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AI-assisted learning tools and student learning outcomes: A cognitive load theory perspective

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A R T I C L E I N F O

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Saudi Universities

A B S T R A C T

Artificial intelligence (AI) is transforming higher education, yet its impact on students' learning outcomes depends on how effectively these tools are used, perceived, and supported within learning environments. Guided by Cognitive Load Theory (CLT), this study examines how AI-Assisted Learning Tools Usage (AIALTU) and the Perceived Usefulness of AI in Education (PUAIE) influence university students' Learning Outcomes (LO), with Student Engagement (SE) as a mediator and Digital Readiness (DR) as a moderator. Data were collected from 400 students across top Saudi universities using a validated bilingual survey instrument and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). Results show that both AIALTU and PUAIE significantly enhance learning outcomes, and SE partially mediates both relationships, highlighting engagement as a key cognitive mechanism through which AI tools contribute to academic success. DR significantly strengthens the effect of perceived usefulness on learning outcomes but does not alter the influence of actual tool usage, suggesting that intuitive AI design reduces dependence on digital skills. These findings extend CLT by demonstrating how technological, cognitive, and learner-readiness factors jointly shape learning effectiveness in AI-supported settings. The study offers practical insights for universities aiming to align AI integration with Vision 2030 goals by prioritizing student engagement, intuitive tool design, and digital readiness development. Overall, the results underscore the importance of combining advanced AI technologies with supportive learning strategies to achieve meaningful improvements in student learning outcomes.

1. Introduction

Artificial intelligence (AI) has rapidly emerged as a transformative force in higher education, reshaping instructional delivery, personalized learning pathways, and cognitive support for students. With the accelerated adoption of AI-assisted learning tools—such as intelligent tutoring systems, adaptive feedback mechanisms, and AI-powered content generation—universities are increasingly exploring how these technologies can support students' learning processes and academic performance (Dahri et al., 2024; Zawacki-Richter et al., 2019). While AI is widely recognized for its potential to facilitate complex learning tasks and enhance understanding, the cognitive mechanisms through which AI-assisted environments are associated with student learning outcomes remain insufficiently theorized, particularly in non-Western higher education contexts.

In Saudi Arabia, AI integration in universities has intensified under

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the national digital transformation agenda aligned with Vision 2030. Higher education institutions are increasingly implementing AI-powered systems to foster instructional innovation, promote student-centered learning, and strengthen digital competencies. Despite these developments, empirical evidence regarding how AI-assisted learning tools relate to student learning outcomes in Saudi universities remains limited. Existing studies have primarily examined students' acceptance, satisfaction, or general digital readiness (Alenezi & Alenezi, 2025), with less attention given to the underlying cognitive processes that connect AI use to academic outcomes. This omission is particularly important in the Saudi context, where sociocultural norms, institutional structures, and technological maturity may shape how students interact with AI-supported learning systems.

Cognitive Load Theory (CLT) provides a robust theoretical foundation for examining these relationships. CLT posits that learners' working memory capacity is limited and that instructional effectiveness depends on managing three types of cognitive load: intrinsic load (task complexity), extraneous load (irrelevant mental effort), and germane load (intentional cognitive effort devoted to schema construction) (Paas et al., 2004). From this perspective, AI-assisted tools may support learning when they reduce extraneous cognitive load—by automating routine processes, structuring information, or providing adaptive guidance—and when they stimulate germane load by encouraging deeper processing and sustained attention (Holmes & Tuomi, 2022). Conversely, poorly designed or misaligned AI systems may increase extraneous load through complex interfaces or excessive information (Kopcha et al., 2021). Although CLT offers a theoretically coherent explanation for how AI-supported environments may relate to learning outcomes, few empirical studies have systematically integrated AI tool usage, cognitive engagement, and learner readiness within a unified CLT-based model, particularly in developing or transitional higher education systems.

Within AI-supported learning ecosystems, two predictors are particularly salient: AI-Assisted Learning Tools Usage (AIALTU) and Perceived Usefulness of AI in Education (PUAIE). AIALTU reflects students' actual behavioral interaction with AI-based systems, including adaptive platforms, automated feedback tools, and AI-driven academic support. In contrast, PUAIE captures students' cognitive appraisal of whether AI tools enhance the effectiveness and efficiency of their learning. Importantly, PUAIE represents a perceptual belief about AI's value, whereas Learning Outcomes (LO) represent academic performance-related achievements such as improved understanding, retention, and task performance. Distinguishing these constructs is essential: perceived usefulness reflects evaluative cognition, while learning outcomes reflect educational attainment. Although prior research shows that technology usage and perceived usefulness are positively associated with performance (Badr et al., 2024; Shahraniza & Abubaker, 2025), these relationships have rarely been examined through the lens of cognitive load mechanisms.

Student Engagement (SE) constitutes a theoretically central mechanism in this process. From a CLT perspective, engagement reflects learners' intentional investment of cognitive effort—closely aligned with germane cognitive load. When students are cognitively, behaviorally, and emotionally involved in learning activities, they are more likely to allocate mental resources toward organizing, integrating, and applying knowledge. AI-supported tools may be associated with enhanced engagement by offering interactive, adaptive, and personalized experiences that maintain attention and sustain effort (Bond et al., 2021). However, engagement should not be viewed merely as an empirical mediator; rather, it represents the core cognitive process through which reductions in extraneous load and activation of germane load may translate into learning gains. Empirical research has yet to adequately examine whether SE statistically mediates the relationship between AI tool usage, perceived usefulness, and learning outcomes within a CLT framework.

In addition to engagement, learners' Digital Readiness (DR) may function as a boundary condition shaping AI-related learning processes. DR reflects students' confidence, competence, and preparedness to interact with digital technologies. From a cognitive load perspective, students with higher digital readiness may manage technological interfaces more efficiently, thereby minimizing extraneous load associated with system navigation and allowing greater allocation of cognitive resources to germane processing (Yaseen et al., 2025). Conversely, students with lower digital readiness may experience additional cognitive burden when interacting with AI tools, potentially weakening the association between AI-related perceptions and learning outcomes. Although technology readiness has been widely examined in information systems research, its moderating role within CLT-based AI learning models remains underexplored.

Taken together, three research gaps emerge. First, prior studies have not sufficiently integrated AI-assisted learning tools into a CLT-driven framework that explicitly distinguishes extraneous and germane cognitive processes. Second, limited research simultaneously examines direct effects (AI usage and perceived usefulness), mediating mechanisms (engagement), and moderating boundary conditions (digital readiness) within a unified structural model. Third, empirical evidence from Saudi higher education—an analytically informative context undergoing rapid digital transformation—remains fragmented. Addressing these gaps is necessary to develop a theoretically grounded and context-sensitive understanding of AI-supported learning effectiveness.

Responding to these gaps, this study applies Cognitive Load Theory to examine how AIALTU and PUAIE are associated with Student Learning Outcomes (LO) among university students in Saudi Arabia. Specifically, the model proposes that (1) AIALTU may relate to LO primarily through reductions in extraneous cognitive load; (2) PUAIE may influence LO by motivating learners to invest germane cognitive effort; (3) SE statistically mediates these associations by capturing intentional cognitive investment; and (4) DR functions as a moderating boundary condition that may strengthen or weaken these relationships by influencing learners' ability to manage technology-related cognitive demands.

Accordingly, the study pursues three objectives:

(1) to examine the direct associations between AI-Assisted Learning Tools Usage, Perceived Usefulness of AI, and Student Learning Outcomes;
(2) to test whether Student Engagement statistically mediates these relationships within a CLT framework; and
(3) to evaluate whether Digital Readiness moderates the strength of these associations by shaping cognitive load management.

By articulating and empirically testing these mechanisms, this study extends Cognitive Load Theory into AI-supported higher education environments and offers a theoretically integrated model that combines technological, cognitive, and learner-based factors. In doing so, it contributes context-sensitive insights for educators, instructional designers, and policymakers seeking to align AI integration with cognitively supportive and pedagogically grounded learning strategies in Saudi Arabia and comparable digitally advancing higher education systems.

