Journal of Information Technology Education: Innovations in Practice

An Official Publication of the Informing Science Institute
InformingScience.org

JITEiip.org

Volume 25, 2026

A Multi-Path Direct Model of AI-Supported Learning: The Roles of Algorithmic Trust, Cognitive Load Management, and Engagement in Driving Learning Innovation Performance

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Abstract

Aim/Purpose	This study addresses a limitation of existing AI-supported learning research: its reliance on linear models that fail to capture the complex interplay among technological, cognitive, and behavioral factors in shaping learning innovation performance.
Background	To overcome this limitation, the study proposes a multi-path direct model that simultaneously examines the roles of AI usage, algorithmic trust, cognitive load management, engagement, and adaptability in a unified framework.
Methodology	The study adopts a quantitative approach using Partial Least Squares Structural Equation Modeling. Data were collected from undergraduate engineering students with experience in AI-supported learning environments, and the analysis followed measurement and structural model evaluation procedures.
Contribution	This study contributes to the literature by advancing a multi-path direct perspective that captures interdependent relationships among key constructs, redefines the roles of engagement and algorithmic trust, and positions self-regulated learning adaptability as the central mechanism driving innovation outcomes.
Findings	The findings show that AI learning companion usage significantly strengthens algorithmic trust and learning adaptability, while cognitive load management enhances both engagement and adaptability. Self-regulated learning adaptability emerges as the strongest predictor of learning innovation performance. In contrast, engagement and algorithmic trust do not directly influence innovation outcomes, indicating that deeper cognitive transformation is required.

Accepting Editor Keith A. Willoughby │ Received: April 11 2026│ Revised: June 3, 2026 │ Accepted: June 13, 2026.

Cite as: Husin, M.. (2026). A multi-path direct model of AI-supported learning: The roles of algorithmic trust, cognitive load management, and engagement in driving learning innovation performance. *Journal of Information Technology Education: Innovations in Practice, 25,* Article 26. https://doi.org/10.28945/5818

Recommendations for Practitioners	Educators should emphasize adaptive learning strategies and critical use of AI tools while designing learning environments that support cognitive regulation rather than focusing solely on engagement.
Recommendations for Researchers	Researchers should adopt integrative, non-linear models to capture the complexity of AI-supported learning better and to investigate indirect mechanisms among key variables further.
Impact on Society	The study provides insights for developing more effective AI-enhanced learning systems that foster innovation, critical thinking, and adaptability in increasingly complex digital environments.
Future Research	Future studies should extend this model across disciplines and cultural contexts, apply longitudinal designs, and incorporate objective performance measures to strengthen causal understanding.

Keywords	AI-supported learning, algorithmic trust, cognitive load management, learning innovation performance

INTRODUCTION

The rapid integration of artificial intelligence (AI) into education has transformed how students learn. Many students now use AI-based tools as learning companions to support problem-solving, content generation, and conceptual understanding (Husin et al., 2025; Kuo et al., 2026). Educators increasingly recognize the potential of these tools to enhance learning outcomes and foster innovation (Ammar et al., 2024). However, the effectiveness of AI-supported learning depends on how students interact with and interpret these technologies. Researchers continue to explore the mechanisms through which AI usage shapes meaningful educational outcomes.

Recent studies have highlighted the importance of cognitive and behavioral factors in technology-enhanced learning environments (Naeem et al., 2023; Sui et al., 2024). Scholars have examined constructs such as cognitive load, student engagement, and self-regulated learning in digital contexts (Wang & Lajoie, 2023). These studies show that learners must actively manage their cognitive resources to benefit from advanced technologies. At the same time, students must adapt their learning strategies to maintain effectiveness in increasingly complex environments. Despite these insights, researchers still struggle to explain how these factors simultaneously operate in AI-supported learning contexts.

In parallel, researchers have introduced the concept of algorithmic trust to explain how users perceive and rely on AI-generated outputs (Yu et al., 2025). Students who trust AI systems tend to use them more effectively and integrate them into their learning processes (Omirali et al., 2025). Conversely, low levels of trust can limit the potential benefits of AI tools (Kim & Song, 2023). Although prior research has examined trust in technology, it rarely connects algorithmic trust with other critical learning variables (Diputra, Husin, Fadhilah, et al., 2025; Jackson & Panteli, 2023). This limitation restricts a comprehensive understanding of how trust interacts with cognitive and behavioral factors in education.

Furthermore, many existing studies rely on linear models that assume direct and isolated relationships between variables (Arif & MacNeil, 2023). Researchers often examine the effect of a single independent variable on a dependent outcome without considering the complexity of learning environments (McDermott, 2023). Such approaches fail to capture the interconnected nature of AI usage, cognitive processes, and engagement. In reality, students experience learning as a dynamic system with multiple simultaneous influences. Therefore, a more integrated, multi-path perspective is necessary to better reflect authentic learning conditions.

A significant research gap arises from the lack of studies that model direct yet interconnected relationships among AI use, cognitive load management, algorithmic trust, and learning behaviors. Few studies investigate how these variables simultaneously influence learning innovation performance without relying on mediation frameworks. This gap limits both theoretical development and practical application in technology-enhanced education. Addressing this limitation can provide a clearer understanding of how students achieve innovative learning outcomes in AI-supported environments. It can also guide educators in designing more effective learning strategies.

This study aims to develop and test a multi-path direct model that explains how AI learning companion usage, digital cognitive load management, and perceived algorithmic trust influence immersive learning engagement, self-regulated learning adaptability, and learning innovation performance. The study focuses on direct relationships to capture the immediate effects among variables while preserving structural complexity. By doing so, the study offers a more realistic representation of student learning experiences in digital environments. The findings aim to contribute to both theory and practice in technology-enhanced learning. Ultimately, this research seeks to provide actionable insights for improving innovation-driven learning outcomes.

