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UNRAVELLING SUCCESS IN AI-POWERED PERSONALIZED LEARNING IN VIETNAM: A STUDY ON THE INTERPLAY OF PLATFORM FEATURES AND PSYCHOLOGICAL RESPONSES

Gia Khuong An	FPT University, Can Tho, Vietnam	khuongagcs171212@fpt.edu.vn
Thi Thuy An Ngo*	FPT University, Can Tho, Vietnam	anntt24@fe.edu.vn

* Corresponding author

ABSTRACT

Aim/Purpose	This study aims to investigate how key characteristics of AI-powered personalized learning platforms influence student learning performance by examining the mediating roles of perceived value and perceived trust, as well as the moderating role of self-efficacy. The research aims to provide a clearer understanding of the psychological mechanisms that drive effective learning outcomes through technological features in the context of Vietnamese higher education.
Background	The rapid advancement of artificial intelligence (AI) has transformed the digital education landscape, particularly with the emergence of AI-driven personalized learning systems. These platforms promise adaptive, learner-centered experiences by leveraging data-driven algorithms to tailor content, feedback, and support to individual needs. However, the success of such technologies is not solely dependent on their technical capabilities; it also hinges on students' psychological responses, including how they perceive the platform's value and trustworthiness. Despite growing implementation, a limited understanding remains of how multiple system characteristics, such as intelligence, personalization, anthropomorphism, and information quality, collectively shape these psychological factors and ultimately influence academic performance. Moreover, individual learner traits, such as self-efficacy, may determine how effectively students can translate positive perceptions into learning success. This study addresses these

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gaps by applying the Stimulus-Organism-Response (S-O-R) framework, integrated with the Information System Success Model (ISSM), to explore the complex interplay between technological features, psychological responses, and learning outcomes in AI-driven education. The research is conducted within the Vietnamese higher education context, offering novel insights from an emerging educational market.

Methodology This study employed a quantitative research design using a structured online questionnaire to collect data from university students in Vietnam who had experience with AI-powered personalized learning platforms. A non-probability convenience sampling method was employed, yielding 462 valid responses. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 3.0 to examine relationships among platform characteristics, perceived value, perceived trust, and learning performance, with self-efficacy as a moderating variable.

Contribution This study advances the theoretical understanding of AI in education by integrating system design characteristics, including intelligence, personalization, anthropomorphism, system quality, and information quality, with psychological constructs such as perceived value and trust, under the S-O-R framework and the ISSM. It also introduces self-efficacy as a key moderating variable. The integration of these frameworks within the context of Vietnamese higher education provides new empirical evidence on how AI-enhanced platforms support learner performance in developing countries, contributing both to global and localized knowledge of technology-enhanced learning.

Findings The findings reveal that intelligence, personalization, information quality, and system quality of AI-powered learning platforms significantly enhance both students' perceived value and trust, whereas anthropomorphic features only boost perceived value but do not directly influence perceived trust. Both perceived value and trust have a positive impact on student learning performance, with perceived value also strengthening perceived trust. Additionally, self-efficacy plays a moderating role, amplifying the effects of perceived value and trust on learning outcomes, suggesting that learners with higher self-efficacy benefit more from these platform features.

Recommendations for Practitioners Developers should prioritize enhancing system intelligence, personalization, and information quality to foster student trust and perceived value. Educators and academic institutions should focus on strengthening students' self-efficacy through digital literacy training and personalized learning support to maximize learning outcomes. These findings provide concrete guidance for technology developers, educators, and policymakers seeking to design and implement effective AI-based learning solutions in higher education environments.

Recommendations for Researchers Researchers should explore other psychological or contextual moderators, such as learning motivation and cognitive load, and validate the model across diverse educational environments and demographic groups to increase generalizability.

Impact on Society By uncovering the mechanisms that drive effective learning in AI-supported environments, this study provides actionable guidance for creating more equitable, engaging, and high-quality digital education systems. The findings contribute to improving academic success, digital competency, and learner empowerment, thereby supporting the broader goal of technology-enabled inclusive education in developing contexts such as Vietnam.

Future Research	Future research could explore longitudinal effects of AI learning tools, incorporate behavioral data, and examine the interplay between affective responses and cognitive evaluations in AI-driven learning dynamics.

