriculum in high schools. Specifically, it integrates Perceived Usefulness and Perceived Ease of Use into Student Motivation as a mediator to analyze the relationship between Learning Processes and Learning Outcomes, moderated by Prior Coding Experience. Using an explanatory quantitative design, data were collected from 114 students at HelloMotion High School, a benchmarking school for national curriculum piloting. Structural Equation Modeling (SEM-PLS) revealed three critical findings. First, the learning process positively predicts learning outcomes ($\beta = 0.244$, $p = 0.005$). Second, student motivation functions as a significant partial mediator (indirect effect: $\beta = 0.361$, $p < 0.001$, which is stronger than the direct effect), confirming that the direct impact of pedagogy remains significant alongside psychological factors. Third, while the formal moderation of coding experience was statistically nonsignificant ($p = 0.321$), exploratory multi-group analysis showed that the learning process significantly impacted students with basic experience ($p = 0.026$) but failed to significantly impact complete novices ($p = 0.160$). These findings suggest that a "one-size-fits-all" curriculum is insufficient, highlighting the urgency for differentiated instructional strategies to support novice learners in national policy implementation.

Keywords: HelloMotion High School; Mediation; Moderation; Motivation; SEM-PLS; Technology acceptance model

Introduction

The Industrial Revolution 4.0 has transformed global education paradigms, shifting from knowledge transmission to the cultivation of digital literacy. UNESCO's 2024 report confirms that by 2022, 15 countries had integrated AI learning objectives into their national curricula (UNESCO, 2024), signalling a fundamental shift in learning ecosystems. World Economic Forum projections for 2025 indicate that future jobs will require coding and AI literacy, creating a global imperative for responsive curriculum transformation. Globally, the proportion of jobs performed by humans is projected to decline by 2030 compared to 2025. Approximately 82% of this reduction is due to advances in automation, while 19% is projected to stem from expanded human-machine collaboration (World Economic Forum, 2025).

In the Indonesian context, digital transformation has accelerated with the issuance of Permendikdasmen No. 13 of 2025 (Kemendikdasmen, 2025), which mandates the integration of Coding and AI into the secondary curriculum to equip young generations with essential Computational Thinking (CT) skills (Angeli & Giannakos, 2020). This policy is a strategic response to the immense economic potential of AI, which is projected to contribute more than USD 1.5 trillion to global GDP (Dhomke, 2023). However, realizing this potential is hindered by a critical talent shortage. Indonesia is projected to face a deficit of 9 million digital

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workers by 2030 (BSKAP, 2025) and currently ranks 51st out of 69 countries in Digital Competitiveness due to gaps in future-readiness (Bris, 2025).

The projected shortage of 9 million digital talents by 2030 (BSKAP, 2025) cannot be resolved solely through short-term vocational training in adulthood. Structural solutions must begin upstream, namely through curriculum interventions at the secondary education level to build a sustainable talent pipeline. According to Mahfud et al. (2020), students' readiness to select specific career paths is significantly shaped by antecedent factors during schooling, particularly by teaching quality and psychological capital.

If the implementation of the Coding-AI curriculum at the high school level fails to foster adequate computational thinking and STEM attitudes, students will not possess the foundational 21st-century skills required to enter the digital workforce (Richardo et al., 2023). Digital literacy competencies are key to adapting to rapid technological advances (Hayyi, 2025). Therefore, evaluating the implementation of the curriculum in high schools is not merely a micro-educational issue but a strategic imperative to ensure the supply of future digital talent.

However, the implementation of this curriculum is constrained by infrastructure realities. National data paints a nuanced picture of the digital divide. UNESCO reports that internet connectivity has reached 92.8% of secondary schools, leaving approximately 7.2% without access (UNESCO, 2024b). This figure corresponds with the Bappenas (2025) report, which identified 10.03% of educational institutions still experiencing internet access challenges (Bappenas, 2025). The convergence of these two data sets confirms that approximately 7-10% of schools are in the gap. These facilitating conditions are crucial because disparities in physical facilities have been shown to hinder technology adoption in educational settings (Basyah et al., 2025; Nuryanna et al., 2021). This data discrepancy likely reflects differences between registered urban schools and remote institutions, underscoring the need for research that extends beyond infrastructure to examine user acceptance (Wijaya, 2023).

Although physical infrastructure is crucial, successful technology integration depends heavily on teachers' visionary leadership and the readiness of the learning environment (Yusuf et al., 2024). According to Celik (2023), transformation involves not merely the adoption of technology but the reconstruction of digital pedagogical competencies at both the teacher and student levels. However, the success of technology adoption ultimately depends on user acceptance (students).