2. Theoretical foundation and relevance to the study: Cognitive Load Theory (CLT)

CLT, originally developed by Sweller (1988) and further refined by Paas et al. (2004), provides a foundational lens for understanding how instructional environments shape learning effectiveness by influencing the mental effort required during the learning process. CLT posits that learners' working memory capacity is limited and can be overloaded when instructional materials impose excessive extraneous cognitive load. Effective learning occurs when instructional tools and strategies minimize unnecessary cognitive burden, manage intrinsic load associated with task complexity, and enhance germane load that supports deeper processing, schema formation, and knowledge construction (Paas & Van Merrienboer, 2020). Within the context of AI-assisted learning environments, CLT offers a robust theoretical explanation for how AI-driven tools may improve or hinder learning outcomes. AI-Assisted Learning Tools (AIALTU)—such as intelligent tutoring systems, generative AI platforms, adaptive feedback mechanisms, and automated content support—have the potential to reduce extraneous load by simplifying routine tasks, offering step-by-step guidance, and personalizing instructional materials based on learners' needs (Holmes & Tuomi, 2022). When used effectively, these tools can help students allocate more cognitive resources toward germane load, enabling deeper engagement and better academic outcomes. Conversely, poorly designed AI tools may increase extraneous load by introducing unfamiliar interfaces, ambiguous prompts, or cognitively overwhelming information displays (Kopcha et al., 2021). Thus, CLT directly supports examining how AIALTU influences Student LO in higher education. PUAIE also fits within the CLT framework as a cognitive appraisal influencing how students interpret the efficiency of AI tools in managing cognitive demands. When learners perceive AI tools as useful, they are more likely to rely on them to reduce cognitive effort, organize complex information, and support learning tasks—thereby enabling the optimization of intrinsic and germane load. This perception shapes engagement and learning outcomes by influencing the degree to which students integrate AI into their study routines (Lin & Chen, 2023). SE represents a critical cognitive and behavioral mechanism in CLT-driven learning environments. Engaged students devote sustained attention, effort, and cognitive investment to learning tasks, which increases germane cognitive load and facilitates meaningful processing (Bond et al., 2021). AI-assisted learning tools may strengthen engagement by offering interactive, adaptive, and personalized learning experiences that help students regulate their cognitive effort. Therefore, SE serves as an essential mediator explaining *how* AIALTU and PUAIE translate into improved learning outcomes from a CLT perspective. DT reflects learners' preparedness to navigate digital technologies and can significantly influence their ability to benefit from AI tools. Through the lens of CLT, DR determines how effectively students can manage extraneous load introduced by technological interfaces. Students with high digital readiness are better equipped to interact with AI tools efficiently, minimize confusion, and focus cognitive capacity on learning tasks. Conversely, learners with lower readiness may experience increased extraneous load due to navigating unfamiliar systems, reducing the effectiveness of AI tools. Although DR does not directly alter intrinsic cognitive load, it functions as a moderating factor that may strengthen or weaken the impact of AI-assisted learning tools on learning outcomes depending on students' digital competence, confidence, and adaptability (Said et al., 2023). Student LO, the central dependent variable in this study, represent the cognitive and academic achievements resulting from instructional processes. According to CLT, effective learning outcomes emerge when instructional environments—including digital tools—help students manage their cognitive load efficiently. AI-assisted tools, when aligned with CLT principles, can support schema development, facilitate knowledge organization, and improve task performance, thereby contributing to positive learning outcomes (Dong et al., 2025). By integrating CLT with contemporary AI-enhanced learning environments, this study positions cognitive load as the theoretical mechanism explaining how AI-assisted tools influence learning outcomes through engagement and readiness-related pathways. This theoretical grounding highlights the need to examine both the direct and indirect effects of AIALTU and PUAIE on learning outcomes, as well as the moderating role of DR, to gain a comprehensive understanding of how AI tools support or impede learning processes in higher education.

3. Operational definition

This study uses well-defined operational constructs to ensure consistency, clarity, and validity in measurement. Each core variable—AI-Assisted Learning Tools Usage (AIALTU), PUAIE, SE, DT, and LO—is conceptualized and measured based on established literature and theoretical grounding. These operational definitions provide a precise framework for assessing how each construct functions within the model and enable meaningful interpretation of the direct, mediating, and moderating relationships examined in the study. All operational definitions of the key variables are presented in Table 1below.

4. Literature review and hypotheses development

This study builds on emerging literature that examines how AI-assisted learning tools and students' perceptions of their usefulness shape academic performance in higher education. Drawing on CLT, which emphasizes the importance of managing cognitive demands for effective learning, the review synthesizes empirical evidence to explain how technology use, engagement, and learner preparedness influence learning outcomes. Based on these theoretical and empirical foundations, the study proposes six hypotheses that investigate the direct effects of AI tool usage and perceived usefulness on learning outcomes, the mediating role of student engagement, and the moderating influence of digital readiness within the context of Saudi universities undergoing rapid digital transformation.

5. Learning outcomes

Learning outcomes—reflecting students' knowledge acquisition, skill development, and academic achievement—remain central indicators of educational effectiveness in higher education. With the increasing adoption of digital and AI-assisted instruction, a growing body of research has examined how such technologies influence academic performance. Naseer et al. (2024) found that AI-based adaptive learning

Table 1
Operational definitions of the variables.

Variables Name	Definitions
AI-Assisted Learning Tools Usage (AIALTU)	AI-Assisted Learning Tools refer to students' actual use of AI-driven educational technologies—such as intelligent tutoring systems, automated feedback tools, adaptive content generators, and AI-supported learning platforms—that assist in completing academic tasks and enhance cognitive processing by reducing extraneous load and supporting instructional efficiency.
Perceived Usefulness of AI in Education (PUAIE)	Perceived Usefulness of AI in Education reflects students' cognitive evaluations of the extent to which AI-based tools improve the quality, effectiveness, and productivity of their learning activities by facilitating understanding, problem-solving, and academic performance.
Student Engagement (SE)	Student Engagement represents students' cognitive, behavioral, and emotional involvement in the learning process, demonstrated through focused attention, active participation, persistence, and meaningful interaction with learning materials—functions that promote germane cognitive load and deeper learning.
Learning Outcomes (LO)	Student Learning Outcomes capture students' perceived academic achievements resulting from the learning process, including improvements in understanding, knowledge acquisition, skill development, task performance, and overall academic success attributed to their engagement with instructional activities and AI-supported learning tools.
Digital Readiness (DR)	Digital Readiness refers to students' confidence, competence, and preparedness to engage with digital learning technologies, including their ability to navigate digital platforms, adapt to new tools, and troubleshoot technological challenges, thereby influencing their capacity to manage cognitive demands in AI-supported environments.

systems significantly enhance learning outcomes by tailoring instructional content to students' individual needs, thereby enabling more efficient learning. Similarly, YildizDurak and Onan (2025) reported that AI-driven feedback mechanisms promote deeper comprehension and knowledge retention, ultimately leading to higher assessment performance. However, the impact of AI on learning outcomes is not universally positive. Tabish (2023) noted that without proper guidance or instructional support, AI tools may overwhelm learners, resulting in cognitive overload and diminished learning effectiveness. This underscores the importance of aligning AI tools with sound pedagogical design. Additionally, factors such as student motivation, engagement, and digital readiness have been shown to mediate or shape the relationship between AI tools and academic gains (Chen, 2025). These findings are consistent with Cognitive Load Theory, which emphasizes that learning improvements depend not only on advanced technologies but also on the learner's ability to manage cognitive demands effectively.

Understanding these dynamics is particularly critical in the context of Saudi Arabia, where higher education institutions are undergoing rapid digital transformation. As universities increasingly integrate AI into teaching and learning, evidence-based insights are necessary to ensure that AI adoption translates into meaningful improvements in student learning outcomes.

6. AI-Assisted Learning Tools Usage (AIALTU) and Learning outcomes (LO)

The integration of AI-Assisted Learning Tools (AIALTU) in higher education has been increasingly associated with improved academic outcomes due to their capacity to support personalized instruction, enhance learning efficiency, and reduce unnecessary cognitive burden. From a CLT perspective, well-designed AI tools minimize extraneous load by automating routine tasks, simplifying complex information, and delivering structured guidance that helps students allocate cognitive resources to deeper processing and meaningful learning (Paas et al., 2004). Such tools also strengthen germane cognitive load by offering adaptive feedback, step-by-step scaffolding, and tailored content that aligns with learners' individual needs, thereby facilitating schema formation and long-term knowledge retention (Feng, 2025). Empirical studies further demonstrate that AI-powered platforms enhance students' comprehension and performance by providing real-time insights, personalized learning pathways, and interactive learning environments that support effective problem-solving and conceptual understanding (Yu, 2024). Recent evidence also indicates that consistent engagement with AI-based tools improves students' confidence, self-directed learning abilities, and overall academic achievement across various disciplines (Hardini et al., 2025; Taylor, 2024). Collectively, these theoretical and empirical insights suggest that the effective use of AI-assisted tools can significantly enhance student learning outcomes by optimizing cognitive load and improving instructional quality. Based on these arguments, the following hypothesis is proposed:

H1. *AIALTU has a positive impact on LO among university students.*

7. Perceived usefulness of AI in education (PUAIE) and Learning Outcomes (LO)

Students' perceptions of the usefulness of AI in education are central to determining how effectively they integrate AI tools into their learning processes. When learners believe that AI enhances their academic performance, clarifies complex concepts, and supports task completion, they are more inclined to engage with these tools consistently and purposefully, leading to improved learning outcomes (Dahri et al., 2024). From a CLT perspective, perceived usefulness operates as a cognitive appraisal that shapes how students interpret the value of AI in managing cognitive demands. When students perceive AI tools as beneficial, they are more likely to use them to reduce extraneous cognitive load, organize information efficiently, and devote cognitive resources to germane processing that supports deeper understanding and schema construction. Empirical studies show that perceived usefulness strengthens learners' motivation, focus, and willingness to adopt deeper learning strategies, which in turn enhance academic achievement (Chauke et al., 2024). Furthermore, alignment between AI functionality and student expectations has been linked to stronger cognitive engagement and higher levels of task persistence, ultimately contributing to better educational outcomes (Supriyanto et al., 2024). These findings suggest that perceived usefulness is not simply a preference for technology but a psychological catalyst that enhances cognitive investment, facilitates meaningful learning, and improves performance. Based on this rationale, the following hypothesis is proposed:

H2. *PUAIE positively influences LO among university students.*

8. Student engagement (SE) as a mediator

The use of AI-assisted learning tools does not inherently guarantee improved academic outcomes; rather, the extent to which students actively engage with these tools largely determines their effectiveness. SE—encompassing cognitive, behavioral, and emotional involvement—serves as a pivotal mechanism through which instructional technologies translate into meaningful learning gains (Ray & Sikdar, 2024). AI-driven systems that offer personalized learning trajectories, immediate feedback, adaptive content, and interactive learning environments can heighten learners' attention and participation, thereby stimulating deeper processing and sustained involvement (Taylor, 2024). From a CLT perspective, engagement is closely tied to germane cognitive load, which reflects the mental effort learners intentionally allocate to understanding, organizing, and integrating new information. When students are engaged, they are more likely to invest the cognitive resources necessary for schema construction and meaningful learning. Conversely, without adequate engagement, even highly sophisticated AI tools may fail to reduce extraneous load or promote deeper understanding, limiting their impact on learning outcomes. Empirical research supports the mediatory role of engagement, demonstrating that SE often acts as the cognitive bridge linking the use of digital tools to improved academic performance and knowledge acquisition (Duterte, 2024). These findings underscore that the benefits of AI-assisted tools are maximized when students are cognitively and behaviorally invested in the learning process. Based on this evidence, the following hypothesis is proposed:

H3. *SE mediates the relationship between AIALTU and LO among university students.*

When students perceive AI tools as genuinely useful for supporting their learning, they are more likely to engage actively and meaningfully in academic tasks—cognitively, behaviorally, and emotionally. Perceived usefulness shapes learners' willingness to invest time, effort, and attention, turning them from passive recipients of information into intentional participants in the learning process (Pertiwi et al., 2024). This positive cognitive appraisal increases motivation, strengthens commitment to learning activities, and encourages sustained interaction with instructional content.