Keywords	AI-powered personalized learning platforms, S-O-R model, student learning performance, self-efficacy, educational technology

INTRODUCTION

The global shift toward digital learning ecosystems has accelerated the integration of artificial intelligence (AI) into educational contexts, with AI-powered personalized learning platforms emerging as a transformative force in contemporary pedagogy. These platforms leverage advanced technologies to deliver individualized learning experiences tailored to students' unique needs, preferences, and progress trajectories (Jian, 2023). Prominent global platforms such as Duolingo, Coursera, edX, and Knewton Alta exemplify this evolution by offering adaptive content delivery, intelligent tutoring, and real-time feedback. This transition represents not only a technological trend but also a structural transformation of education systems worldwide, characterized by the increasing use of AI to support curriculum design, learner assessment, and personalized engagement strategies (Kim et al., 2025). The increasing reliance on such systems is further underscored by market projections, which anticipate the global AI in education market to grow from USD 5.88 billion in 2024 to USD 32.27 billion by 2030, reflecting a compound annual growth rate of 31.2% (Grand View Research, 2024). This remarkable expansion highlights the increasing recognition of AI's transformative potential in reshaping educational accessibility, effectiveness, and equity on a global scale.

Building on this momentum, AI-powered personalized learning refers to the application of advanced AI technologies such as machine learning, natural language processing, and predictive analytics to create dynamic, individualized learning experiences at scale (Yao & González-Vélez, 2025). These platforms continuously collect and analyze data on student performance, learning behaviors, and interaction patterns to generate customized content, feedback, and instructional pathways. In doing so, they provide timely, relevant support tailored to each learner's needs, thereby enhancing engagement, motivation, and academic achievement. At the global level, such capabilities are redefining how education systems address diverse learning needs and bridge gaps in accessibility and inclusiveness, particularly in the post-pandemic digital landscape (Mohammadieh et al., 2024).

More importantly, the growing adoption of AI-integrated personalized learning platforms represents a paradigm shift in education, positioning adaptive technologies as critical tools for improving learning outcomes (Castro et al., 2024). However, while technical sophistication enables efficiency and scalability, the long-term success of these platforms depends fundamentally on how students cognitively and emotionally respond to them. As educational institutions increasingly rely on these intelligent systems, it becomes essential to investigate the internal mechanisms through which they influence student learning, particularly cognitive and emotional processes that mediate performance gains (Tan et al., 2025). This shift from traditional, uniform instruction toward highly adaptive, data-driven personalization reflects a broader transformation in educational philosophy. These systems, empowered by real-time data analytics and content adaptability, are designed not only to deliver instruction but also to optimize the entire learning experience (Strielkowski et al., 2025). Consequently, a deeper understanding of how these technologies impact learner outcomes via psychological and cognitive pathways is both timely and critical for the future of educational research and practice.

In line with this evolution, existing research on AI-powered personalized learning has expanded across diverse educational contexts, reflecting growing interest in how intelligent technologies shape learning experiences and outcomes. In developed countries, scholars have predominantly examined the role of adaptive algorithms and personalization mechanisms in enhancing educational effectiveness (du Plooy et al., 2024). These studies often adopt theoretical frameworks such as the Stimulus–

Organism–Response (S-O-R) model to explore how system features influence cognitive and emotional learner responses, which in turn affect performance outcomes (Pan et al., 2024). For example, Nazaretsky et al. (2025) investigated the relationship between personalization features and student trust in the learning system, while Al-Abdullatif (2023) focused on perceived value as a determinant of technology acceptance in personalized learning environments. In contrast, in the Asian context, an increasing number of studies have addressed sociocultural influences on learners' interaction with AI-based educational technologies. Payadnya et al. (2024) examined how cultural dimensions shape student attitudes toward adaptive learning systems, highlighting the importance of localized design and implementation. Specifically in Vietnam, empirical efforts have explored the integration of AI-powered personalized platforms in higher education settings. Bui et al. (2025) analyzed factors affecting student acceptance and learning effectiveness, while T. H. Nguyen and Ha (2025) examined the role of technology self-efficacy in promoting student engagement with personalized learning tools. Despite this regional progress, there remains a limited understanding of how multiple system characteristics act jointly to shape key psychological mechanisms such as perceived trust and perceived value, and how these mechanisms, in turn, influence actual learning performance.