Most of these studies, including a systematic literature review on the Technology Acceptance Model (TAM), only focus on overall success and often ignore variations in students' initial readiness (novice vs. expert) (Sutiyono et al., 2024). While the classic Technology Acceptance Model (TAM) (Davis, 1989; Teo, 2011) effectively predicts adoption based on utility. Recent educational studies suggest that intrinsic psychological factors are equally critical for complex subjects like AI. In the Indonesian context, student achievement in science is significantly mediated by motivation and support systems (Cahyani & Setiawan, 2024). This suggests that infrastructure availability alone is insufficient; students' internal motivation is also required. Although motivation is recognized as a strong predictor of learning success (Zhang & Liu, 2025), its specific role as a mediator, bridging the gap between digital pedagogy and learning outcomes, remains under-researched in Indonesia's high school coding curriculum.

This phenomenon is also reflected in the Technology Implementation Paradox, which posits that the complexity of technology often hinders micro-level adoption. Psychologically, the effectiveness of educational technology implementation depends heavily on end-user acceptance factors. A meta-analysis by Hwang et al. (2022) of 125 educational technology intervention studies found that intrinsic motivation serves as a critical mediator between technology exposure and learning outcomes (Hwang & Chien, 2022).

To analyze this adoption, the Technology Acceptance Model (TAM) remains a robust framework. However, standard TAM often overlooks the psychological nuances of complex subjects like AI. Therefore, integrating student motivation as a mediator is crucial to this research. The Acceptance Model comprises Perceived Usefulness and Ease of Use as predictors of technology adoption (Basyah et al., 2025).

On the other hand, technology acceptance models sometimes overlook prior knowledge or previous experience. This is a crucial research gap. In coding learning, students entering classes with a basic understanding certainly have different perceptions and levels of acceptance than students with no prior experience. Cognitive Load Theory (Sweller et al., 2019) and the Expertise Reversal Effect (Kalyuga et al., 2011) show that learning interventions effective for beginners may be ineffective (or even hindering) for experts, and vice versa. Previous studies' failure to integrate experience as a moderator variable in this new curriculum context creates the gap this research seeks to address. If the curriculum is implemented uniformly without accounting for this 'readiness gap,' it may fail to accommodate beginners. Therefore, integrating prior coding experience as a moderator is crucial for diagnosing whether the national curriculum is inclusive of students with varying levels of initial competency.

This study aims to fill this gap by examining an expanded technology acceptance model in the unique context of coding-AI curriculum implementation in Indonesia. Unlike previous research, this model integrates learning processes as antecedents, student motivation as a mediator, and prior coding experience as a moderator, to analyze learning impact as an outcome. The novelty of this study lies in its critical evaluation of the effectiveness of the Coding-AI curriculum for novice students. When a curriculum is applied uniformly ('one-size-fits-all'), there is a risk that even sophisticated learning processes may fail for students with no prior coding experience.

To provide empirical clarity, this study operationalizes the "Learning Process" not merely as tool usage, but as the active utilization of the Apple ecosystem (iPad and Swift Playgrounds) integrated with Project-Based Learning (PjBL) (Putri et al., 2023; Safitri et al., 2024). Adopted from the DeLone & McLean IS Success Model framework applied in education (Sutiyono et al., 2024), the indicators measured students' perceived usefulness, ease of use, and engagement. Meanwhile, "Learning Impact" is measured by improvements in Logical Thinking and Technology Career Interest (Asrizal et al., 2023; Dhany et al., 2025). Based on these definitions, this study addresses three research questions: (1) Does the technology-integrated learning process significantly influence student learning impact in the context of the Coding-AI curriculum? (2) Does student motivation (perception and interest) mediate the relationship between the learning process and learning impact? (3) Does prior coding experience moderate the relationships within this acceptance model?

Method

This study employed a quantitative approach with an ex post facto design. According to Mahfud et al. (2020), this design is appropriate when the researcher does not directly control or manipulate the independent variables, because the events (e.g., the learning process) have already occurred naturally (Creswell, 2014). Therefore, this study examines the predictive structural relationships and associations among the learning process ecosystem, student motivation, and learning impact using Structural Equation Modeling (SEM), rather than establishing absolute causality through experimental manipulation.

To ensure clarity and reproducibility, the research procedure is visualized in Figure 1, following the flowchart style used by (Hayyi, 2025).