Literature Review and Hypothesis Development

AI Learning Companion Usage and Algorithmic Trust

The increasing use of artificial intelligence (AI) in education has transformed how students approach learning tasks (George & Wooden, 2023). Students actively use AI learning companions to generate ideas, solve problems, and support understanding (Kuo et al., 2026). Frequent interaction with AI systems allows students to evaluate the consistency and usefulness of AI-generated outputs (Er et al., 2025). This experience builds familiarity and reduces uncertainty when using AI tools. As a result, students develop stronger trust in algorithmic systems. In addition, AI usage encourages students to explore different ways of learning and problem-solving (Moşoi et al., 2025). Students who frequently interact with AI tools tend to experiment with various strategies and adapt their approaches (Demartini et al., 2024). This process strengthens their ability to regulate their own learning in dynamic environments. Therefore, AI usage not only shapes trust but also enhances adaptive learning behavior.

H1: AI learning companion usage influences perceived algorithmic trust.

H2: AI learning companion usage influences self-regulated learning adaptability.

Algorithmic Trust and Learning Behavior

Algorithmic trust refers to an individual’s confidence in the accuracy, reliability, consistency, and appropriateness of outputs generated by algorithmic systems (Jackson & Panteli, 2023). Unlike general technological trust, which reflects trust in a technology as a whole, algorithmic trust specifically concerns users’ beliefs about the decision-making processes and recommendations produced by AI algorithms (Wu et al., 2024). This distinction is particularly important in AI-supported learning environments because students frequently rely on AI-generated explanations, feedback, and problem-solving suggestions when making learning decisions. As AI systems increasingly influence learning processes, understanding algorithmic trust becomes essential for explaining how students evaluate and utilize AI-generated knowledge.

Perceived algorithmic trust plays a critical role in determining how students engage with AI-supported learning (Qiu, 2025). Students who trust AI systems are more willing to rely on their outputs and integrate them into learning activities (Omirali et al., 2025). This trust reduces hesitation and deepens interaction with technology. As a result, students become more engaged in immersive learning experiences. Higher levels of trust encourage continuous interaction and exploration (Cai et al., 2025). Moreover, trust influences how students adjust their learning strategies in digital environments

(Omirali et al., 2025). Students who perceive AI as reliable tend to incorporate it into their self-regulated learning processes (Jin et al., 2023). They actively use AI feedback to refine their understanding and improve performance (Guo et al., 2025). This behavior strengthens their adaptability in managing learning tasks.

H3: Perceived algorithmic trust influences immersive learning engagement.

H4: Perceived algorithmic trust influences self-regulated learning adaptability.

Digital Cognitive Load Management in Learning

Digital learning environments expose students to large amounts of information and multiple technological tools (Alenezi et al., 2023). Students must manage their cognitive resources effectively to avoid overload. Effective cognitive load management allows students to process information efficiently and maintain focus (Howie et al., 2023). This condition supports deeper engagement in learning activities. Consequently, students who manage cognitive load effectively tend to experience greater immersion (Sari et al., 2024). Furthermore, cognitive load management influences students' ability to adapt their learning strategies. Students who can regulate their mental effort are better able to adjust to changing learning demands (Grund et al., 2024). They can allocate attention strategically and avoid cognitive fatigue (Kok, 2022). This ability enhances their adaptability in self-regulated learning. Therefore, cognitive load management plays a key role in shaping both engagement and adaptive learning.

H5: Digital cognitive load management influences self-regulated learning adaptability.

H6: Digital cognitive load management influences immersive learning engagement.

Self-Regulated Learning, Adaptability, and Innovation Performance

Self-regulated learning adaptability reflects a student's ability to plan, monitor, and adjust learning strategies (Raković et al., 2022). Students who demonstrate high adaptability can respond effectively to complex and technology-rich environments (Avdiel & Blau, 2025). They actively evaluate their learning progress and modify their approaches when necessary. This flexibility enables them to explore new ideas and develop creative solutions. As a result, adaptive learners achieve higher levels of innovation performance (Chughtai et al., 2024). In AI-supported environments, adaptability becomes even more important due to the dynamic nature of learning tools (Jallali et al., 2026). Students must continuously adjust their strategies to maximize the benefits of AI systems (George & Wooden, 2023). Those who succeed in this process can integrate knowledge more effectively and generate innovative outcomes (Ragazou et al., 2022). Therefore, self-regulated learning adaptability directly contributes to learning innovation performance.

H7: Self-regulated learning adaptability influences learning innovation performance.

Immersive Learning Engagement and Innovation Performance

Immersive learning engagement represents the extent to which students actively participate in technology-enhanced learning activities (Maričić & Lavicza, 2024). Engaged students demonstrate higher levels of attention, motivation, and involvement (Diputra, Husin, Karimi, et al., 2025; Ferrer et al., 2022; Hellín et al., 2023). They interact more deeply with learning materials and explore concepts in greater detail. This active participation fosters creativity and critical thinking (Gonzalez-Mohino et al., 2023). As a result, engagement becomes a strong predictor of innovation performance. Moreover, immersive engagement allows students to connect knowledge across different contexts (Husin et al., 2024; Shi et al., 2024). Students who are deeply engaged can experiment with ideas and apply them in novel ways (Marougkas et al., 2023). This process enhances their ability to produce innovative solutions. Therefore, immersive learning engagement plays a significant role in improving learning outcomes.

H8: Immersive learning engagement influences learning innovation performance.

Algorithmic Trust And Learning Innovation Performance

Perceived algorithmic trust may also contribute directly to learning innovation performance. Students who perceive AI systems as reliable and accurate are more likely to utilize AI-generated insights, recommendations, and problem-solving support in their learning activities (Allam et al., 2025). High levels of trust encourage students to integrate AI outputs into knowledge-creation processes and to explore alternative solutions to academic challenges (Wu et al., 2024). When students confidently rely on AI-generated information, they may become more willing to experiment with new ideas and innovative approaches. Previous studies have suggested that trust in intelligent systems can enhance performance outcomes by facilitating effective technology utilization (Della Corte et al., 2023; Jalali et al., 2023). Therefore, perceived algorithmic trust is expected to positively influence learning innovation performance.

H9: Perceived algorithmic trust influences learning innovation performance.