Parallel to these discussions, recent work grounded in the Information Systems Success Model (ISSM) (DeLone & McLean, 2003) provides a complementary perspective, emphasizing the roles of system quality and information quality in driving the adoption of educational technologies. For example, Sayaf (2023) integrated ISSM with constructivist theory to explain e-learning adoption, finding that high-quality systems and information features significantly enhance student satisfaction and collaborative learning. Similarly, Alyoussef (2023) applied an extended ISSM framework to assess students' acceptance of e-learning at Jazan University, confirming the influence of platform quality on continued usage intention.

While these studies offer valuable insights, two notable limitations remain. First, many studies have focused on isolated technological features or specific psychological constructs, lacking a unified framework that accounts for the interplay between multiple system characteristics and learners' cognitive and affective responses. Second, while the ISSM is applied widely to evaluate digital platform performance, its application in AI-powered personalized learning environments remains limited, particularly when combined with behavioral models such as the S-O-R framework. Therefore, to understand AI-powered learning success fully, researchers must look beyond technical efficiency to include the psychological mechanisms that shape how learners perceive, trust, and engage with intelligent systems. This underscores a critical gap in understanding how various platform features simultaneously shape psychological mechanisms, such as perceived value and trust, and ultimately impact student learning outcomes. Addressing this limitation requires an integrated theoretical approach that enables a holistic connection among system characteristics, learner perceptions, and learning performance.

To address these gaps, this study proposes a novel conceptual model that integrates the S-O-R framework with key constructs from the ISSM. Specifically, it investigates how five platform characteristics, including intelligence, anthropomorphism, personalization, information quality, and system quality, affect student learning performance, mediated by perceived value and perceived trust. Additionally, the model introduces self-efficacy as a moderating variable, recognizing the importance of individual differences in shaping learners' psychological and behavioral responses. Accordingly, the study seeks to address the following research questions: (1) How do AI-powered learning platform characteristics influence learners' perceived value and trust? (2) How do perceived value and trust affect student learning performance? (3) How does self-efficacy moderate the relationship between psychological perceptions and learning outcomes?

This integrated approach represents a significant advancement in understanding AI-enhanced personalized learning, as it considers multiple platform characteristics and their combined effects on learning outcomes through both cognitive and affective mediating pathways. Furthermore, while the research is conducted in Vietnam, its implications extend globally. The framework and findings contribute to broader international discussions on AI in education, providing insights applicable to both developing and developed educational contexts. By situating Vietnam's experience within the global expansion of AI in education, this study bridges localized evidence with universal theoretical understanding, highlighting the shared challenges and opportunities in human–AI collaboration for learning.

From a theoretical perspective, the study advances research on AI in education by identifying and validating the mechanisms through which platform design affects learning outcomes. The inclusion of multiple mediating pathways provides a more nuanced understanding of the psychological processes that influence learning outcomes in personalized learning environments. From a practical standpoint, the findings offer actionable insights for educational institutions, instructional designers, and AI developers, enabling the creation of more effective, engaging, and psychologically supportive learning environments. By uncovering the pathways linking platform features to student success, this research contributes to the design of future-ready educational technologies that are both technically sophisticated and pedagogically sound. Ultimately, as educational systems worldwide continue to embrace AI-driven personalization, understanding its impact on student learning is not only timely but essential. This study lays the groundwork for future empirical research and provides a foundation for optimizing the design and implementation of AI-powered personalized learning in diverse educational contexts.

LITERATURE REVIEW

THE EXPECTATION-CONFIRMATION MODEL (ECM)

AI-powered personalized learning platforms

AI-powered personalized learning platforms have become a pivotal innovation in educational technology, resulting in a significant transformation in the way instructional content is delivered, accessed, and experienced in contemporary learning environments (Rekha et al., 2024). These platforms integrate advanced AI technologies, such as machine learning, natural language processing, and adaptive algorithms, to create individualized learning pathways that dynamically adjust to each student's needs and behavioral patterns (Katiyar et al., 2024).

Unlike traditional educational systems that deliver standardized content to all learners, AI-powered platforms continuously collect and analyze data on learner interactions, performance trends, and engagement behaviors. This real-time data processing enables the platforms to adapt learning materials, feedback, and assessments automatically to align with each learner's proficiency level, cognitive style, and personal learning preferences (Abrar et al., 2025). Through this personalized approach, the learning process evolves from a standardized experience into a highly responsive and tailored journey, promoting deeper engagement and improved learning outcomes. Notable examples of such platforms include Duolingo, Coursera, edX, and Knewton Alta, all of which provide adaptive learning experiences across various educational contexts to meet the diverse needs of learners.