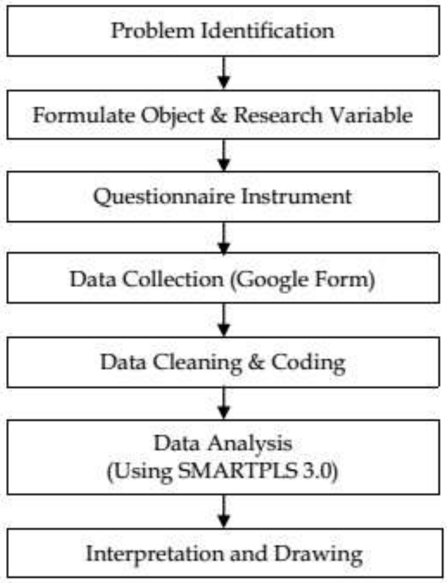

Figure 1. Research methodology flowchart source: PLS data processing result

The research was conducted at HelloMotion High School in South Tangerang, a creative school that had implemented coding instruction since the 2022/2023 Academic Year. This school was purposively selected as it holds the status of an Apple Distinguished School (ADS) and serves as a national benchmarking school for the Coding and AI Curriculum pilot by the Ministry of Education. In this unique ecosystem, the iPad and Swift Playgrounds are not optional tools but constitute the primary instructional environment.

The research population comprised all grade X, XI, and XII students at HelloMotion High School who were participating in coding and AI learning. A purposive sampling technique was used, as it allows researchers to deliberately select participants based on specific criteria to obtain in-depth data on the Coding and Artificial Intelligence learning that had been conducted. From distributed questionnaires, 114 valid responses were received. Respondent characteristics included: Gender (Female 58.8%, Male 41.2%), Grade Level (X 35.1%, XI 38.6%, XII 26.3%).

The respondents were categorized based on prior coding experience into two groups for the Multi-Group Analysis: Novice (students with no prior experience, 45.6%) and Experienced (students with some prior experience, 54.4%). This binary grouping is consistent with that of Putri et al. (2023), enabling a robust analysis of how prior knowledge influences critical-thinking adaptability (Putri et al., 2023).

The research instrument was a closed-ended questionnaire using a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). To address the construct validity, the variables were operationalized to measure students' perceptions and psychological engagement rather than the mere frequency of tool usage: (1) Learning Process (Independent Variable): Following the framework of Sutiyono et al. (2024) this variable is conceptualized as "Perceived System Quality" and "Instructional Engagement" (Sutiyono et al., 2024). System Quality: Measures the perceived ease and helpfulness of the Apple ecosystem. Sample item: "The interactive interface of Swift Playground helps me visualize abstract coding logic." In the Instructional Engagement Within the Learning Process variable, the indicators for Project-Based Learning (PBL) and Collaboration were designed to measure students' psychological engagement and perceived effectiveness; (2) Student Motivation (Mediator): This variable assesses intrinsic interest and the drive to learn, serving as the psychological bridge between the tool and the outcome; (3) Learning Impact (Dependent Variable): This variable measures the perceived improvement in cognitive skills and career orientation.

The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 3.0 software. The analysis proceeded in two stages: (1) Measurement Model (Outer Model): evaluated convergent validity (Loading Factor > 0.5, AVE > 0.5) and reliability (Cronbach's Alpha > 0.7, Composite Reliability > 0.7). Discriminant validity was assessed using the Fornell-Larcker criterion; (2) Structural Model (Inner Model): assessed the path coefficients (β) and coefficient of determination (R2) to test the direct and indirect hypotheses; (3) Advanced Analysis such as : Mediation Analysis: performed to test the indirect effect of Student Motivation, and Multi-Group Analysis (MGA): conducted to examine the moderating role of prior coding experience (Novice vs. Experienced) by comparing path coefficients between subgroups. Moderation testing used Multi-Group Analysis (MGA). All significance testing used bootstrapping with 5000 subsamples to ensure the robustness of the results (Hair & Alamer, 2022).

Result and Discussion

Quantitative data were collected through a questionnaire distributed to 114 student respondents (N=114) who had participated in Coding and Artificial Intelligence learning. The questionnaire instrument used a 5-point Likert Scale (1 = Strongly Disagree to 5 = Strongly Agree) to measure three primary constructs: Perception & Motivation (PM), Learning Process (PP), and Learning Impact (DP).

Generally, student response distributions showed diverse dynamics between technology enthusiasm and cognitive difficulties experienced by students. Response percentage details for each indicator are presented in Table 1.