Although prior studies have investigated AI usage, algorithmic trust, cognitive load management, engagement, and self-regulated learning in educational settings, the existing literature remains fragmented. Most studies examine these variables through isolated or linear relationships, focusing on specific predictor–outcome associations without considering their simultaneous interactions within AI-supported learning environments. As a result, the complex interplay among technological, cognitive, and behavioral factors remains insufficiently understood. Furthermore, previous research often assumes that engagement and trust directly lead to positive learning outcomes. At the same time, limited attention has been given to the possibility that adaptive learning behaviors may play a more central role in transforming AI-supported experiences into innovative performance. This limitation creates an important theoretical gap because learning in AI-enhanced environments involves multiple interconnected processes rather than independent causal effects. Therefore, a more comprehensive framework is needed to explain how AI usage, algorithmic trust, cognitive load management, engagement, and adaptability collectively contribute to learning innovation performance. The present study addresses this gap by proposing a multi-path direct model that integrates these dimensions within a unified framework.

Theoretical Framework

This study is grounded in three complementary theoretical perspectives that explain the technological, cognitive, and behavioral dimensions of AI-supported learning. First, the Technology Acceptance Model (TAM) suggests that users' interactions with technology shape their perceptions, attitudes, and subsequent acceptance behaviors. Within the context of AI-supported learning, repeated use of AI learning companions can strengthen students' confidence in AI-generated outputs and foster greater algorithmic trust. This perspective provides a theoretical basis for understanding how technology usage contributes to trust formation and adaptive learning behavior.

Second, Cognitive Load Theory explains how learners process information under limited cognitive resources. In digital learning environments, students are exposed to large volumes of information and multiple technological stimuli. Effective cognitive load management enables learners to allocate attention efficiently, avoid cognitive overload, and maintain engagement with learning tasks. The theory, therefore, supports the proposed relationships among digital cognitive load management, immersive learning engagement, and self-regulated learning adaptability.

Third, Social Cognitive Theory emphasizes the reciprocal interaction between personal factors, behaviors, and environmental influences. The theory highlights self-regulation as a critical mechanism through which learners monitor, evaluate, and adjust their learning strategies to achieve desired outcomes. In AI-supported learning environments, students who demonstrate stronger adaptability are more capable of utilizing technological resources effectively, generating creative solutions, and achieving higher levels of learning innovation performance.

By integrating these theoretical perspectives, the present study develops a multi-path direct framework that captures the interconnected roles of AI learning companion usage, algorithmic trust, cognitive load management, immersive learning engagement, self-regulated learning adaptability, and learning innovation performance. This integrated perspective provides a more comprehensive explanation of learning processes in AI-enhanced educational environments than traditional linear approaches.

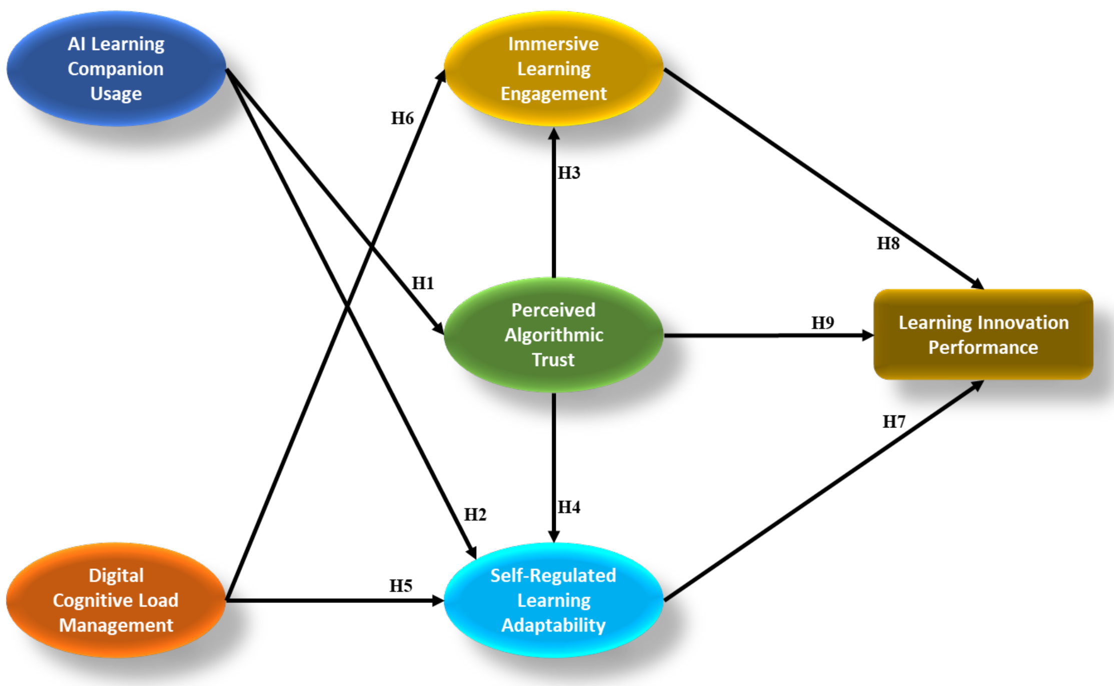

Figure 1. Research model

Methodology

Research Design

This study applies a quantitative research design to examine the relationships among AI learning companion usage, digital cognitive load management, perceived algorithmic trust, self-regulated learning adaptability, immersive learning engagement, and learning innovation performance. The study adopts a cross-sectional approach to collect data at a single point in time (Jeilani & Abubakar, 2025). This approach allows the researcher to capture perceptions and behaviors in AI-supported learning environments (Msomi & Behara, 2026). The study uses a positivist paradigm to test the proposed hypotheses. Structural Equation Modeling based on Partial Least Squares (SEM-PLS) is employed to analyze the data. Although demographic information, such as gender and year of study, was collected and reported to describe the sample characteristics, the primary objective of this study was theory testing rather than group comparison. Therefore, demographic variables were not incorporated as control variables in the structural model. Future studies may further examine the potential moderating or control effects of demographic and academic characteristics on AI-supported learning outcomes.

Population and Sample

The study population consists of undergraduate students in the Faculty of Engineering at a public university in Indonesia. These students actively engage in digital learning environments and have exposure to artificial intelligence-based learning tools in their academic activities. The study focuses on this population because engineering students frequently interact with technology-enhanced learning systems, which makes them well-suited for examining AI-supported learning behaviors. A purposive sampling technique is applied to ensure that respondents have relevant experience with digital learning technologies and AI learning companions.