Key functionalities of AI-powered platforms include adaptive content sequencing that adjusts the order and complexity of instructional materials based on learner progress; intelligent tutoring systems that provide contextualized support and scaffolding; automated feedback systems offering immediate, personalized guidance; and dynamic assessment tools that evolve alongside the learner's development (Tan et al., 2025). Recent technological advancements have expanded the capabilities of AI-enhanced learning platforms significantly by incorporating features such as emotion recognition, which enables systems to detect and respond to learners' affective states; cognitive load monitoring, which assesses mental effort during learning; and predictive analytics, which anticipate learning trajectories and suggest timely interventions to enhance educational outcomes (Halkiopoulos & Gkintoni, 2024).

Collectively, these developments have contributed to a paradigm shift in education from the traditional "one-size-fits-all" model to a learner-centered approach that prioritizes adaptability, personalization, and inclusivity. By supporting diverse learning needs and promoting autonomy, intelligent educational platforms are gaining increasing recognition as vital tools for enhancing educational equity, engagement, and academic success in digitally mediated learning environments. Importantly, this shift is not only technological but also pedagogical. From a constructivist learning perspective, AI-powered platforms provide scaffolding that enables learners to construct knowledge actively through adaptive pathways and feedback (Strielkowski et al., 2025). From a socio-cultural perspective, features such as anthropomorphism and social presence contribute to socially mediated learning, emphasizing interaction, collaboration, and cultural adaptation (Zhang et al., 2024). Thus, AI-powered education should be understood as both a technological innovation and a reconfiguration of learning processes aligned with contemporary pedagogical theories.

Stimulus-organism-response (S-O-R) model

The Stimulus-Organism-Response (S-O-R) model was developed by Mehrabian and Russell (1974), offers a robust theoretical framework for examining how external stimuli influence individual behaviors through internal psychological processes. According to this model, external environmental stimuli (S) impact the internal cognitive and emotional states of an individual (O), which shape subsequent behavioral responses (R). The framework has been adopted widely across disciplines to explain user behavior, particularly in contexts involving human-technology interaction. In educational technology research, the S-O-R framework has proven valuable in explaining how platform features can serve as stimuli that activate learners' psychological responses, such as emotions, perceptions, and cognitive evaluations, which affect learning behaviors and outcomes ultimately (Cheng, 2023; Duong et al., 2024).

Recent studies have demonstrated the model's applicability in various learning contexts. For instance, Pan et al. (2024) employed the S-O-R framework to examine how different types of online learning interactions act as stimuli influencing perceived ease of use and usefulness (organism variables), which, in turn, affect learning outcomes (response). Similarly, Peng et al. (2023) applied the model to mobile-assisted language learning and found that perceived convenience (stimulus) significantly influenced curiosity and self-efficacy (organism), which in turn shaped learners' intention to use the technology (response). These examples underscore the model's versatility and relevance in capturing the internal mechanisms through which educational technologies influence user behavior.

However, while the S-O-R model has explanatory strength, existing studies often limit their focus to individual features such as convenience and ease of use, neglecting the complex interplay of multiple technological attributes. This restricts its ability to explain fully how AI-powered platforms, which combine diverse design characteristics, affect both cognitive and affective learner responses simultaneously.

In the context of this study, the "stimulus" components are defined as five critical characteristics of AI-powered personalized learning platforms: intelligence, anthropomorphism, personalization, information quality, and system quality. These features serve as environmental triggers that shape learners' perceptions. The "organism" component refers to the internal psychological states of learners, operationalized as perceived value and perceived trust, two constructs that reflect how users evaluate their experiences with the platform both cognitively and affectively. The "response" component captures the resulting behavioral and performance outcomes, represented by students' learning performance. By applying the S-O-R framework in this manner, this study not only extends prior work but also critically addresses its limitations by examining how the features of multiple platforms jointly shape learner perceptions and performance.