Table 1. Student Questionnaire Response Percentage Distribution (Respondents N=114)

Code	Question (Indicator)	Score (%)				
		1	2	3	4	5
PM1	I feel interested in Coding and AI subjects	8.77	27.19	35.09	22.81	6.14
PM2	Coding and AI learning materials are easy to understand	3.51	33.33	38.6	21.05	3.51
PM3	Coding and AI learning are beneficial for my future	3.51	21.05	30.70	34.21	10.53
PM4	I feel motivated to learn more deeply about Coding	9.65	26.32	43.86	14.04	6.13
PP1	iPad usage in coding learning (Swift) helps my understanding	3.51	12.28	37.72	36.84	9.65
PP2	Coding practice with Swift is fun and challenging	1.75	22.81	36.84	28.07	10.53
PP3	Project-based learning improves my computational thinking skills	1.75	20.18	36.84	34.21	7.02
PP4	Collaboration in groups helps understand difficult material	4.39	22.81	24.56	37.72	10.52
DP1	Coding learning improves my logical thinking ability	2.63	12.28	38.6	35.09	11.4
DP2	I become more confident in using technology	6.14	19.3	42.11	21.93	10.52
DP3	AI ethics material makes me wiser in using technology	1.75	19.3	37.72	28.07	13.16
DP4	I consider technology career after Coding-AI learning	29.82	32.46	22.81	9.65	5.26

Measurement Model Evaluation (Outer Model)

Based on the initial external loading analysis of all indicators used in this study, the results obtained were as shown in Table 2. Based on the convergent validity analysis of the initial measurement model, two indicators were identified as not meeting validity criteria: PM2 in the Perception & Interest construct and PP4 in the Learning Process construct. Indicator PM2 showed a loading factor of 0.469, well below the minimum threshold of 0.5, indicating that it accounted for only 21.9% of the variance in the measured construct. Meanwhile, indicator PP4 indicated a more critical condition, with a loading factor of 0.379, which fell short of the 0.4 threshold, suggesting it accounted for only 14.4% of the variance in the Learning Process construct. The low loading factor values for both indicators indicated that measurement noise or disturbance was more dominant than the substantive signal or information intended to be captured.

Table 2. Initial Outer Loading Results of All Indicators

Construct	Indicator	Outer Loading	Description
Learning Process (X)	PP1	0.681	Meets
	PP2	0.804	Meets
	PP3	0.818	Meets
	PP4	0.379	Does Not Meet
Perception & Motivation (Z)	PM1	0.851	Meets
	PM2	0.469	Does Not Meet
	PM3	0.738	Meets
	PM4	0.829	Meets
Learning Impact (Y)	DP1	0.734	Meets
	DP2	0.867	Meets
	DP3	0.783	Meets
	DP4	0.694	Meets

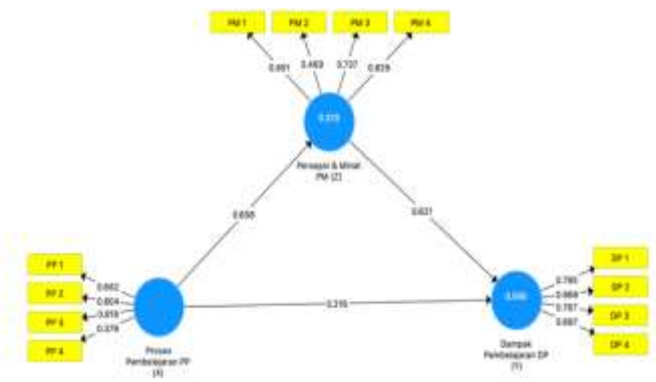

Figure 2. Initial outer loading results of all indicators

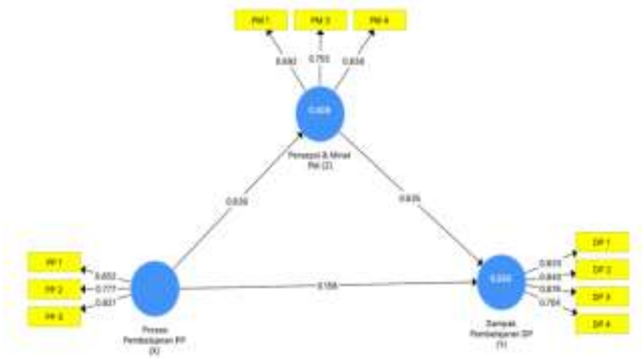

Figure 3. Initial outer loading results of after eliminating two indicators

After eliminating these two indicators, model quality improved significantly, with all remaining indicators achieving loadings above 0.65, Composite Reliability (CR) above 0.80, and Average Variance Extracted (AVE) above 0.55. Specifically, the Learning Process construct achieved AVE 0.598 and CR 0.815; the Perception & Motivation construct, AVE 0.679 and CR 0.864; and the Learning Impact construct achieved, AVE 0.619 and CR 0.866.