Students were recruited through official faculty communication channels, including institutional learning management systems and class-based announcements distributed by course coordinators. Participation was voluntary and limited to students who had prior experience using AI-based learning tools, such as generative AI assistants, intelligent tutoring systems, or AI-supported educational applications, for academic purposes. To be eligible, respondents had to be enrolled as undergraduate engineering students and report having used AI tools in learning activities during the current academic year. Data were collected between January and March 2026 through an online survey platform. Before accessing the questionnaire, participants received an information sheet explaining the study objectives, confidentiality procedures, voluntary participation, and data usage. Informed consent was obtained electronically, and only students who agreed to participate were allowed to proceed to the survey.

The data collection process initially obtained 510 responses from undergraduate engineering students. Data screening was conducted to identify incomplete questionnaires, duplicate submissions, and responses exhibiting patterns of inattentive answering. After this validation process, 435 responses were deemed valid and suitable for analysis, representing 85.29% of the total collected data. This final sample size exceeds the minimum requirements for Structural Equation Modeling based on Partial Least Squares (SEM-PLS), ensuring adequate statistical power for model estimation. The sample size is appropriate for analyzing complex relationships among multiple constructs in the proposed research model. All responses were collected voluntarily and anonymously to ensure data integrity and reduce response bias.

INSTRUMENT VALIDATION AND DATA-COLLECTION PROCEDURE

This study develops a structured questionnaire to measure all constructs in the proposed model. The researchers generate the measurement items based on an extensive review of prior studies and adapt them to fit the research context. All measurement items were assessed using a 5-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). The use of a 5-point scale was considered appropriate for capturing respondents' perceptions while minimizing response complexity and improving completion rates. The researchers conduct a pilot test with 60 undergraduate students not included in the main sample to evaluate the instrument's clarity and reliability. The pilot results indicate strong internal consistency across all constructs. Cronbach's alpha values range from 0.78 to 0.91, while composite reliability values range from 0.84 to 0.93, both exceeding the recommended threshold of 0.70 (Youssef et al., 2023). Indicator loadings range from 0.71 to 0.89, demonstrating adequate item reliability (Hair & Alamer, 2022).

In addition, Average Variance Extracted (AVE) values range from 0.55 to 0.72, confirming acceptable convergent validity (Hair & Alamer, 2022). Based on feedback from the pilot participants, several refinements were introduced to improve item clarity and readability. Technical terms related to AI-supported learning were simplified, ambiguous wording was replaced with clearer language, and several items were rephrased to ensure consistent interpretation among respondents. Minor adjustments were also made to item sequencing and questionnaire instructions to improve the flow of responses while preserving the original conceptual meaning of each construct.

These revisions enhance the instrument's overall quality. After confirming the adequacy of the measurement instrument, the researchers administered the final questionnaire via an online survey platform to collect the main data. Table 1 presents the full set of measurement items.

Table 1. Measurement items for all constructs

Construct	Code	Indicator
AI Learning Companion Usage	ALCU1	I use AI tools to help me understand course materials.
	ALCU2	I use AI tools to generate ideas for assignments.
	ALCU3	I rely on AI tools when solving academic problems.
	ALCU4	I frequently use AI tools during my study activities.
Digital Cognitive Load Management	DCLM1	I can focus well when using digital learning tools.
	DCLM2	I can manage the amount of information I receive from digital platforms.
	DCLM3	I know how to avoid feeling overwhelmed when studying online.
	DCLM4	I can organize digital information effectively.
	DCLM5	I can control my mental effort when learning with technology.
Perceived Algorithmic Trust	PAT1	I trust the results provided by AI tools.
	PAT2	I believe AI tools give reliable information.
	PAT3	I feel confident using AI-generated answers in my learning.
	PAT4	I think AI systems work consistently.
Self-Regulated Learning Adaptability	SRLA1	I adjust my learning strategies when needed.
	SRLA2	I can change my approach if I do not understand something.
	SRLA3	I monitor my learning progress regularly.
	SRLA4	I set my own learning goals.
	SRLA5	I improve my strategies based on feedback.
Immersive Learning Engagement	ILE1	I feel fully involved when learning with digital tools.
	ILE2	I stay focused during technology-supported learning.
	ILE3	I actively participate in learning activities.
	ILE4	I feel interested when using digital learning systems.
Learning Innovation Performance	LIP1	I can generate new ideas in my learning.
	LIP2	I can solve problems creatively.
	LIP3	I can apply knowledge in new situations.

DATA ANALYSIS

This study analyzes the data using Partial Least Squares Structural Equation Modeling (PLS-SEM), a method suitable for complex models that does not require strict normality assumptions. PLS-SEM was selected instead of covariance-based SEM (CB-SEM) for several reasons. First, the primary objective of this study is prediction and theory extension rather than strict theory confirmation. Second, the proposed model includes multiple endogenous constructs and simultaneous direct relationships, making PLS-SEM particularly suitable for handling complex predictive models. Third, PLS-SEM is robust when analyzing behavioral and educational research data that may not fully satisfy multivariate normality assumptions. Finally, the method is appropriate for maximizing explained variance and identifying the relative importance of predictor constructs in emerging research contexts such as AI-supported learning. The analysis follows a two-step approach: the assessment of the measurement and structural models. The researchers evaluate internal consistency reliability using Cronbach's alpha and composite reliability, with acceptable values of 0.70 or higher (Youssef et al., 2023). They assess convergent validity through indicator loadings and Average Variance Extracted (AVE), where loadings should exceed 0.70, and AVE values should exceed 0.50 (Hair & Alamer, 2022). Discriminant validity is examined using the Heterotrait-Monotrait ratio (HTMT), with values below 0.85 indicating adequate distinction between constructs (Cheung et al., 2024).