Information system success model (ISSM)

The Information System Success Model (ISSM), first developed by DeLone and McLean (1992) and refined by DeLone and McLean (2003), provides a comprehensive framework for evaluating the effectiveness of information systems across various domains, including organizational and educational settings. The model identifies six interrelated dimensions that contribute to system success: system quality, information quality, service quality, use, user satisfaction, and net benefits. Among these, system quality and information quality are particularly relevant in the context of technology-enhanced learning, as they directly shape users' evaluations of a system's usability, reliability, functionality, and the value of the information provided.

In AI-powered personalized learning environments, system quality encompasses the platform's technical performance, ease of navigation, stability, and responsiveness. Information quality, meanwhile, refers to the relevance, accuracy, completeness, and timeliness of the educational content delivered to learners. These two dimensions serve as critical antecedents of user trust, satisfaction, and continued engagement with the platform (Huang & Zhi, 2023; W. Li & Xue, 2021). Extensive research in educational technology underscores the positive influence of system and information quality on learners' perceived value, engagement, and academic outcomes. For instance, Fitria et al. (2024) and Zheng et al. (2023) emphasize that high-quality systems and information significantly enhance learners' overall experiences. Mohammed et al. (2024) found that these dimensions contribute directly to student satisfaction and academic performance in online learning environments. Similarly, Aldabbas et al. (2025) reported that system and information quality have positive effects on engagement and achievement in AI-driven platforms, while S. Wang et al. (2024) demonstrated their role in fostering trust and encouraging the adoption of adaptive learning technologies.

In this study, the ISSM provides a theoretical basis for incorporating system quality and information quality as key stimulus variables within the broader S-O-R framework. By integrating these constructs, the study aims to examine how the technical and informational attributes of AI-powered learning platforms influence students' internal psychological states, specifically perceived trust and perceived value, and how these, in turn, shape learning performance. This integrated approach does not simply summarize prior models but advances them critically. While ISSM ensures evaluative rigor of technological features, S-O-R explains how these features activate psychological mechanisms. The combination is novel as it connects system-level success metrics with learner-centered cognitive and affective pathways. In this way, the ISSM-S-O-R integration provides a more comprehensive theoretical foundation that balances both technological robustness and pedagogical relevance.

Student learning performance

Student learning performance in AI-enhanced educational environments encompasses a broad range of cognitive, behavioral, and academic outcomes. Rather than being limited to conventional indicators such as grades or test scores, this construct reflects a more holistic perspective on learning effectiveness and efficiency in digitally mediated contexts (Adewale et al., 2024). The concept includes not only knowledge acquisition but also the development of problem-solving skills, critical thinking, conceptual understanding, and the ability to apply learned content in practical and novel situations (Sarker et al., 2024).

Within AI-enabled learning environments, the evaluation of student learning performance integrates both quantitative and qualitative dimensions. Quantitative indicators such as test scores, course completion rates, and learning pace offer objective measures of academic achievement (Das et al., 2023; Shoaib et al., 2024). At the same time, qualitative aspects such as depth of understanding, knowledge transfer, critical reasoning, and metacognitive skills are emphasized as essential components of meaningful and sustainable learning (Lan & Zhou, 2025; Silva et al., 2024). Moreover, contemporary research highlights the need to assess both short-term learning gains and long-term outcomes (X. Wang et al., 2024), such as knowledge retention and the cultivation of self-regulated learning strategies. This dual perspective allows for a more comprehensive evaluation of how AI-enhanced learning environments support not only immediate academic success but also enduring cognitive and behavioral development.

In this study, student learning performance is conceptualized as the response variable within the S-O-R framework. This construct represents the ultimate educational outcome of AI-driven personalization, shaped by learners' internal psychological states such as perceived trust and perceived value.

This multifaceted approach enables a nuanced exploration of how technological features in AI-powered systems translate into tangible and sustainable learning benefits.

HYPOTHESIS DEVELOPMENT

Intelligence

System intelligence, in the context of intelligent personalized learning systems, refers to the system's capacity to mimic human-like cognitive functions through advanced computational capabilities. These include adaptive learning algorithms, intelligent content recommendations, personalized feedback, and predictive analytics that anticipate learner needs and forecast learning outcomes (Alawneh et al., 2024). Modern AI-powered platforms utilize complex algorithms to analyze student learning performance patterns, identify learning gaps, and adjust instructional content in real time to meet individual learning needs (Salman & Chaya, 2024).