Discriminant Validity

Based on the Fornell-Larcker criterion analysis, the measurement model demonstrates adequate discriminant validity. As shown in the Table, each construct accounts for more variance among its own indicators than among indicators of other constructs, confirming their distinctiveness.

Table 3. Discriminant Validity Assessment (Fornell-Larcker Criterion)

Construct:	Learning Impact (Y)	Prior Coding Experience (M)	Perception & Motivation (Z)	Learning Process (X)
Learning Impact (Y)	0.787			
Prior Coding Experience (M)	0.390	1.000		
Perception & Motivation (Z)	0.747	0.339	0.824	
Learning Process (X)	0.604	0.299	0.600	0.773

Note: Diagonal values (in bold) represent the square root of the AVE for each construct. Off-diagonal values represent inter-construct correlations

Learning Impact (Y) has an AVE square root of 0.787, which is higher than its correlations with other constructs (0.390, 0.747, and 0.604), confirming its discriminant validity. Previous Coding Experience (M) shows perfect discriminant validity with an AVE square root of 1,000, being significantly higher than its correlations with other constructs. Perception & Motivation (Z) demonstrates adequate discriminant validity with an AVE square root of 0.824, exceeding all inter-construct correlations.

Learning Process (X) exhibits sufficient discriminant validity with an AVE square root of 0.773, which is higher than its correlations with other constructs.

These results confirm that all constructs in the measurement model are empirically distinct and measure distinct theoretical concepts, thereby meeting the requirements for discriminant validity for further analysis.

Structural Model Evaluation (Inner Model) and Hypothesis Testing

Hypothesis testing using 5,000 bootstrap subsamples produced complex and nuanced findings. The first hypothesis (H1), testing the direct influence of the Learning Process on the Learning Impact, contributed significantly with a path coefficient of 0.244 (t = 2.799, p = 0.005). The second hypothesis (H2), regarding the Motivation mediation role (Perception & Interest), obtained strong empirical support with an indirect effect coefficient of 0.361 (t = 5.888, p = 0.000). Since both the direct effect (H1) and indirect effect (H2) were statistically significant, Motivation functioned as a partial mediator in this model.

Table 4. Hypothesis Testing Results Summary (Overall Model)

Hypothesis	Testing Path	Coefficient (Beta)	T Statistics	P Values	Description
H1	Learning Process → Learning Impact (Direct Effect)	0.244	2.799	0.005	Supported
H2	Process → Motivation → Impact (Mediation Effect)	0.361	5.888	0.000	Supported (Partial Mediation)
H3	Moderation by Coding Experience (MGA Test)	-	-	0.321	Not Supported

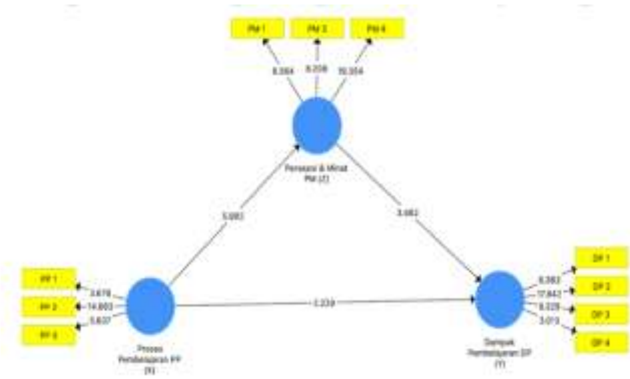

Figure 4. Structural model evaluation (inner model) and hypothesis testing

Determination Coefficient (R^2)

This research model explains 61.1% of the variance in Learning Impact (R^2 = 0.611), which is considered substantial in educational research. Meanwhile, the Learning Process variable accounts for 36.0% of the variance in Student Motivation (R^2 = 0.360). The adjusted R^2 value showed result consistency after adjusting for model complexity.

Multi Group Analysis H3

The third hypothesis (H3) regarding the moderating effect of Coding Experience was statistically rejected based on the Multi-Group Analysis (MGA), which showed no significant difference between experienced and beginner groups (p = 0.321).