The researchers also assess multicollinearity using the Variance Inflation Factor (VIF), with values below 5.0 considered acceptable (Daoud et al., 2025). For the structural model, they evaluate path coefficients and test their significance using bootstrapping procedures, where t-values should exceed 1.96, and p-values should be below 0.05 at a 5% significance level (Boru et al., 2025). In addition, the coefficient of determination (R^2) is used to assess explanatory power, with values of 0.25, 0.50, and 0.75 indicating weak, moderate, and substantial levels, respectively (Kamranfar et al., 2023). The researchers further examine predictive relevance (Q^2), where values greater than zero indicate predictive capability (Király et al., 2022), and effect size (f^2), with values of 0.02, 0.15, and 0.35 representing small, medium, and large effects (Batra, 2025; Fadhilah & Husin, 2023).

RESULTS

The respondents consist of students from various engineering disciplines, including Civil Engineering (110; 25.29%), Mechanical Engineering (95; 21.84%), Electrical Engineering (80; 18.39%), Mining Engineering (60; 13.79%), Automotive Engineering (50; 11.49%), and Electronics Engineering (40; 9.20%). In terms of gender, 238 respondents (54.71%) are male, and 197 (45.29%) are female. The majority of respondents are aged 19-22. Based on year of study, most respondents are in their second and third year, followed by first-year and fourth-year students.

MODEL COMMON METHOD VARIANCE

Because all constructs were measured using self-reported responses collected through a single survey instrument, common method variance (CMV) was assessed. Following the full collinearity assessment procedure, variance inflation factor (VIF) values were examined for all latent constructs. All VIF values were below the recommended threshold of 3.3, indicating that common method bias was unlikely to threaten the validity of the findings. In addition, procedural remedies were implemented during questionnaire design, including respondent anonymity, voluntary participation, and the use of clearly worded measurement items to reduce evaluation apprehension and response consistency bias.

MEASUREMENT MODEL

The measurement model is assessed to evaluate the reliability and validity of all constructs included in the study. As shown in Table 2, all indicators load strongly on their respective constructs, indicating adequate indicator reliability. The constructs demonstrate strong internal consistency, as reflected in the reliability measures. In addition, the results confirm satisfactory convergent validity, showing that the indicators adequately represent their underlying constructs. Furthermore, the collinearity assessment indicates that all indicators fall within acceptable limits, suggesting that multicollinearity is not a concern in the model. The results presented in Table 2 confirm that the measurement model meets the required criteria for reliability and validity and is suitable for further structural analysis.

Discriminant validity is assessed using the Heterotrait-Monotrait ratio (HTMT) to examine whether each construct is empirically distinct from the others. As presented in Table 3, all HTMT values remain below the recommended threshold, indicating adequate discriminant validity across the constructs. This result confirms that each construct captures a unique aspect of the model and does not overlap excessively with other constructs.

Table 2. Results of the measurement model evaluation

Construct	Indicator	Outer loadings	Cronbach's alpha	Composite reliability	Ave	VIF
AI Learning Companion Usage	ALCU1	0.858	0.875	0.914	0.727	2.163
	ALCU2	0.840				2.032
	ALCU3	0.852				2.187
	ALCU4	0.861				2.255
Digital Cognitive Load Management	DCLM1	0.715	0.765	0.842	0.515	1.404
	DCLM2	0.723				1.453
	DCLM3	0.717				1.388
	DCLM4	0.706				1.382
	DCLM5	0.728				1.431
Perceived Algorithmic Trust	PAT1	0.880	0.891	0.935	0.782	2.553
	PAT2	0.882				2.652
	PAT3	0.887				2.741
	PAT4	0.888				2.697
Self-Regulated Learning Adaptability	SRLA1	0.813	0.881	0.913	0.753	1.970
	SRLA2	0.830				2.110
	SRLA3	0.834				2.166
	SRLA4	0.817				1.971
	SRLA5	0.820				2.051
Immersive Learning Engagement	ILE1	0.858	0.907	0.924	0.753	2.270
	ILE2	0.867				2.414
	ILE3	0.867				2.304
	ILE4	0.879				2.525
Learning Innovation Performance	LIP1	0.774	0.729	0.847	0.649	1.376
	LIP2	0.819				1.470
	LIP3	0.823				1.487

Table 3. HTMT results for discriminant validity

	ALCU	DCLM	ILE	LIP	PAT	SRLA
AI Learning Companion Usage (ALCU)	-					
Digital Cognitive Load Management (DCLM)	0.599	-				
Immersive Learning Engagement (ILE)	0.783	0.519	-			
Learning Innovation Performance (LIP)	0.757	0.816	0.615	-		
Perceived Algorithmic Trust (PAT)	0.627	0.401	0.812	0.476	-	
Self-Regulated Learning Adaptability (SRLA)	0.615	0.741	0.776	0.843	0.581	-

STRUCTURAL MODEL

The structural model is evaluated to examine the explanatory power, predictive relevance, and effect sizes of the proposed relationships. As shown in Table 4, the endogenous constructs demonstrate acceptable levels of explanatory power, indicating that the model adequately accounts for the variance in key outcome variables. In addition, the predictive relevance assessment confirms that the model has sufficient predictive capability across all endogenous constructs. The effect-size analysis reveals varying levels of influence across the predictor–outcome relationships. Some relationships exhibit strong effects, indicating substantial contributions to the explained variance of the endogenous variables. Other relationships show moderate effects, suggesting meaningful but less dominant contributions. Meanwhile, several paths demonstrate weak effects, indicating relatively limited influence within the model. These results indicate that the structural model has adequate explanatory power and predictive relevance, with varying effect sizes across the proposed relationships. These findings support the model's suitability for further hypothesis testing.

Table 4. Structural model assessment (R^2, Q^2, and effect sizes)

Endogenous variable	R^2	Q^2	Predictor → Outcome	f^2
Immersive Learning Engagement (ILE)	0.572	0.426	DCLM→ILE	0.090
			PAT→ILE	0.904
Learning Innovation Performance (LIP)	0.460	0.292	ILE→LIP	0.001
			PAT→LIP	0.001
			SRLA→LIP	0.393
Perceived Algorithmic Trust (PAT)	0.313	0.242	ALCU→PAT	0.455
Self-Regulated Learning Adaptability (SRLA)	0.500	0.333	ALCU→SRLA	0.036
			DCLM→SRLA	0.278
			PAT→SRLA	0.105

Figure 2 presents the structural model with standardized path coefficients and coefficients of determination (R^2), providing a visual representation of the relationships among the constructs and the model's explanatory power.