The relationship between system intelligence and perceived value has been documented extensively in educational technology research. When learning platforms demonstrate sophisticated intelligence through accurate content recommendations and adaptive learning paths, students perceive higher value in their learning experience (Contrino et al., 2024). Intelligent features, such as real-time, contextually relevant feedback, accurate prediction of learning difficulties, adaptive content difficulty, intelligent explanations, and sophisticated assessment strategies, significantly enhance students' perception of the platform's utility and effectiveness in supporting their learning goals (Vieriu & Petrea, 2025). The ability of intelligent systems to adapt dynamically to students' learning preferences and challenges fosters a sense of relevance and utility that traditional static systems often fail to provide (Bhutoria, 2022). In addition to these pedagogical benefits, ethical transparency in algorithmic decision-making, such as explainable AI and fairness in data use, supports sustained learner trust and helps ensure equitable outcomes across diverse student groups (Simbeck, 2023).

System intelligence has also been identified as a key driver of trust in AI-powered learning environments. Trust in these systems arises when users perceive them as competent, reliable, and consistent in supporting their learning activities (Nazaretsky et al., 2025). This trust is particularly vital in educational contexts, where students often depend on platform-generated recommendations to make important learning decisions. The trust-building process is reinforced when intelligent systems demonstrate high accuracy in content recommendations, effectively diagnose learning difficulties, employ transparent decision-making processes, and provide reliable, context-sensitive support. Research by Afroogh et al. (2024) indicates that when students experience these intelligent features consistently, they develop stronger trust in the system's capabilities and recommendations. As learners experience these intelligent interactions over time, their confidence in the system's ability to facilitate meaningful learning increases. Higher levels of system intelligence are associated with greater student trust in the platform's ability to support their learning goals (Musyaffi et al., 2024).

Based on this understanding, the hypotheses are proposed:

- **H1:** Intelligence has a positive effect on perceived value.
- **H2:** Intelligence has a positive effect on perceived trust.

Anthropomorphism

Anthropomorphism in AI-powered learning environments refers to the attribution of human-like characteristics, behaviors, and communication styles to digital systems (Yu & Lan, 2024), aiming to make user interactions more natural, relatable, and engaging. This concept embraces natural language processing for conversational interactions, emotional intelligence capabilities, personality traits in system responses, human-like avatars, social presence indicators, and empathetic response mechanisms that make the learning experience more human-like and relatable (Kim & Im, 2023). These anthropomorphic elements have seen increasing incorporation into educational platforms to foster a sense of social interaction and emotional support during the learning process (Polyportis & Pahos, 2024).

An increasing number of studies support the notion that anthropomorphism enhances the learner's perceived value of educational technologies. Systems that simulate human-like interaction styles tend to create more engaging, emotionally resonant, and relatable learning environments. Gkintoni et al. (2025) and Kolomaznik et al. (2024) found that when educational platforms exhibit well-crafted anthropomorphic qualities such as warmth, responsiveness, and social presence, they enhance students' perceived value by making the learning process more interactive, emotionally engaging, and socially connected, thereby strengthening user attachment to the system. Furthermore, N. Ma et al. (2025) emphasized that students report greater satisfaction and value when the AI system presents appropriate human-like behaviors in its communication, thereby reinforcing the platform's overall usefulness and appeal.

The influence of anthropomorphic features on trust formation represents another crucial aspect of AI-powered learning platforms. Trust development is strengthened significantly when AI systems exhibit human-like qualities that foster emotional resonance, convey a sense of authentic social presence, demonstrate empathy toward students' challenges, facilitate natural conversational flow, and maintain consistent personality traits (Hancock et al., 2023). A study by Alabed et al. (2022) suggested that these anthropomorphic elements contribute significantly to building trust relationships between students and AI systems. By incorporating human-like characteristics, these platforms are able to convey social presence and establish emotional connections, which in turn enhance trust in the platform's guidance and recommendations (Q. Li et al., 2023). Moreover, students tend to place greater trust in AI platforms that exhibit appropriate anthropomorphic features, such as empathetic responses and personable interactions, while still clearly delineating their artificial nature (Liu et al., 2024), thereby avoiding the risk of perceived deception or over-humanization. However, designers should avoid over-humanization; pedagogically grounded anthropomorphic cues must preserve system transparency so that emotional engagement does not substitute for competence or obscure the system's artificial nature.