Deeper analysis at the group level revealed contrasting findings, although H3 was rejected. In student groups with basic coding experience, the learning process showed a significant direct influence on learning impact (β = 0.346, p = 0.026). Conversely, in student groups without prior experience, the same direct effect was not statistically significant (β = 0.158, p = 0.160). These findings indicated that although the moderation effect was negligible in MGA analysis, there were substantive differences in technology acceptance mechanisms between the two student groups.

Table 5. Novelty Analysis - Comparison Between Experience Groups

Hypothesis Path	Group: Experience (n=62) β (P-Value)	Group: Novice (n=52) β (P-Value)	Interpretation
H1: Learning Process → learning Impact	0.346 (P = 0.026)	0.158 (P = 0.160)	Key Difference!
Description	Significant	Not Significant	Learning process only directly impacts students with basic foundation
Mediation Path (a): Process → Motivation	0.568 (P = 0.000)	0.639 (P = 0.000)	Process successfully motivates both groups
Mediation Path (b): Motivation → Impact	0.491 (P = 0.001)	0.635 (P = 0.000)	Motivation successfully impacts both groups

The Technology-Integrated Learning Process Significantly Influences Student Learning Impact

The significant finding of direct learning process influence on learning impact (H1) (β = 0.244, p = 0.005) confirms that structured learning processes, comprising iPad usage, coding application using Swift Playground, project-based learning (PjBL), and the involvement of collaborative projects, significantly predict logic improvement, technology confidence, and career interest. This finding aligns with the literature on the effectiveness of integrating digital technology and adopting active pedagogy in improving student learning outcomes (Timotheou et al., 2023).

This finding suggests that when students perceive the "System Quality" of the tools and the "Instructional Quality" of the PjBL method as effective, their logical thinking and career interest improve. This aligns with Sutiyono et al. (2024), who utilized the DeLone & McLean model to demonstrate that system and service quality are critical antecedents to user satisfaction and net benefits in e-learning environments (Sutiyono et al., 2024).

The findings of this study, which confirm that the use of Swift and iPads significantly influences students' learning outcomes (H1), align with the broader consensus in the computer science education literature. While introductory coding often relies on block-based environments (such as Scratch) to lower entry barriers, this research demonstrates the efficacy of text-based coding (Swift) in fostering logical thinking and career interest. This suggests that the cognitive benefits of programming are not limited to visual interfaces but are deeply rooted in the structural and algorithmic thinking required by text-based languages (Lindberg et al., 2019).

The positive impact of Swift observed in this study mirrors findings regarding other text-based languages, such as Python. For instance, recent research in Indonesia demonstrated that structured coding instruction using Python significantly improved senior high school students' logical thinking and problem-solving abilities by forcing them to understand the input-process-output logic (Muhammad & Rahmania, 2025). Similarly, the findings of this study suggest that Swift, which also requires attention to syntax and structure, engages similar cognitive mechanisms. Unlike block-based coding, where syntax errors are impossible, text-based languages like Swift require students to internalize grammar and logic simultaneously, potentially leading to a more rigorous development of computational thinking skills once the initial learning curve is overcome (Lindberg et al., 2019).

Although Swift is a text-based language, its deployment on iPads in this study likely facilitated the positive outcomes by leveraging the device's interactive affordances. Research indicates that iPads can serve as effective "focal points" for student attention and collaboration, helping to bridge the gap between abstract code and tangible results. Even when using text-based coding, the iPad's tactile nature and the immediate visual feedback provided by the Swift environment can scaffold learning, making complex logical structures more accessible to learners than traditional desktop environments (Falloon, 2020). This aligns with findings that mobile devices, when paired with appropriate pedagogy, can enhance engagement and support the acquisition of digital literacy (Falloon, 2024).

The study’s confirmation that the learning process impacts career interest is supported by the view that coding is a "new literacy" essential to the 21st-century workforce (Papadakis et al., 2016). By engaging with a professional-grade text-based language like Swift, students are not just playing a game; they are acquiring "hard" skills that are directly transferable to the software industry. This authenticity likely contributes to the increase in career interest observed in the study. Furthermore, the rigorous thinking required to debug and structure text-based code fosters resilience and higher-order thinking skills, such as decomposition and pattern recognition, which are critical for future employability in STEM fields (Mills et al., 2025).

Furthermore, the positive impact of the PjBL component in our study resonates with Putri et al. (2023), who found that problem-based learning (PBL) models significantly enhance critical thinking skills compared to traditional methods (Putri et al., 2023). Similarly, Safitri et al. (2024), found that STEM-based engineering design processes significantly enhance students' creative and critical thinking abilities. In addition, Dhany et al. (2025) argue that integrating design thinking strategies into STEM-PjBL effectively stimulates students' entrepreneurial thinking and problem-solving skills (Dhany et al., 2025; Safitri et al., 2024).