From a CLT perspective, perceived usefulness influences how students allocate their cognitive resources. When AI tools are viewed as effective, students are more inclined to rely on them to reduce extraneous cognitive load, organize complex information, and channel their mental effort toward germane load associated with deeper understanding and schema construction. This redirection of cognitive effort fosters engagement, which is essential for activating meaningful learning processes. Empirical evidence consistently shows that students who regard educational technologies as beneficial demonstrate higher levels of attention, motivation, and interaction with content—factors closely associated with improved academic outcomes (Hmoud et al., 2025; Hardini et al., 2025). Thus, engagement emerges as the mechanism through which perceived usefulness translates into measurable learning gains, highlighting its mediating role within AI-supported learning environments. Based on this reasoning, the following hypothesis is proposed:

H4. *SE mediates the relationship between PUAIE and LO.*

9. Digital readiness (DR) as a moderator

The effectiveness of AI-assisted learning tools can vary substantially among students, and one key factor shaping this variability is DT. Students who possess strong digital readiness—demonstrated through confidence, technical competence, and familiarity with digital environments—are better positioned to navigate AI-based learning platforms efficiently and integrate them into their study routines (Asal et al., 2025). Such learners tend to experience fewer difficulties with interface complexity or system navigation, enabling them to engage more deeply with instructional content. In contrast, students with low digital readiness may struggle to adapt to AI tools, resulting in confusion, cognitive overload, and reduced engagement. These challenges can diminish the potential benefits of AI integration and limit learning outcomes. From a CLT perspective, high digital readiness helps minimize extraneous cognitive load by reducing the mental effort required to operate technological tools. This frees cognitive resources for germane processing—efforts directed toward understanding, organizing, and applying new information—which is critical for meaningful learning. Empirical research supports the moderating role of digital competence in technology-enhanced learning environments, indicating that students with higher levels of digital literacy experience greater academic satisfaction, improved performance, and stronger learning gains when using digital tools (Alam, Hidayat-ur-Rehman, et al., 2025). These findings underscore the notion that individual preparedness significantly shapes how effectively students can benefit from AI-assisted learning tools. Therefore, the following hypothesis is proposed:

H5. *DR moderates the relationship between AIALTU and LO, such that the relationship is stronger when digital readiness is high.*

Students may perceive AI tools as highly valuable for their learning, yet still fail to achieve optimal outcomes if they lack the digital competencies required to use these tools effectively. Research shows that effective engagement with educational technologies is shaped not only by perceived usefulness but also by learners' preparedness to interact with digital platforms (Karafil & Uyar, 2023). When students possess high digital readiness—characterized by confidence, familiarity with digital interfaces, and the ability to troubleshoot technological challenges—they are more likely to explore, personalize, and meaningfully integrate AI tools into their academic routines, thereby enhancing their learning experiences. Conversely, even when AI is viewed as beneficial, students with low digital proficiency may struggle to apply AI tools effectively, resulting in frustration, cognitive overload, or disengagement (Yaseen et al., 2025). These difficulties can diminish the positive influence of perceived usefulness on academic performance. From a CLT perspective, digital readiness functions as a capability that determines whether learners can minimize extraneous cognitive load associated with navigating AI systems. High DR enables students to direct more cognitive resources toward germane processing—such as understanding, organizing, and applying information—while low DR increases the likelihood that cognitive resources will be consumed by technical complexity rather than learning. Thus, digital readiness operates as a conditional enabler, shaping the strength of the relationship between perceived usefulness and learning outcomes. Therefore, the following hypothesis is proposed:

H6. *DR moderates the relationship between PUAIE and LO, such that the relationship is stronger when digital readiness is high.*

10. Conceptual and empirical integration of the proposed model

The proposed model is conceptually grounded in Cognitive Load Theory (CLT), which posits that learning effectiveness depends on the management of intrinsic, extraneous, and germane cognitive load. Within this framework, AI-Assisted Learning Tools Usage (AIALTU) is theorized to reduce extraneous cognitive load by structuring tasks, providing adaptive feedback, and simplifying complex processes. Empirical findings supporting H1 confirm that structured AI usage is positively associated with Learning Outcomes (LO), consistent with CLT's premise that minimizing unnecessary cognitive burden enhances academic performance. Perceived Usefulness of AI in Education (PUAIE) reflects learners' cognitive appraisal of AI's instructional value. Supporting H2, its positive association with LO suggests that when students evaluate AI as beneficial, they are more likely to allocate germane cognitive resources toward meaningful learning. Student Engagement (SE) functions as a central mediating mechanism, as supported by H3 and H4. From a CLT perspective, SE operationalizes germane cognitive load, representing intentional mental effort devoted to schema construction and knowledge integration. Digital Readiness (DR), examined as a moderator, introduces learner-level boundary conditions. The significant moderation in H6 indicates that digital competence strengthens the translation of perceived usefulness into academic outcomes, while the non-significant moderation in H5 suggests that intuitive AI tools may reduce reliance on advanced digital skills. Based on these theoretical and empirical linkages, a conceptual framework integrating technological, cognitive, and learner-level variables is proposed in Fig. 1.

11. Methodology

This study adopted a quantitative research design to examine the relationships among AI-Assisted Learning Tools Usage (AIALTU), Perceived Usefulness of AI in Education (PUAIE), Student Engagement (SE), Digital Readiness (DR), and Learning Outcomes (LO). Given the predictive orientation of the study, the inclusion of both mediating and moderating effects, and the structural complexity of the proposed model, Partial Least Squares Structural Equation Modeling (PLS-SEM) was employed as the primary analytical technique. PLS-SEM is particularly appropriate for exploratory and prediction-oriented research, complex structural relationships, and models incorporating interaction effects, while remaining robust to deviations from multivariate normality.

Data were collected through a structured online survey distributed to students enrolled in top-ranked public universities in Saudi Arabia, as identified by the QS World University Rankings. These institutions were selected because of their active integration of AI-supported learning systems, ensuring that respondents had meaningful exposure to AI-assisted tools. Participants represented diverse academic disciplines and levels of study, including undergraduate and postgraduate programs. Eligibility criteria required that respondents had prior academic experience using AI-assisted learning tools, thereby ensuring relevance to the study constructs.

The measurement instrument was specifically developed to capture the integrated CLT-based framework of this study. To enhance content validity and conceptual clarity, the initial item pool underwent expert evaluation by scholars in educational technology and instructional design. A pilot study was subsequently conducted to assess reliability and preliminary validity, resulting in minor refinements before full-scale data collection. The final questionnaire measured five reflective constructs—AIALTU, PUAIE, SE, LO, and DR—using a five-point Likert scale ranging from strongly disagree to strongly agree.

To ensure linguistic inclusiveness and semantic equivalence, the survey was administered bilingually in English and Arabic. A formal translation and back-translation procedure was conducted by a certified bilingual expert to preserve conceptual consistency between language versions.

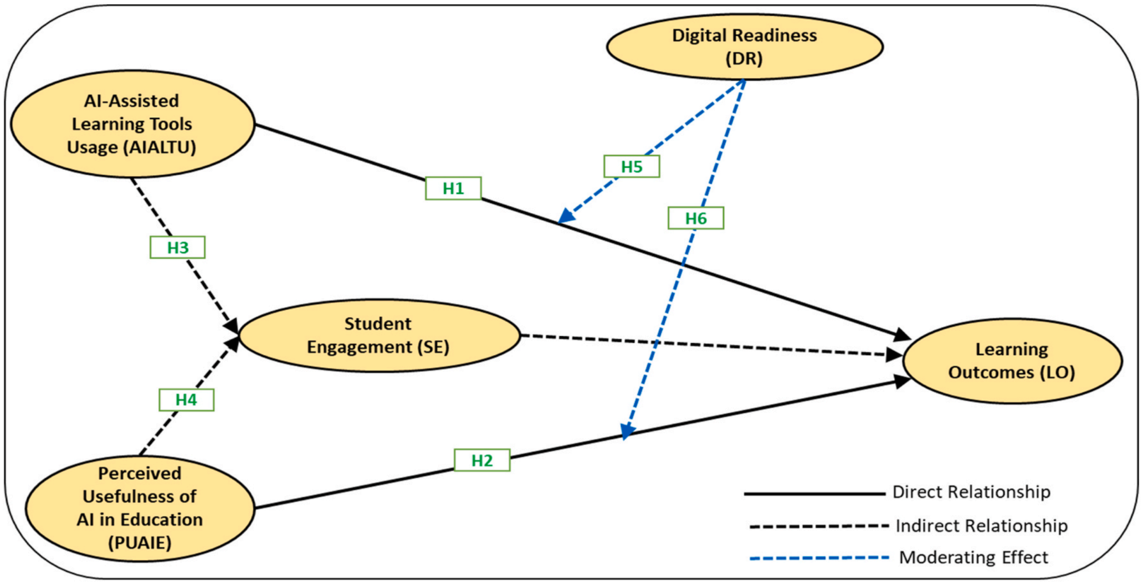

Fig. 1. Conceptual framework.

Data collection was conducted electronically between January and March 2025 using Google Forms. The survey link was disseminated through institutional mailing lists, official student portals, academic platforms, and university-affiliated networks. Participation was voluntary and anonymous. A total of 414 responses were initially received. After screening for incomplete submissions and response inconsistencies, 400 valid cases were retained for analysis. This sample size exceeds recommended thresholds for PLS-SEM and is adequate relative to the model's structural complexity, providing sufficient statistical power for hypothesis testing.