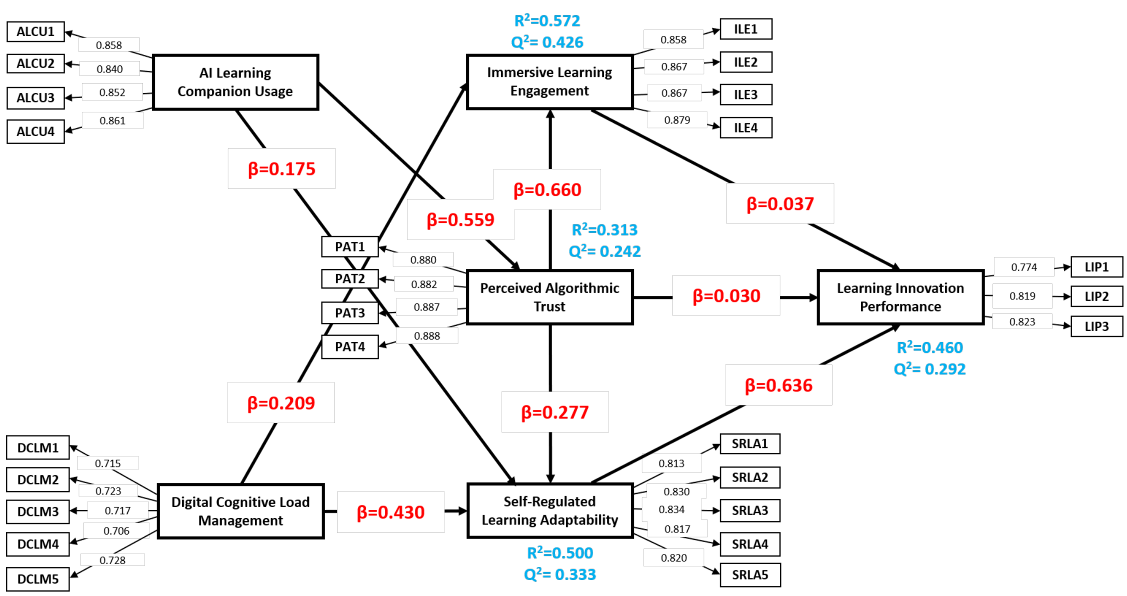

Figure 2. Structural model with standardized path coefficients and R^2 values

Bootstrapping analysis tests the significance of the proposed hypotheses. Table 5 shows that most hypothesized relationships are significant, indicating strong connections among the key constructs. AI Learning Companion Usage significantly influences Perceived Algorithmic Trust and Self-Regulated Learning Adaptability. Perceived Algorithmic Trust significantly affects Immersive Learning Engagement and Self-Regulated Learning Adaptability. Digital Cognitive Load Management also significantly influences both Self-Regulated Learning Adaptability and Immersive Learning Engagement. Self-Regulated Learning Adaptability strongly influences Learning Innovation Performance, highlighting its important role in driving innovative learning outcomes. However, Immersive Learning Engagement does not significantly influence Learning Innovation Performance. Perceived Algorithmic Trust also does not show a significant direct effect on Learning Innovation Performance. These results indicate that some relationships contribute more strongly than others in explaining the outcome variable. Figure 3 presents the bootstrapping results of the structural model.

Table 5. Hypotheses testing results

Hypothesis	Path coefficients (β)	T-statistics	P-values	Decision
H1: ALCU→PAT	0.559	12.252	< 0.001	Supported
H2: ALCU→SRLA	0.175	2.038	0.042	Supported
H3: PAT→ILE	0.660	13.939	< 0.001	Supported
H4: PAT→SRLA	0.277	4.049	< 0.001	Supported
H5: DCLM→SRLA	0.430	6.418	< 0.001	Supported
H6: DCLM→ILE	0.209	4.594	< 0.001	Supported
H7: SRLA→LIP	0.636	9.064	< 0.001	Supported
H8: ILE→LIP	0.037	0.606	0.544	Not Supported
H9: PAT→LIP	0.030	0.655	0.513	Not Supported