PjBL can create active, meaningful, and challenging learning atmospheres. Through PBL, students are encouraged to think critically, creatively, and collaboratively and to develop solutions. In pedagogy, PBL is often associated with experiential learning that enables students to understand concepts through direct practice and reflection. This project-based learning context is crucial because Coding and AI aim to develop 21st-century competencies, such as computational thinking (including logical and analytical thinking) and problem-solving skills (BSKAP, 2025; Fitrah et al., 2025).

Similarly, according to students’ views on the coding education application process, there were improvements in the sequencing, classification, comparison, and evaluation sub-dimensions of analytical thinking skills (Kocaman, 2023). This finding supports the core premise of Permendikdasmen No. 13 of 2025 that structured curricular interventions can produce desired outcomes.

In the context of this study, the use of project-based learning allows students to engage in 'hands-on' and 'minds-on' activities, which are essential for mastering complex topics like AI. Furthermore, Syaflita et al. (2024) argue that design thinking strategies in learning foster creativity by guiding students through empathy and ideation stages, a process mirrored in the coding projects at HelloMotion High School (Syaflita et al., 2024).

The findings of this study confirm that the implementation of the Coding and Artificial Intelligence curriculum significantly and positively influences students' learning outcomes, particularly in logical thinking, computational thinking (CT), and career interest in technology. This aligns with the fundamental premise that coding is not merely a technical skill but a new literacy essential for developing 21st-century competencies (Mills et al., 2025). Kocaman (2023) found that coding education develops students' analytical thinking skills. Similar to Muhammad et al. (2025), the structured learning process within the AI - Coding curriculum, which integrates Python programming, visual blocks, and project-based learning (PBL), has been shown to foster cognitive abilities such as decomposition, pattern recognition, and algorithmic design (Muhammad & Rahmania, 2025; Nabihah et al., 2025).

However, it is crucial to interpret this finding within the context of the study's ex post facto design, which examines predictive structural relationships based on existing conditions rather than experimental manipulation (Mahfud et al., 2020). Therefore, this result reflects the success of a "best-case scenario" at HelloMotion High School, which possesses an established digital ecosystem. As warned by Nuryanna et al. (2021) in their study on technology acceptance in boarding schools, disparities in facility availability can significantly hinder adoption (Nuryanna et al., 2021). Thus, while the learning process is a strong predictor in this pilot school, its success at a national level will depend heavily on equitable infrastructure readiness (Dhany et al., 2025; Safitri et al., 2024).

While this study confirms that the learning process significantly impacts outcomes (H1 accepted), it is crucial to contextualize this finding within the digital divide framework (Folabit et al., 2025). A study conducted at a unique school, SMA HelloMotion, which has adopted Apple technology since 2019, confirms findings that the use of digital tools, when properly integrated into learning processes, improves teachers' success in coding instruction (Akyuz, 2022). Thus, the positive impact observed here serves as a benchmark, implying that the national curriculum's success depends heavily on the government's ability to provide equitable facilities and teaching quality (Mahfud et al., 2020) comparable to the pilot school studied. Thus, although H1 was significant, replication success in more diverse contexts requires greater consideration of contextual factors.

Crucial Motivation Role as Mediator

This study provides empirical evidence of partial mediation, where the direct effect of the learning process remains significant (β=0.244) even after accounting for the strong indirect effect through motivation (β=0.361). This underscores that while good pedagogy is crucial, its impact is amplified when students are intrinsically motivated. This finding suggests that while the Coding-AI curriculum directly improves skills, its effect is substantially amplified when it successfully triggers students' intrinsic motivation. This mechanism echoes the findings of Cahyani et al. (2024) in Indonesian science education, which identified psychological support factors as critical mediators of student achievement. Consequently, the learning process serves a dual function: directly building competence and indirectly fostering the motivation necessary for sustained engagement. The role of motivation is also linked to the perceived value of the technology, as noted by Sutiyono et al. (2024). When students perceive a system as applicable and satisfying, their net benefits increase. Therefore, the curriculum must not only transfer knowledge but also spark interest, as Hayyi (2025) emphasizes, by fostering digital literacy within supportive environments (Hayyi, 2025).

In this model, the motivation variable mediates the relationship between the Learning Process and Learning Outcomes. The Learning Process Encourages Motivation, and Motivation Encourages Learning Outcomes. Learning methods, particularly PBL, collaboration, and engaging device use, are closely associated with improvements in student motivation (Timotheou et al., 2023).