The final dataset was analyzed using Smart-PLS 4.0 following established two-stage PLS-SEM procedures. The measurement model was evaluated in terms of internal consistency reliability, convergent validity, discriminant validity, and multicollinearity diagnostics. The structural model was assessed through path coefficient estimation, bootstrapping procedures, effect sizes (f^2), coefficients of determination (R^2), and predictive relevance (Q^2). This systematic analytical approach enhances transparency, replicability, and statistical robustness in evaluating the hypothesized direct, mediating, and moderating relationships within the proposed CLT-based framework.

12. Instrument development and pilot study

Because no single existing instrument comprehensively captured the integrated constructs examined in this study—AI-Assisted Learning Tools Usage (AIALTU), Perceived Usefulness of AI in Education (PUAIE), Student Engagement (SE), Learning Outcomes (LO), and Digital Readiness (DR)—a context-specific survey instrument was developed. While prior studies have measured these constructs individually, no validated scale simultaneously operationalized them within a unified Cognitive Load Theory (CLT)-based AI learning framework in the Saudi higher education context. Therefore, a customized instrument was deemed necessary to ensure conceptual coherence and contextual relevance. Each construct was operationalized using five reflective items designed to align with its theoretical definition and empirical grounding. Item development was guided by established literature in AI-assisted learning, technology usefulness, student engagement, digital competence, and academic performance. Particular attention was given to ensuring conceptual distinction between perceptual constructs (e.g., PUAIE) and outcome-oriented constructs (e.g., LO) to minimize construct overlap. To establish content validity, the initial pool of items underwent expert evaluation by scholars specializing in educational technology, instructional design, and AI integration in higher education. Experts assessed item clarity, theoretical alignment, redundancy, and contextual suitability for Saudi universities. Based on their feedback, several items were reworded for precision, and minor adjustments were made to enhance conceptual specificity and cultural appropriateness. The questionnaire was originally drafted in English and subsequently translated into Arabic to ensure linguistic inclusivity. A formal translation and back-translation procedure was conducted by a certified bilingual expert to preserve semantic equivalence and eliminate ambiguity between language versions. Discrepancies were discussed and resolved to ensure conceptual consistency across both instruments.

13. Pilot study

A pilot study was conducted with 110 university students from Saudi institutions to evaluate the reliability and preliminary validity of the instrument. Internal consistency reliability was assessed using Cronbach's Alpha, with all constructs exceeding the recommended threshold of 0.70 (AIALTU = 0.792; PUAIE = 0.764; SE = 0.779; LO = 0.753; DR = 0.781), indicating satisfactory internal consistency. Exploratory Factor Analysis (EFA) was conducted using SPSS v26 to assess dimensionality and construct structure. The data were deemed suitable for factor analysis, as indicated by a Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy of 0.880 (well above the 0.60 benchmark) and a statistically significant Bartlett's Test of Sphericity ($p = 0.001$). All communalities exceeded 0.70, demonstrating that items shared substantial variance with their respective factors. The EFA extracted five distinct factors with eigenvalues greater than 1, collectively explaining 83.065% of the total variance. The rotated component matrix revealed strong primary loadings and no significant cross-loadings, supporting factorial clarity and preliminary construct validity. These findings suggest that the instrument demonstrates satisfactory internal structure and psychometric stability at the pilot stage. Based on the pilot results, only minor wording refinements were required before proceeding to full-scale data collection. The finalized questionnaire and detailed EFA outputs are provided in the supplementary materials to enhance transparency and support replication.

14. Sampling and data collection

Saudi Arabia's higher education sector—currently undergoing rapid digital transformation under Vision 2030—provides an analytically

Table 2
Demographic profile of the respondents.

Demographic Profile	Categories	Frequency	Percent
Gender	Male	179	44.75
	Female	184	46.00
	Prefer not to say	37	9.25
Age	Less than 20 years	176	44.00
	21-25	62	15.50
	26-30	96	24.00
	Above 30 years	66	16.50
EducationalQualification	Undergraduate	127	31.75
	Graduate	229	57.25
	Postgraduate	44	11.00
Field of Study	Business	205	51.25
	Engineering	80	20.00
	Medical	44	11.00
	Science	32	8.00
	Others	39	9.75
Do you have prior experience with AI-assisted learning tools?	Yes	400	100.00

informative context for examining AI-assisted learning processes. The study targeted students enrolled in technology-enhanced programs across multiple public universities that have actively integrated AI tools into instructional practices. Focusing on institutions with established AI-supported learning environments ensured that respondents had meaningful exposure to AI-assisted tools relevant to the study constructs.

The target population included undergraduate, graduate, and postgraduate students from diverse academic disciplines and varying levels of digital proficiency. This heterogeneity strengthens the analytical robustness of the model by capturing variability in AI usage, engagement, and digital readiness across different educational contexts. A convenience sampling strategy was employed to efficiently access students with prior experience using AI-assisted learning tools. This approach is common in educational technology research where eligibility criteria require specific exposure to technological systems. To enhance relevance and reduce sampling error, participation was limited to respondents who confirmed prior academic use of AI-assisted tools. Data were collected through institutional mailing lists, official student portals, academic platforms, and university-affiliated digital networks, thereby increasing coverage across disciplines and programs.

The survey instrument was administered bilingually (English and Arabic) to ensure linguistic inclusiveness. The Arabic version underwent formal validation through translation and back-translation procedures, ensuring semantic equivalence and contextual appropriateness. Data collection was conducted electronically between January and March 2025 using Google Forms. The questionnaire link was distributed via email, WhatsApp groups, and official student communication channels to maximize accessibility and response rates. Participation was voluntary and anonymous. A total of 414 responses were initially received. Following data screening procedures—including checks for incomplete entries, response inconsistency, and straight-lining patterns—14 responses were excluded. The final dataset consisted of 400 valid cases. The final sample size exceeds recommended thresholds for PLS-SEM analysis. Based on the model's structural complexity (six primary structural paths and two interaction effects), the sample satisfies the commonly applied “10-times rule” and provides adequate statistical power to detect medium-sized effects at conventional significance levels. Accordingly, the retained sample offers a robust empirical foundation for testing the proposed CLT-based structural model.

15. Demographic profile of the respondents

In Table 2, the demographic profile of the respondents reveals a fairly balanced gender distribution, with 46.00% (184) identifying as female, 44.75% (179) as male, and 9.25% (37) preferring not to disclose their gender. In terms of age, the largest group falls under the category of less than 20 years (44.00%, 176), followed by those aged 26–30 years (24.00%, 96), above 30 years (16.50%, 66), and 21–25 years (15.50%, 62). Regarding educational qualifications, the majority of participants are graduate students (57.25%, 229), followed by undergraduates (31.75%, 127) and postgraduates (11.00%, 44). The field of study is dominated by business students (51.25%, 205), with engineering (20.00%, 80), medical (11.00%, 44), science (8.00%, 32), and other disciplines (9.75%, 39) represented. Notably, 100% (400) of the respondents reported having prior experience with AI-assisted learning tools, indicating a highly relevant and informed sample for this research. This demographic composition ensures a rich diversity of perspectives, drawn from varied academic levels and disciplines, thereby contributing to a comprehensive and nuanced understanding of the impact of AI-assisted learning in Saudi universities.

16. Common method bias (CMB)

Given that data for all constructs were collected using a self-report survey, it was essential to assess the potential influence of Common Method Bias (CMB). Following Kock (2015), the full collinearity approach was applied by examining the full collinearity variance inflation factors (VIFs) for all constructs. The highest full collinearity VIF value was 2.381, well below the conservative threshold of 3.3, indicating that CMB is unlikely to be a concern. In addition, Harman's single-factor test was conducted as a supplementary diagnostic. The unrotated factor solution did not produce a single factor accounting for the majority of the variance, further confirming that no single factor dominated the data. These combined results suggest that CMB does not pose a significant threat to the validity of the study's findings, consistent with recommendations from Kock (2015), Tehseen et al. (2017), and Podsakoff et al. (2012).

17. Means, SD, and correlations of the study variables

Table 3 presents the descriptive statistics and inter-relationships among the study variables, demonstrating significant correlations between all constructs—AIALTU, PUAIE, SE, DR, and LO. Among these constructs, SE recorded the highest mean value at 3.720, while AIALTU exhibited the lowest mean value at 3.586. These findings provide valuable insights into the respondents' perceptions of each construct and their interconnections within the study framework.

Table 3
Means, SD, and Correlations of the Study Variables.

Variables	AIALTU	PUAIE	SE	DR	LO	Mean	SD
AIALTU	1					3.586	0.717
PUAIE	.376**	1				3.637	0.730
SE	.575**	.466**	1			3.720	0.771
DR	.554**	.389**	.439**	1		3.635	0.724
LO	.676**	.607**	.719**	.522**	1	3.568	0.803

Note: n = 400, *$p < 0.05$, **$p < 0.01$(2-tailed).

18. Data analysis by PLS-SEM using Smart-PLS 4.0

Data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) in Smart-PLS 4.0, following established guidelines by Hair Jr, Howard, and Nitzl (2020). PLS-SEM was selected due to the study's predictive orientation, the presence of multiple mediating and moderating relationships, and the formative-like behavior of certain composite constructs—all of which make PLS-SEM more suitable than covariance-based SEM for this research context. Although preliminary analyses performed in SPSS v26 indicated that the data approximated normality, PLS-SEM was preferred for its robustness in handling complex models and its ability to accommodate non-normal data distributions when present. Before conducting the structural analysis, data preparation procedures were undertaken, including checks for missing values, outliers, linearity, and common method bias. Smart-PLS 4.0 was then used to evaluate both the measurement and structural models, employing bootstrapping and model-fit diagnostics to assess reliability, convergent and discriminant validity, multicollinearity, and the significance of path relationships. This analytical approach ensured a rigorous, comprehensive, and methodologically sound assessment of the hypothesized relationships within the proposed conceptual framework.