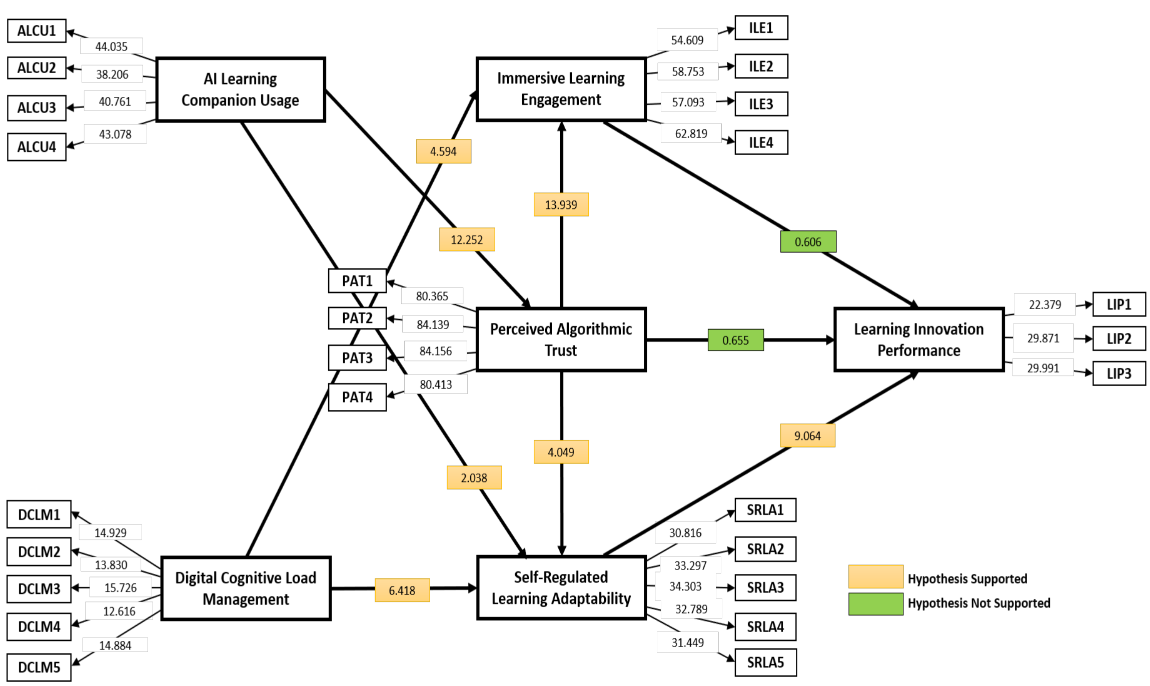

Figure 3. Bootstrapping results of the structural model

A closer examination of the path coefficients reveals important differences in the relative strength of the proposed relationships. The strongest overall relationship in the structural model is observed between Perceived Algorithmic Trust and Immersive Learning Engagement ($\beta = 0.660$), indicating that students who perceive AI systems as reliable and trustworthy are substantially more likely to become actively engaged in AI-supported learning activities. This finding highlights the importance of developing transparent and dependable AI learning environments to encourage meaningful student participation.

Among the relationships predicting Learning Innovation Performance, Self-Regulated Learning Adaptability emerges as the strongest predictor ($\beta = 0.636$). This finding suggests that innovation in learning is driven primarily by students' ability to adjust learning strategies, monitor progress, and respond effectively to changing learning demands. While technological support and engagement contribute to the learning process, adaptive self-regulation appears to be the key mechanism that transforms learning experiences into innovative outcomes.

In contrast, the weakest relationships are observed between Immersive Learning Engagement and Learning Innovation Performance ($\beta = 0.037$) and between Perceived Algorithmic Trust and Learning Innovation Performance ($\beta = 0.030$), both of which are statistically insignificant. These findings indicate that engagement and trust alone are insufficient to generate innovative learning outcomes unless they are accompanied by deeper cognitive adaptation and strategic learning behaviors.

DISCUSSION

This study advances the understanding of AI-supported learning by proposing and validating a multi-path direct model that integrates technological use, cognitive regulation, and behavioral engagement. The results show that learning outcomes emerge from interconnected processes rather than isolated factors. This perspective departs from traditional linear approaches and captures the complexity of real learning environments (Bhardwaj et al., 2025). The model reveals that different constructs play distinct roles in shaping learning innovation performance. Some variables act as direct drivers, while others function as enabling conditions. This distinction provides a more nuanced explanation of how students interact with AI tools. Consequently, the model offers a more realistic representation of learning dynamics in digital contexts and strengthens the theoretical foundation for analyzing AI-supported learning beyond simplified assumptions.

AI learning companion usage plays a foundational role in shaping students' perceptions and behaviors. Frequent interaction with AI tools builds familiarity, supporting confident and consistent use (Khartabil et al., 2025). This repeated exposure allows students to evaluate the quality and usefulness of AI-generated outputs (Er et al., 2025). Over time, students develop stronger trust in algorithmic systems. This pattern aligns with prior research linking system use to trust development (Dang & Li, 2026; Pandey & Kushwaha, 2025). At the same time, the findings extend earlier work by embedding trust within a broader system of learning processes (Payne et al., 2023). Trust emerges through continuous interaction rather than as an isolated perception (Peng et al., 2025). This insight underscores the importance of experiential learning in AI-supported environments.

AI learning companion usage also enhances self-regulated learning adaptability. Students adjust their learning strategies when integrating AI tools into their study routines (Berisha Qehaja, 2025). They experiment with different approaches and refine their methods based on feedback (Wiboolyasarin et al., 2024). This behavior reflects a higher level of cognitive engagement with learning tasks. Previous studies emphasize the role of technology in supporting self-regulation (Sohail et al., 2026; Sui et al., 2024). However, these results indicate that AI tools actively stimulate adaptive thinking rather than merely providing information. Students become more responsive to learning challenges and opportunities. As a result, their ability to manage complex learning situations improves significantly.

Perceived algorithmic trust plays a critical role in shaping both engagement and adaptability. Students who trust AI systems interact with them more confidently and consistently (Martín-Moncunill & Alonso Martínez, 2025). This confidence reduces hesitation and encourages deeper involvement in learning activities (Nguyen et al., 2024). The results support prior findings on the importance of trust in technology adoption (Capestro et al., 2024). At the same time, they extend this perspective by showing that trust influences how students regulate their learning processes. Learners treat trusted AI systems as partners in refining understanding (Tanchuk & Taylor, 2025). This interaction promotes more effective learning strategies. Trust, therefore, functions as a key enabler of meaningful engagement.

A key novel finding lies in the absence of a direct relationship between immersive learning engagement and learning innovation performance. This result challenges the dominant assumption that higher engagement automatically leads to better outcomes (Schiller et al., 2024). Many studies treat engagement as a primary predictor of academic success (Liu et al., 2023; Meng & Zhang, 2023). However, the evidence indicates that engagement alone does not guarantee innovative learning. Students may feel involved without transforming their experiences into creative outputs. This pattern suggests that engagement must interact with deeper cognitive processes to produce innovation (Wei et al., 2023). It shifts the focus from participation to transformation and refines existing engagement theories.

Another important insight concerns the role of perceived algorithmic trust in relation to innovation performance. Trust does not directly influence learning innovation outcomes. This finding contrasts with prior research that positions trust as a direct determinant of performance (Della Corte et al., 2023; Jalali et al., 2023). Instead, trust operates through intermediate learning processes. Students who trust AI systems use them more effectively, yet this alone does not produce innovation (Martín-Moncunill & Alonso Martínez, 2025). This perspective reframes trust as a facilitating condition rather than a direct driver. It emphasizes how students use AI rather than whether they trust it (Omirali et al., 2025). This clarification contributes to a more precise understanding of trust in AI-supported learning.