Joyful and meaningful learning is a key principle in modern pedagogy (BSKAP, 2025). When students enjoy the learning process, their intrinsic motivation increases, fostering curiosity, creativity, and active engagement, resulting in memorable learning experiences. Motivation, interest, and positive attitudes toward technology are strong determinants of better learning outcomes and 21st-century skills development (Behnamnia et al., 2025; Timotheou et al., 2023).

This finding also strengthens theoretical frameworks of technology acceptance, such as the Technology Acceptance Model (TAM) and Self-Determination Theory (SDT), underscoring that user motivation and interest are crucial for successful adoption of educational technology (Su et al., 2022). The finding that motivation partially mediates (H2) provides an essential theoretical contribution to understanding the psychological mechanisms underlying educational technology acceptance. This result is consistent with the Expectancy-Value Theory framework (Eccles & Wigfield, 2020), which posits that motivation is a central mechanism in academic achievement. This aligns with findings from Cahyani et al. (2024) using PISA data, which highlight that motivation and support systems significantly mediate student achievement in science and technology (Cahyani & Setiawan, 2024; Sutiyono et al., 2024).

Nevertheless, H2's original contribution ultimately lies in demonstrating that, in new curriculum implementation contexts, motivation functions as a critical bridge, transmitting learning-process influence into substantive impact. This mechanism is crucial, especially for novice students who rely entirely on motivational pathways to achieve optimal learning outcomes.

The Nuance of Prior Experience

Statistically, the moderating effect of prior coding experience was not significant (p=0.321), indicating that the strength of the relationship between the learning process and impact does not differ substantially across groups. However, a deeper exploratory subgroup analysis revealed a nuanced pattern. The learning process had a significant direct effect on students with 'Basic' experience (p=0.026), but not on 'Novices' (p=0.160). This suggests a potential 'expertise reversal effect' or cognitive load issue. Novices may struggle with the complexity of AI and coding without sufficient scaffolding. This aligns with Asrizal et al. (2023), who emphasized that learning modules must be tailored to student capacity to improve critical thinking effectively (Asrizal et al., 2023). Furthermore, Dhany et al. (2025) suggest that integrating specific strategies like Design Thinking in STEM-PjBL can help bridge these gaps by providing structured stages for creative thinking, which may be particularly beneficial for beginners who need more guidance than experienced peers (Dhany et al., 2025).

This finding aligns with the "prior knowledge" theory discussed by Putri et al. (2023), who demonstrated that students with varying levels of initial knowledge require different levels of instructional scaffolding to achieve critical thinking outcomes (Putri et al., 2023). Novice students appear to struggle to translate technical learning into outcomes, likely due to cognitive load. Instead, they rely almost entirely on the motivational pathway. This implies that, for beginners, the curriculum must first focus on building confidence and interest. Consequently, a standardized "one-size-fits-all" national curriculum may risk leaving novice learners behind if it does not incorporate differentiated strategies that prioritize motivational scaffolding for beginners.

Conclusion

This study confirms that the technology-integrated learning process, specifically utilizing the Apple ecosystem and Project-Based Learning, significantly predicts positive learning impacts in high school settings. The findings indicate that high-quality learning ecosystems are critical antecedents of student success. Furthermore, this research highlights the pivotal role of Student Motivation as a partial mediator, suggesting that while the curriculum's technical infrastructure is essential, its effectiveness is substantially enhanced when it successfully elicits students' intrinsic interest. Regarding the role of prior experience, the formal moderation test was not statistically significant, indicating that the model generalizes to the general student population. However, exploratory analysis provided a critical pedagogical insight: the direct influence of the learning process was robust for students with basic experience but less effective for complete novices. This suggests that students with no prior coding knowledge rely almost entirely on the motivational pathway to achieve learning outcomes, whereas experienced students can leverage the technical tools directly. Based on the finding that novice students rely heavily on the indirect path through motivation, future research should prioritize experimental designs that test specific interventions for beginners. Researchers are encouraged to investigate gamification strategies or interactive onboarding modules to enhance user acceptance and motivation. Additionally, future studies should expand the demographic scope to include vocational and public schools with varying levels of infrastructure readiness to validate the model's applicability across Indonesia's diverse educational landscape.

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The authors declare that no conflict of interest could affect the objectivity, integrity, or results of this research. The entire data collection, analysis, and report preparation process was conducted independently, without any influence from third parties, sponsors, or institutions with financial or non-financial interests in the research results.

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