19. Measurement model (outer model) evaluation

The measurement model was assessed to ensure the reliability and validity of all reflective constructs, following the guidelines of Hair Jr et al. (2021). Internal consistency reliability was evaluated using Cronbach's Alpha (CA) and Composite Reliability (CR). As presented in Fig. 2 and Table 4, all CA and CR values exceeded the recommended threshold of 0.70, indicating strong internal consistency and stable measurement of the constructs. Convergent validity was examined through indicator loadings and the Average Variance Extracted (AVE). Consistent with Hulland (1999) and Hair Jr et al. (2021), indicator loadings should exceed 0.40 (with >0.70 preferred), and AVE values must be greater than 0.50. The results revealed that all items loaded significantly on their respective constructs, with loadings above 0.70, demonstrating excellent indicator reliability. Similarly, all AVE values surpassed the 0.50 benchmark, confirming that each construct explains more than half of the variance in its indicators. Collectively, these results affirm that the measurement model demonstrates robust internal consistency reliability and strong convergent validity, meeting the recommended standards for reflective measurement evaluation in PLS-SEM.

Discriminant validity was assessed using two widely recommended techniques: the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT). First, the Fornell–Larcker criterion was applied by comparing the square root of each construct's Average Variance Extracted (AVE) with its correlations with other constructs. As shown in Table 5, the square roots of the AVE (displayed on the diagonal) are greater than the corresponding inter-construct correlations, indicating that each construct shares more variance with its own indicators than with other constructs. This satisfies the Fornell and Larcker (1981) criterion and provides evidence of discriminant validity.

In addition to the Fornell–Larcker assessment, discriminant validity was further evaluated using the heterotrait–monotrait ratio (HTMT), which compares correlations across constructs with correlations among indicators of the same construct. Following the guidelines of Henseler et al. (2015), HTMT values below the conservative threshold of 0.90 indicate adequate discriminant validity. As shown in Table 6, all HTMT ratios fell well below this benchmark, confirming that the latent variables are empirically distinct and that each construct captures a unique dimension of the model. These results reinforce that the measurement model exhibits strong discriminant validity.

20. Assessment of structural (inner) model

After confirming the reliability and validity of the measurement model, the structural (inner) model was evaluated using established PLS-SEM criteria in Table 7, including the coefficient of determination (R^2), effect sizes (f^2), collinearity diagnostics (inner VIF), model fit indices, and predictive relevance (Q^2). The R^2 values indicate the model's explanatory power for the endogenous constructs. Learning Outcomes (LO) achieved an R^2 value of 0.713, suggesting substantial explanatory power, while Student Engagement (SE) recorded an R^2 of 0.405, indicating moderate explanatory capability according to Cohen's (1989) benchmarks. These findings suggest that the exogenous constructs collectively account for a considerable proportion of variance in LO and a meaningful share in SE. In particular, the high R^2 value for LO indicates that AI-assisted learning tool usage, perceived usefulness, engagement, and digital readiness jointly explain a substantial portion of variability in students' perceived academic outcomes.

Effect size (f^2) analysis was conducted to assess the relative contribution of each predictor within the structural model. Following Cohen's (1989) guidelines (0.02 = small, 0.15 = medium, 0.35 = large), perceived usefulness of AI (PUAIE) exerted a medium effect on LO (f^2 = 0.261) and a small effect on SE (f^2 = 0.122). AI-Assisted Learning Tools Usage (AIALTU) demonstrated a small direct effect on LO (f^2 = 0.118) but a medium effect on SE (f^2 = 0.314), suggesting that its influence is more strongly associated with engagement than with direct outcome

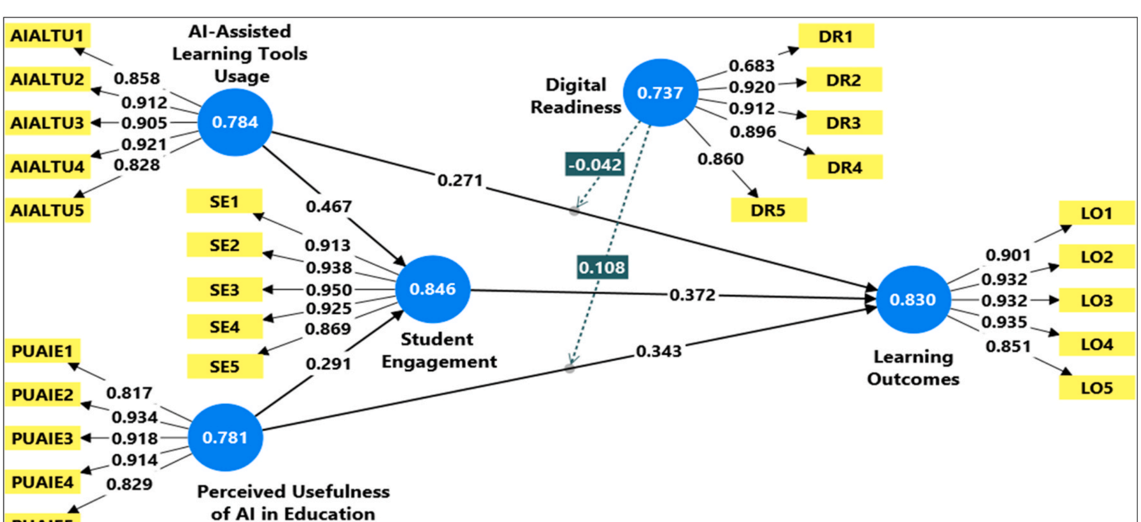

Fig. 2. Measurement model with outer loadings and AVE values from PLS-Algorithm.

Table 4
Constructs validity and reliability.

Constructs	Items	Statement	F.L	CA	CR (rho_a)	CR (rho_c)	AVE
AIALTU	**AIALTU1**	I regularly use AI-based tools for learning tasks.	**0.858**	**0.931**	**0.932**	**0.948**	**0.784**
	AIALTU2	AI tools help me complete assignments more efficiently.	**0.912**				
	AIALTU3	I rely on AI tools to understand complex topics.	**0.905**				
	AIALTU4	I find AI-based platforms easy to integrate into my studies.	**0.921**				
	AIALTU5	I use AI tools to personalize my learning experience.	**0.828**				
DR	**DR1**	I am confident using digital technologies for learning.	**0.683**	**0.907**	**0.910**	**0.933**	**0.737**
	DR2	I can quickly adapt to new learning technologies.	**0.920**				
	DR3	I have access to reliable internet and digital devices.	**0.912**				
	DR4	I possess the skills needed to use AI tools effectively.	**0.896**				
	DR5	I am comfortable troubleshooting basic tech issues during online learning.	**0.860**				
LO	**LO1**	AI-assisted tools help me achieve better grades.	**0.901**	**0.948**	**0.950**	**0.961**	**0.830**
	LO2	I can retain information better through AI-assisted learning.	**0.932**				
	LO3	AI tools contribute to my academic success.	**0.932**				
	LO4	I perform better on assessments when using AI tools.	**0.935**				
	LO5	AI learning platforms enhance my problem-solving skills.	**0.851**				
PUAIE	**PUAIE1**	AI enhances my academic performance.	**0.817**	**0.929**	**0.933**	**0.947**	**0.781**
	PUAIE2	AI tools make learning more effective.	**0.934**				
	PUAIE3	I find AI-supported learning more engaging.	**0.918**				
	PUAIE4	Using AI improves my understanding of course content.	**0.914**				
	PUAIE5	AI tools are valuable for achieving learning goals.	**0.829**				
SE	**SE1**	I am actively involved in AI-based learning activities.	**0.913**	**0.954**	**0.957**	**0.965**	**0.846**
	SE2	AI tools motivate me to participate in class.	**0.938**				
	SE3	I feel more focused when using AI tools in learning.	**0.950**				
	SE4	I enjoy the learning process more with AI.	**0.925**				
	SE5	AI increases my interest in academic content.	**0.869**				

Notes: CR: Composite Reliability; AVE: Average Variance Extracted; CA: Cronbach's Alpha.

Table 5
Discriminant validity- Fornell Larcker.

Constructs	AIALTU	DR	LO	PUAIE	SE
AIALTU	0.885				
DR	0.552	0.859			
LO	0.676	0.521	0.911		
PUAIE	0.378	0.389	0.608	0.884	
SE	0.576	0.439	0.721	0.467	0.920

The off-diagonal values are the correlations between latent variables, and the diagonal is the square root of AVE.

perceptions. Student Engagement showed a medium effect on LO ($f^2 = 0.276$), reinforcing its central role in the structural model. In contrast, Digital Readiness (DR) exhibited a negligible direct effect on LO ($f^2 = 0.013$), consistent with its theorized function as a moderating boundary condition rather than a primary explanatory variable.

Collinearity diagnostics further supported model stability. Inner VIF values ranged from 1.166 to 2.381, remaining well below the recommended threshold of 5.0 (Hair Jr et al., 2021). These results indicate that multicollinearity does not threaten the interpretability of the structural relationships and that parameter estimates are statistically stable.

Model fit was assessed using the Standardized Root Mean Square Residual (SRMR), Chi-square, and the Normed Fit Index (NFI). The SRMR values for both the saturated model (0.066) and the estimated model (0.067) fall below the recommended threshold of 0.08, indicating acceptable approximate model fit. Although the NFI values (0.648 and 0.650) are below conventional covariance-based SEM benchmarks, such results are not uncommon in complex PLS-SEM models, which prioritize predictive accuracy and variance explanation over strict global fit indices. Taken together, these indicators suggest that the structural model demonstrates adequate fit within a variance-based modeling framework.

Beyond explanatory power, predictive relevance was evaluated using Q^2 values obtained through the blindfolding procedure. Consistent with Hair et al. (2017), Q^2 values greater than zero indicate that the model has predictive relevance for a given endogenous construct. Student Engagement achieved a Q^2 value of 0.251, indicating strong predictive relevance, while Learning Outcomes recorded a Q^2 value of 0.089, reflecting acceptable predictive capability. These findings suggest that the model not only explains substantial variance but also demonstrates meaningful predictive strength, particularly for

Table 6
Discriminant validity- HTMT.