Digital cognitive load management emerges as a critical factor supporting both engagement and adaptability. Students who effectively manage cognitive demands maintain focus and process information efficiently (Marougkas et al., 2023). This ability reduces the negative effects of information overload in digital environments. Prior studies highlight the importance of cognitive load in learning contexts (Skulmowski & Xu, 2022). The present findings confirm its relevance within AI-supported environments. They also show that cognitive management supports both behavioral and cognitive outcomes. Students become more engaged and adaptive when they regulate their mental effort (Grund et al., 2024). It reinforces the importance of cognitive strategies in technology-enhanced learning.

Self-regulated learning adaptability stands out as the strongest driver of learning innovation performance. Students who adapt their strategies demonstrate greater creativity and problem-solving ability. This observation aligns with research emphasizing the importance of self-regulation in academic success (Koh et al., 2022; Ragusa et al., 2023). At the same time, the results highlight adaptability as the most critical dimension of self-regulation. Learners continuously adjust their approaches in response to changing conditions (Susnjak et al., 2022). This flexibility enables them to generate new ideas and apply knowledge in novel ways. The focus, therefore, shifts from static strategies to dynamic adaptation. Adaptability becomes the core mechanism underlying innovation.

The integration of these findings reveals a coherent mechanism within AI-supported learning environments. Technological use influences trust, which in turn shapes engagement and adaptability (Li et al., 2022). Adaptability then drives innovation performance as the primary outcome. This pathway highlights the indirect role of several constructs in the model. Not all variables contribute equally or directly to learning outcomes. This insight advances the understanding of causal mechanisms in digital learning. It also demonstrates the value of examining multiple pathways simultaneously. The model provides a deeper explanation of how learning processes unfold.

This study makes a significant theoretical contribution by advancing a multi-path, direct perspective on AI-supported learning. Unlike traditional models that rely on linear or mediation-based assumptions, the results demonstrate that learning outcomes emerge from a network of simultaneous and interdependent relationships. This perspective offers a more realistic representation of how students interact with AI technologies in dynamic learning environments. The findings challenge the dominance of simplified causal explanations and encourage more integrative modeling approaches. In particular, the roles of engagement and trust are redefined by showing that their effects depend on deeper cognitive processes rather than acting as direct determinants of innovation. This shift directs attention toward the quality of cognitive and behavioral transformation in AI-supported learning. It also highlights adaptability as the central mechanism linking technological and cognitive factors to meaningful outcomes. Overall, these insights strengthen the foundation for developing more comprehensive, context-sensitive theories of technology-enhanced learning.

LIMITATIONS, RECOMMENDATIONS, AND FUTURE DIRECTIONS

This study provides valuable insights into AI-supported learning; however, several limitations should be acknowledged. First, the study focuses on undergraduate engineering students from a single institutional context, which may limit the generalizability of the findings to other disciplines or educational settings. Learning behaviors and interactions with AI tools may differ across fields with varying cognitive demands and pedagogical approaches. Second, the cross-sectional design captures student perceptions at a single point in time, which restricts the ability to observe changes in learning behavior and adaptation over time. Learning processes in AI-supported environments are inherently dynamic, and longitudinal evidence would provide a deeper understanding of these evolving patterns. Third, the study relies on self-reported data, which may introduce response bias despite efforts to ensure anonymity and voluntary participation. Students' perceptions may not fully reflect their actual learning behaviors in practice.

Building on these limitations, future research should extend the model to diverse educational contexts, including non-engineering disciplines and different cultural settings, to enhance external validity. Comparative studies across academic fields could reveal how disciplinary differences shape the role of AI in learning. In addition, future studies should adopt longitudinal or experimental designs to capture the dynamic nature of AI-supported learning and to establish stronger causal inferences. Such approaches allow researchers to examine how trust, engagement, and adaptability evolve with continued exposure to AI technologies. Further research could also integrate objective learning performance data, such as academic outcomes or behavioral tracking, to complement self-reported measures and provide a more comprehensive assessment of learning processes.

From a practical perspective, the findings offer important implications for educators and designers of AI-supported learning systems. Educators should focus on fostering students' adaptive learning skills rather than emphasizing engagement alone, as adaptability plays a central role in driving innovation outcomes. Instructional strategies should encourage students to reflect on AI-generated outputs critically and actively adjust their learning approaches. At the same time, developers of AI learning tools should prioritize transparency, reliability, and user control to strengthen algorithmic trust and support meaningful interaction. Designing systems that help students manage cognitive load can further enhance both engagement and adaptability. By aligning technological design with cognitive and behavioral processes, educational institutions can maximize AI's potential to support innovative and effective learning.

CONCLUSION

This study develops and validates a multi-path direct model to explain how AI-supported learning shapes learning innovation performance through the interplay of technological use, cognitive regulation, and behavioral engagement. The findings demonstrate that learning outcomes do not emerge from isolated factors but from a system of interconnected processes. AI learning companion usage strengthens both perceived algorithmic trust and self-regulated learning adaptability, while digital cognitive load management enhances students' ability to engage and adapt within complex learning environments. These results highlight the importance of combining technological interaction with cognitive control in achieving effective learning outcomes. The study reveals that self-regulated learning adaptability serves as the central mechanism driving learning innovation performance. Students who actively adjust their strategies and respond to dynamic learning conditions demonstrate stronger creativity and problem-solving capabilities.

In contrast, immersive learning engagement and perceived algorithmic trust do not directly translate into innovation outcomes. These findings challenge prevailing assumptions in the literature and show that engagement and trust require deeper cognitive processing to produce meaningful results. This perspective shifts the focus from surface-level interaction toward adaptive learning behavior as the key driver of innovation. By adopting a multi-path direct approach, this study offers a more realistic representation of AI-supported learning compared to traditional linear models. The findings contribute to theory by redefining the roles of trust and engagement and by positioning adaptability as the core mechanism that links technological and cognitive dimensions to learning outcomes. This study provides a comprehensive and context-sensitive framework for understanding how students achieve innovation performance in AI-enhanced learning environments, while offering a strong foundation for future research and practice in technology-enhanced education.

CONFLICT OF INTEREST

The authors stated that there are no potential conflicts of interest regarding the research, authorship, or publication of this article.

FUNDING

This study did not receive any financial support.

ETHICAL APPROVAL

This research has followed the institutional ethics board policy.

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