Constructs	AIALTU	DR	LO	PUAIE	SE
AIALTU					
DR	0.601				
LO	0.720	0.561			
PUAIE	0.404	0.424	0.647		
SE	0.611	0.471	0.756	0.495	

Table 7
Structural Model Assessment results (R^2, F^2, Inner VIF, Model Fit, and Q^2).

R-Square	Endogenous Variables	R Square		R Square Adjusted	Threshold
	LO	0.713		0.708	0.26: Substantial, 0.13: Moderate, 0.02: Weak (Cohen, 1989)
	SE	0.405		0.402	
Effect Size (F-Square)	**Exogenous Variables**	**LO**		**SE**	**Threshold**
	AIALTU	0.118		0.314	0.35: Substantial,
	DR	0.013			0.15: Medium effect,
	PUAIE	0.261		0.122	0.02: Weak effect (Cohen, 1989)
	SE	0.276			
Collinearity (Inner VIF)	**Exogenous Variables**	**LO**		**SE**	**Threshold**
	AIALTU	2.164		1.166	VIF ≤ 5.0 (Hair et al., 2017)
	DR	2.381			
	PUAIE	1.572		1.166	
	SE	1.739			
Model Fit	**Criteria**	**Saturated model**		**Estimated model**	**Threshold**
	SRMR	0.066		0.067	SRMR <0.08
	Chi-square	5225.631		5207.639	
	NFI	0.648		0.650	NFI >0.9
Predictive Relevance (Q^2)	**Endogenous Variables**	**Q^2 Predict**	**RMSE**	**MAE**	**Threshold**
	LO	0.089	0.883	0.746	A Q^2 value greater than 0 indicates the exogenous contracts predictive relevance for the endogenous constructs (Hair et al., 2017).
	SE	0.251	0.697	0.857	

engagement. The accompanying RMSE and MAE values further support the model's predictive adequacy, indicating reasonable out-of-sample predictive performance.

Overall, the structural assessment indicates that the proposed CLT-based model exhibits substantial explanatory power, stable structural estimates, and adequate predictive relevance. These results provide a statistically robust foundation for hypothesis testing and support the interpretation of the direct, mediating, and moderating relationships among AI-assisted learning tool usage, perceived usefulness, student engagement, digital readiness, and learning outcomes in AI-integrated higher education environments.

21. Hypotheses testing results

Table 8 and Fig. 3 present the results of the structural model, estimated through bootstrapping with 10,000 subsamples. The standardized path coefficients (β) indicate the strength and direction of each relationship, while the associated t-values, p-values, and 95% bias-corrected confidence intervals (LL–UL) are used to assess statistical significance. A relationship is considered significant when the p-value is below 0.05, the t-value exceeds 1.96, and the confidence interval does not include zero. For H1, which examines the effect of AIALTU on Learning Outcomes, the results support the hypothesis. The path coefficient is positive and significant (β = 0.271, t = 3.373, p = 0.001), and the confidence interval [0.088, 0.410] does not contain zero, confirming the reliability of this relationship. Likewise, H2 is supported, as the Perceived Usefulness of AI demonstrates a strong and significant positive effect on Learning Outcomes (β = 0.343, t = 3.317, p = 0.001). The confidence interval [0.132, 0.529] also excludes zero, further validating the robustness of this effect.

Both mediation hypotheses are supported by the findings. For H3, the indirect effect is significant, as indicated by a p-value of 0.002 (less than 0.05) and a t-value of 3.142 (greater than 1.96). The confidence interval, with a lower limit of 0.093 and an upper limit of 0.311, does not include zero, further confirming the presence of a significant mediation effect. Importantly, this mediation is classified as partial mediation, because both the direct relationship between the use of AI-assisted learning tools and learning outcomes and the indirect pathway through Student Engagement are significant. This indicates that Student Engagement explains part—but not all—of the impact of AI tool usage on learning outcomes. Overall, the results suggest that the positive influence of AI-assisted learning tools on academic performance is strengthened when students are actively engaged in the learning process. Similarly, for H4, the mediation effect is also supported. The

Table 8
Hypotheses testing result.

Hypotheses	OS/Beta	SD	95% Con. Inter. Bias Corrected LL	UL	T	P	Decision	Mediation
H1: AIALTU -> LO	0.271	0.080	0.088	0.410	3.373	0.001	Supported	
H2: PUAIE -> LO	0.343	0.103	0.132	0.529	3.317	0.001	Supported	
H3: AIALTU -> SE -> LO	0.173	0.055	0.093	0.311	3.142	0.002	Supported	Partial
H4: PUAIE -> SE -> LO	0.108	0.060	0.034	0.283	2.815	0.040	Supported	Partial
H5: DR x AIALTU -> LO	-0.042	0.038	-0.119	0.034	1.107	0.269	Not Supported	
H6: DR x PUAIE -> LO	0.108	0.040	0.037	0.195	2.671	0.008	Supported	

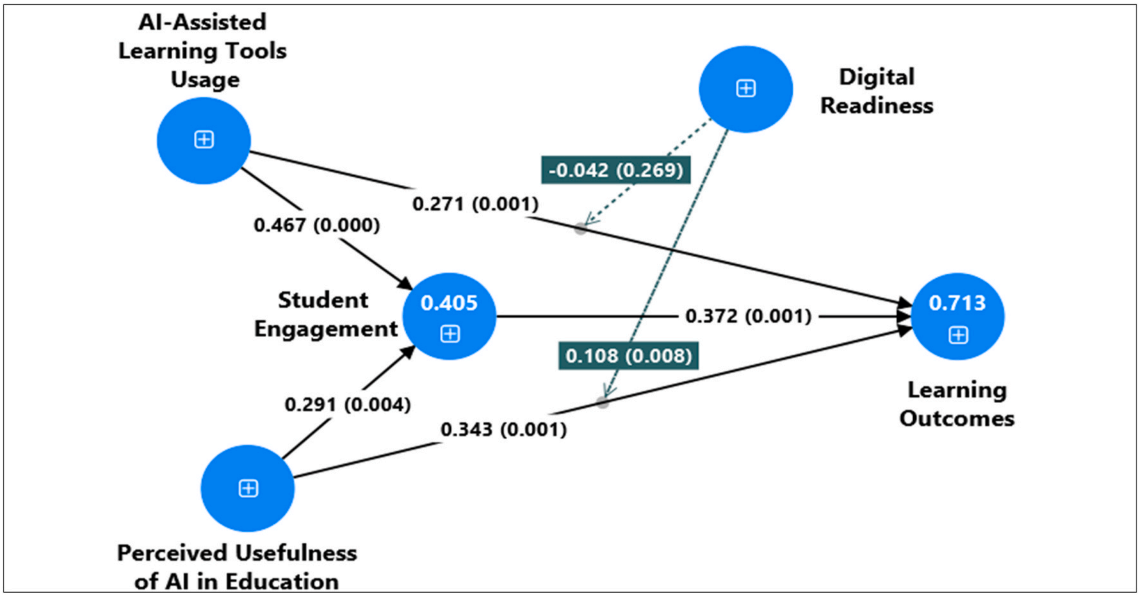

Fig. 3. Structural Model with path coefficient (beta) and p-values from bootstrapping test.

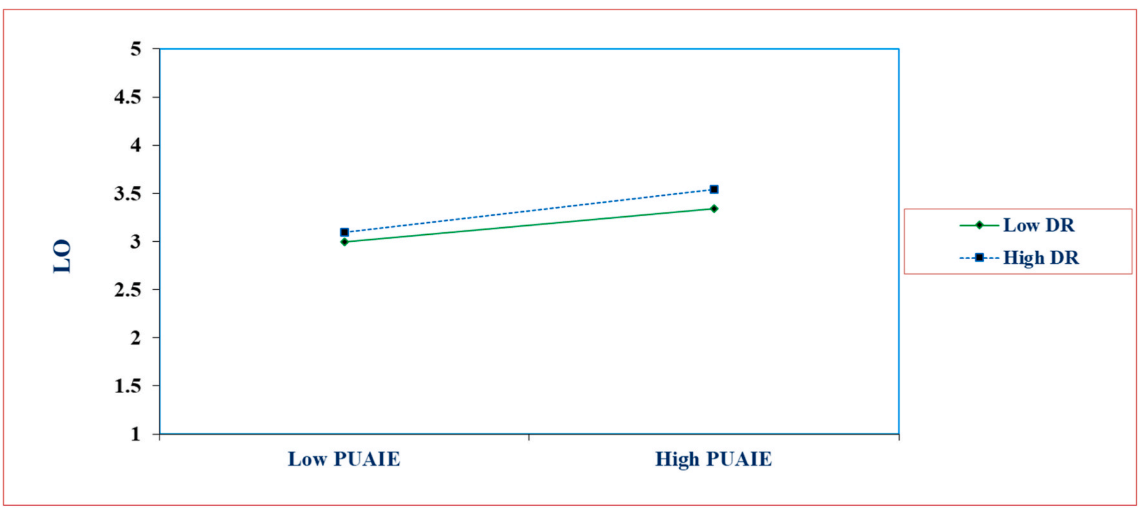

Fig. 4. Interactive effect of DR in between PUAIE and LO

indirect pathway is significant, as shown by a p-value of 0.040 (below the 0.05 threshold) and a t-value of 2.815 (exceeding the critical value of 1.96). The confidence interval ranges from 0.034 to 0.283, and because zero does not fall within this interval, the significance of the mediation is further confirmed. Similar to H3, this represents partial mediation, as both the direct effect of perceived usefulness of AI on learning outcomes and the indirect effect through Student Engagement are significant. This indicates that Student Engagement partially explains how students' perceptions of AI's usefulness translate into improved learning outcomes. In essence, when students find AI tools beneficial, their level of engagement becomes a key factor that amplifies the positive impact on their academic performance.

The results for the moderating hypotheses indicate mixed outcomes. H5 is not supported, as the interaction between Digital Readiness and the use of AI-assisted learning tools is not statistically significant ($\beta = -0.042$, $t = 1.107$, $p = 0.269$). The confidence interval [–0.119, 0.034] includes zero, confirming the absence of a moderating effect. This means that Digital Readiness does not meaningfully change the strength of the relationship between AI tool usage and learning outcomes. In contrast, H6 is supported, with a significant positive interaction effect observed between Digital Readiness and the perceived usefulness of AI ($\beta = 0.108$, $t = 2.671$, $p = 0.008$). The confidence interval [0.037, 0.195] excludes zero, indicating that Digital Readiness strengthens the positive association between students' perceptions of AI's usefulness and their learning outcomes. Overall, five of the six hypotheses (H1, H2, H3, H4, and H6) receive empirical support, demonstrating robust direct and indirect effects within the model and highlighting the conditional role of Digital Readiness in enhancing the impact of perceived usefulness on academic performance.

Fig. 4 visually illustrates the moderating effect of DR on the relationship between PUAIE and LO. The figure shows that the influence of PUAIE on LO is more pronounced at higher DR levels and weaker at lower DR levels. To further examine this interaction, separate path analyses were conducted for high TR (1 SD above the mean) and low TR (1 SD below the mean). The results indicate a stronger PUAIE-LO relationship at high DR levels (higher beta) and a weaker relationship at low DR levels (lower beta), emphasizing DR's significant role in moderating this relationship.

22. Discussion

The findings related to H1 indicate that AI-Assisted Learning Tools Usage (AIALTU) is positively associated with Learning Outcomes (LO) among university students in Saudi Arabia. This result is consistent with prior research suggesting that AI-supported systems are linked with improved instructional efficiency, personalized learning pathways, and adaptive academic support (Asem et al., 2024). Within AI-integrated learning environments, features such as automated feedback, structured content delivery, and personalized recommendations may help students organize information more effectively and interact with course materials in a systematic manner. From a Cognitive Load Theory (CLT) perspective, this association is plausibly explained by reductions in extraneous cognitive load. When AI tools simplify complex tasks, provide stepwise guidance, and automate routine processes, students may expend less mental effort on peripheral demands and allocate greater cognitive resources to germane processing, such as schema construction and conceptual integration (Paas et al., 2004; Nawaz et al., 2023). In the context of Saudi Arabia's digitally advancing higher education sector, this finding suggests that the structured and adaptive nature of AI tools may correspond with more efficient cognitive processing, which in turn is associated with stronger perceived academic outcomes.

Similarly, the results for H2 demonstrate that Perceived Usefulness of AI in Education (PUAIE) is positively related to Learning Outcomes. This finding aligns with literature indicating that when students evaluate educational technologies as beneficial, they are more likely to incorporate them into their learning routines and adopt deeper processing strategies (Mat Yusoff et al., 2025; Thapa et al., 2025). Importantly, PUAIE represents a cognitive appraisal rather than actual tool usage. From a CLT perspective, such appraisal may influence how learners allocate cognitive effort. When students believe that AI tools support their academic effectiveness, they may be more willing to invest germane cognitive load in engaging with AI-supported tasks, organizing information, and refining knowledge structures. In this sense, perceived usefulness does not directly alter intrinsic task complexity but may shape learners' motivation to engage in meaningful cognitive processing. Within the Saudi higher education context, where AI integration is expanding rapidly, this result suggests that students' evaluative beliefs about AI play a meaningful role in how technological systems are cognitively leveraged.

The mediation results further clarify these relationships. The support for H3 indicates that Student Engagement (SE) statistically mediates the relationship between AIALTU and LO. This suggests that the association between AI tool usage and learning outcomes is partially explained through students' cognitive, behavioral, and emotional involvement in learning activities. From a CLT standpoint, engagement closely corresponds to germane cognitive load—the intentional mental effort directed toward understanding, organizing, and integrating knowledge. Thus, while AIALTU may be associated with reductions in extraneous load through structured and adaptive support, it is students' engagement that reflects the active allocation of cognitive resources necessary for meaningful learning. The mediation finding does not imply causality but indicates that engagement represents a statistically significant pathway linking AI usage and perceived outcomes. In digitally advanced Saudi universities, this suggests that the mere presence of AI tools is insufficient; their association with academic outcomes is stronger when students are actively and cognitively invested in the learning process.

The support for H4 extends this interpretation by showing that SE also mediates the relationship between PUAIE and LO. Students who perceive AI as useful are more likely to demonstrate higher engagement, which in turn is associated with stronger learning outcomes which is supported from the study of Alam, Alharbi, et al. (2025). From a CLT perspective, perceived usefulness may function as a motivational precursor that encourages learners to devote germane cognitive effort to AI-supported tasks. Engagement then reflects the behavioral manifestation of that effort. This finding reinforces the theoretical distinction between perceptual beliefs (PUAIE) and performance-related outcomes (LO), with engagement serving as the bridging mechanism. In the Saudi context, where AI adoption is institutionally encouraged, this result highlights that favorable perceptions alone do not automatically correspond with improved outcomes; rather, engagement represents the cognitive channel through which perceived value is translated into meaningful learning activity.

The moderation findings provide additional nuance. The results for H5 indicate that Digital Readiness (DR) does not significantly moderate the relationship between AIALTU and LO. This suggests that the association between AI tool usage and learning outcomes is relatively consistent across varying levels of digital competence within the sample. One plausible explanation is that AI tools implemented in these universities may be sufficiently intuitive and user-friendly to minimize technological complexity, thereby reducing extraneous cognitive load regardless of individual digital readiness. In such environments, even students with moderate levels of digital competence may navigate AI systems without substantial additional cognitive burden. Another possible explanation relates to sample characteristics: given that participants were drawn from technologically integrated institutions, overall digital readiness levels may be relatively homogeneous, limiting observable moderation effects. From a CLT perspective, this finding suggests that when instructional tools are well designed and cognitively supportive, individual differences in digital skill may exert less influence on outcome perceptions.

In contrast, the findings for H6 reveal that DR significantly moderates the relationship between PUAIE and LO, such that the positive association between perceived usefulness and learning outcomes is stronger for students with higher digital readiness. This indicates that while students may evaluate AI as beneficial, their ability to translate this perception into effective learning experiences depends partly on their digital competence. From a CLT perspective, higher digital readiness may reduce the extraneous cognitive load associated with navigating AI interfaces, thereby allowing learners' positive perceptions to more fully activate germane cognitive processing. In other words, when students are digitally prepared, their belief in AI's usefulness is more readily operationalized into meaningful engagement and cognitive investment. Within Saudi higher education, this finding underscores that cognitive appraisal and digital capability function together: perceived usefulness alone may not be sufficient unless students possess the competencies required to effectively manage technological systems.

Taken together, the findings support a CLT-informed interpretation in which AI-assisted learning tools are associated with learning outcomes through a combination of reduced extraneous load and activated germane processing. Engagement emerges as a central cognitive pathway, while digital readiness functions as a boundary condition influencing how perceptual beliefs translate into academic outcomes. These results suggest that in AI-integrated higher education environments, the cognitive effectiveness of technological tools depends not only on their functional features but also on learners' evaluative beliefs, active engagement, and digital preparedness.

23. Theoretical implications

This study contributes to the technology-enhanced learning literature by advancing and refining the application of Cognitive Load Theory (CLT) within AI-supported higher education environments. Rather than merely applying CLT descriptively, the findings empirically examine how AI-assisted learning processes correspond with distinct cognitive load mechanisms—particularly extraneous and germane load—and how these mechanisms operate within a structurally integrated model.

First, the positive associations between AI-Assisted Learning Tools Usage (AIALTU), Perceived Usefulness of AI (PUAIE), and Learning Outcomes (LO) provide empirical support for CLT's central premise that instructional environments are more effective when they reduce extraneous cognitive load and facilitate germane cognitive processing. The results suggest that AI tools may function as cognitive structuring mechanisms that correspond with reduced unnecessary mental effort and improved allocation of cognitive resources. Importantly, the inclusion of both behavioral usage (AIALTU) and cognitive appraisal (PUAIE) extends CLT beyond traditional instructional design features by incorporating learners' evaluative perceptions as part of the cognitive processing environment. This highlights that cognitive load is shaped not only by technological architecture but also by how learners interpret and value instructional tools.

Second, the mediating role of Student Engagement (SE) advances CLT by empirically positioning engagement as a measurable manifestation of germane cognitive load. While CLT conceptually distinguishes between extraneous and germane load, empirical operationalization of germane load has often been indirect. By demonstrating that engagement statistically mediates the associations between AI-related predictors and learning outcomes, this study provides evidence that active cognitive investment functions as a key mechanism within AI-supported learning environments. This shifts the theoretical emphasis from technology presence to learner cognitive activation, reinforcing that learning effectiveness depends on intentional mental effort rather than technological exposure alone.

Third, the moderation findings extend CLT by introducing Digital Readiness (DR) as a boundary condition influencing cognitive load dynamics. Although DR did not significantly moderate the AIALTU–LO relationship, its significant moderating effect on the PUAIE–LO association suggests that individual competence shapes how cognitive appraisals are translated into meaningful learning outcomes. This finding expands CLT beyond instructional design variables by incorporating learner-level capabilities as factors that influence cognitive load management. It implies that extraneous load reduction may depend partly on learners' technological fluency, particularly when they must operationalize perceived usefulness into action. The nuanced moderation pattern further refines CLT: when AI tools are intuitive and structured, digital readiness may exert limited influence; however, when cognitive appraisal drives engagement, digital competence becomes a more salient enabler of effective germane processing.

Finally, the study contributes context-sensitive validation of CLT within a rapidly digitizing higher education system. Conducted in Saudi Arabia—a setting characterized by accelerating AI adoption under Vision 2030—the findings demonstrate that cognitive load mechanisms operate within technologically advancing yet culturally distinct educational ecosystems. By integrating technological features (AI usage), cognitive appraisals (perceived usefulness), behavioral mechanisms (engagement), and learner characteristics (digital readiness), the study advances a more holistic theoretical model that situates CLT within contemporary AI-mediated learning environments.

Collectively, these contributions extend CLT from a primarily instructional design-focused framework toward a multi-layered explanatory model that incorporates technological affordances, learner perceptions, engagement processes, and individual readiness. In doing so, the study enriches theoretical understanding at the intersection of cognitive load theory and AI-integrated higher education, offering a more comprehensive account of how learning effectiveness may emerge in digitally transforming academic contexts.

24. Practical implications

The findings of this study offer several important practical implications for educators, instructional designers, and policymakers operating within AI-integrated higher education environments, particularly in the context of Saudi Arabia's Vision 2030 digital transformation agenda. The positive associations between AI-Assisted Learning Tools Usage (AIALTU), Perceived Usefulness of AI (PUAIE), and Learning Outcomes (LO) suggest that AI integration should not be treated merely as technological modernization, but as a cognitively informed instructional strategy.

First, institutions should prioritize the adoption of AI platforms that are pedagogically structured and cognitively supportive. From a Cognitive Load Theory (CLT) perspective, AI systems that provide adaptive scaffolding, structured feedback, and personalized learning pathways may help reduce extraneous cognitive load and allow students to allocate greater cognitive resources toward meaningful processing. The non-significant moderating role of Digital Readiness (DR) in the AIALTU–LO relationship further suggests that well-designed and intuitive AI tools can support learners across varying levels of digital competence. Therefore, simplicity, clarity of interface, and instructional alignment should be central criteria when selecting or developing AI-supported platforms.

Second, the mediating role of Student Engagement (SE) highlights that AI adoption alone is insufficient to optimize learning experiences. The benefits associated with AI tools appear stronger when students are cognitively and behaviorally invested in learning tasks. Educators should therefore design AI-supported activities that actively promote interaction, reflection, and sustained attention. Examples include AI-enabled formative assessments with feedback loops, interactive simulations, guided problem-solving tasks, and structured inquiry activities. Importantly, faculty development programs should move beyond technical training and emphasize pedagogical integration strategies that foster engagement. Instructors who understand how to align AI tools with learning objectives and cognitive principles are better positioned to create environments conducive to germane cognitive processing.

Third, the significant moderating effect of DR on the PUAIE–LO relationship underscores the importance of digital capacity-building initiatives. While students may perceive AI tools as beneficial, their ability to translate that perception into effective academic engagement appears contingent on digital competence. Universities should therefore implement structured digital literacy programs, orientation modules, and targeted workshops aimed at strengthening students' confidence and operational fluency in AI-supported systems. Micro-credentialing initiatives or competency-based digital skill certifications may further support students in navigating AI platforms effectively, thereby minimizing technology-related cognitive burden.

Finally, these implications are particularly salient in Saudi Arabia's rapidly evolving higher education landscape. As institutions expand their reliance on AI-based learning technologies, strategic investment should extend beyond infrastructure acquisition to include cognitive design principles, faculty training, and student readiness development. A balanced approach that integrates intuitive AI tool design, engagement-centered pedagogy, and digital skill enhancement is more likely to create learning ecosystems in which AI functions as a cognitive support mechanism rather than a source of additional complexity. By aligning AI implementation with cognitive and pedagogical considerations, Saudi universities can more effectively leverage technological innovation to support sustainable improvements in student learning experiences.

25. Limitations and future research directions

Despite its theoretical and empirical contributions, this study has several limitations that warrant careful consideration. First, the cross-sectional research design restricts causal inference. Although the structural model identifies statistically significant associations among AI-assisted learning tools, perceived usefulness, engagement, digital readiness, and learning outcomes, these relationships reflect correlations observed at a single point in time. Consequently, the directionality of effects cannot be definitively established. Future research should employ longitudinal, panel, or experimental designs to examine how AI-related engagement patterns and cognitive processing evolve over time and to better isolate causal mechanisms within AI-supported learning environments.

Second, the study relied exclusively on self-reported measures, including perceived learning outcomes. While statistical diagnostics indicated that common method bias (CMB) was not a substantial concern, self-report designs may still inflate associations due to shared measurement context, social desirability, or perceptual consistency effects. In particular, perceived learning outcomes may not fully correspond to objective academic performance. Future studies should incorporate objective indicators such as GPA, course grades, standardized assessments, or behavioral analytics derived from learning management systems and AI platforms. Combining perceptual and behavioral data would strengthen validity and provide a more comprehensive understanding of AI's relationship with measurable academic performance.

Third, although the measurement instrument demonstrated satisfactory reliability and validity, all constructs were operationalized using self-developed scales tailored to the study's conceptual framework. While this approach ensured contextual and theoretical alignment, it may limit comparability with prior studies using standardized instruments. In addition, despite theoretical clarification of the distinction between Perceived Usefulness of AI (PUAIE) and Learning Outcomes (LO), some degree of perceptual proximity between these constructs may persist, given that both relate to academic effectiveness. Future research could refine these constructs through multidimensional modeling, incorporate established validated scales where appropriate, and conduct cross-validation studies across diverse educational contexts to further strengthen discriminant validity.

Fourth, the sample was drawn from top-ranked, technologically advanced public universities in Saudi Arabia. These institutions are likely characterized by relatively high digital infrastructure and comparatively homogeneous levels of digital readiness. This context may partly explain the non-significant moderation effect observed in the AIALTU–LO relationship and limits the generalizability of findings to institutions with lower levels of technological maturity. Replication studies across a broader spectrum of universities—including smaller, rural, or less digitally integrated institutions—would allow for greater variability in digital readiness and potentially reveal more nuanced boundary conditions.

Finally, the study focused primarily on cognitive and behavioral dimensions of AI-supported learning. Emotional and socio-psychological factors, such as AI-related anxiety, digital confidence, trust in AI systems, or perceived autonomy, were not included in the current model. Future research could extend the framework by examining additional mediating mechanisms (e.g., self-regulation, metacognitive strategies, cognitive absorption) and moderating variables (e.g., AI literacy, instructional quality, disciplinary differences). Such extensions would contribute to a more comprehensive understanding of how technological affordances, cognitive processes, and learner characteristics interact in increasingly AI-mediated higher education ecosystems. By addressing these limitations, future research can further refine theoretical models linking AI integration to cognitive load processes and academic outcomes, thereby advancing a more nuanced and generalizable understanding of AI-supported learning effectiveness.

26. Conclusion

This study investigated how AI-Assisted Learning Tools Usage (AIALTU) and Perceived Usefulness of AI in Education (PUAIE) are associated with Learning Outcomes (LO) among university students in Saudi Arabia, with Student Engagement (SE) functioning as a mediator and Digital Readiness (DR) as a moderating boundary condition. Grounded in Cognitive Load Theory (CLT), the findings provide empirical insight into how AI-supported learning environments correspond with cognitive processing mechanisms in digitally advancing higher education contexts.

The results indicate that both AI tool usage and perceived usefulness are positively associated with learning outcomes. Importantly, engagement emerged as a central pathway linking these predictors to academic outcomes, reinforcing the CLT-informed proposition that meaningful learning depends on learners' active allocation of cognitive resources toward germane processing. AI tools alone are not sufficient; their association with improved outcomes appears stronger when students are cognitively and behaviorally invested in learning activities.

The moderation findings add further nuance. While digital readiness did not significantly alter the association between AI tool usage and learning outcomes, it strengthened the relationship between perceived usefulness and outcomes. This suggests that learners' digital competence plays a more critical role when translating cognitive appraisals of AI into effective academic engagement than when interacting with intuitively designed tools. These findings highlight that both technological design and learner preparedness shape how cognitive load processes unfold in AI-mediated environments.

Within the broader context of Saudi Arabia's Vision 2030 digital transformation agenda, the study underscores the importance of aligning AI integration with cognitively supportive instructional design, engagement-centered pedagogy, and student digital capacity-building initiatives. Institutions seeking to leverage AI in higher education should therefore consider not only technological infrastructure but also learner engagement dynamics and digital readiness development.

Theoretically, this research extends CLT into contemporary AI-enhanced learning ecosystems by integrating technological usage, perceptual appraisal, engagement processes, and individual competence within a unified explanatory framework. As AI continues to reshape educational systems globally, future research should further explore additional cognitive, motivational, and contextual factors that influence learning in AI-integrated environments. Advancing such inquiry will contribute to the development of more inclusive, evidence-based, and cognitively aligned AI-supported higher education models.

CRediT authorship contribution statement

Mohammad Nurul Alam: Writing – original draft, Project administration, Methodology, Investigation, Data curation, Conceptualization. **Md Aminul Islam:** Visualization, Validation, Supervision, Software, Resources, Data curation. **Mohamedelhassan O.A. Babiker:** Writing – review & editing, Visualization, Validation, Supervision, Software, Resources, Investigation. **Mohd Shuaib Siddiqui:** Writing – review & editing, Visualization, Validation, Supervision, Software, Resources, Data curation. **Mohammad Bin Amin:** Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Judit Oláh:** Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Funding acquisition.

Consent to participate

The researchers of this study have informed and collected both oral and written "consent letter" from each of the respondents. Thus, all participants provided written informed consent.

Ethical clarance

In this research, ethical standards were maintained following Helsinki declarations. To attain the ethical approval, before starting the data collection, the researchers of this study applied attaching the questionnaire, sampling details, and all other ethical requirements to the "COBA Research Committee of the Prince Mohammad bin Fahd University" which is an academic authority for the ethical clearance. After assessing all ethical concerns and guidelines, the committee approved and provided the certificate (ref no: RCCOBA/PMU/24/20), for further survey process.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chbr.2026.100986.

Data availability

Data will be made available on request.

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