Based on this understanding, the hypotheses are proposed:

H3: Anthropomorphism has a positive effect on perceived value.
H4: Anthropomorphism has a positive effect on perceived trust.

Personalization

Personalization, in the context of AI-powered learning, represents the system's ability to adapt educational experiences to the unique needs, preferences, learning styles, and academic goals of individual students (Vorobyeva et al., 2025). This personalization is operationalized through the use of advanced algorithms that analyze a range of student data, such as student prior academic performance, interaction history, engagement levels, and behavioral cues, to generate tailored content, customized pacing, individualized assessments, and adaptive learning strategies (Gutierrez et al., 2025). These systems are designed to adjust dynamically to learners' evolving needs, optimizing educational outcomes through personalized learning pathways (Naseer et al., 2024).

The connection between personalization and perceived value is well-established in educational technology literature. The presence of highly personalized experiences, achieved through adaptive content selection, customized learning paths, and individualized feedback mechanisms, leads students to recognize greater value in their learning journey (Dumont & Ready, 2023). Personalization features such as dynamic content adaptation, individualized pace control, customized assessment approaches, and tailored learning resources significantly enhance students' perception of the platform's value proposition. Alrawashdeh et al. (2023) found that students place greater value on systems that can adapt effectively to their changing learning needs and preferences over time. Similarly, F. Ma (2025) revealed that students tend to perceive high value in systems that provide stable, personalized, and contextually relevant learning experiences. Ethically, personalization must also balance adaptivity with data privacy and cultural sensitivity to ensure equitable and respectful treatment of all learners, particularly in cross-cultural educational contexts (Tertulino, 2025).

In parallel, personalization has been recognized as a central determinant of trust formation in AI-powered learning platforms. Trust develops when systems demonstrate a consistent ability to understand individual learners' needs, preferences, and progress, translating these insights into personalized and contextually relevant learning experiences (Tanchuk & Taylor, 2025). When platforms identify learning styles effectively, adapt to students' performance trajectories, and deliver timely, customized feedback, learners perceive them as more reliable, competent, and supportive (Iyamuremye et al., 2024). Moreover, systems capable of recognizing students' challenges and responding with targeted interventions foster stronger emotional assurance and confidence in the platform's educational value (Sharma et al., 2025). Additionally, Khor and Mutthulakshmi (2024) highlighted that maintaining detailed learner profiles and delivering tailored experiences play a critical role in cultivating and sustaining student trust.

Based on this understanding, the hypotheses are proposed:

H5: Personalization has a positive effect on perceived value.

H6: Personalization has a positive effect on perceived trust.

Information quality

Information quality, in the context of AI-powered learning, refers to the accuracy, relevance, completeness, and timeliness of educational content and system-generated information provided to students (Srimulyo et al., 2024). This characteristic integrates various aspects, including content accuracy, instructional clarity, information currency, and the pedagogical soundness of learning materials (Lachheb et al., 2025). High-quality information is characterized by its alignment with educational standards, accuracy of knowledge representation, and effectiveness in supporting learning objectives (Atuhurra & Kaffenberger, 2022).

The relationship between information quality and perceived value has been well-documented in the literature on educational technology. When learning platforms consistently deliver high-quality, accurate, and pedagogically sound content, students recognize greater value in their learning experience (Alterkait & Alduaij, 2024). Research indicates that aspects of information quality, including content accuracy, instructional clarity, timely updates, and pedagogical effectiveness, significantly influence students' value perception of the learning platform (X. Li & Zhu, 2022). The quality of information directly affects students' engagement with learning materials and their assessment of the platform's educational value (Kedia & Mishra, 2023). The provision of accurate, meaningful, and clearly organized content has been identified as a major influence on students' perceptions of educational technology value (Lai et al., 2022). Furthermore, ethically responsible and culturally sensitive information delivery reinforces students' perception of the system's educational integrity, enhancing their perceived value in diverse learning contexts (Vidaurre et al., 2024).

The influence of information quality on trust formation represents a critical aspect of student-platform relationships. Trust is more likely to emerge when learners perceive the information provided as consistently accurate, contextually appropriate, and pedagogically sound (Viberg et al., 2024). Students tend to place greater trust in systems that deliver reliable content, maintain up-to-date materials, and communicate information in a clear and structured manner (Nazaretsky et al., 2022). Ethical transparency and fairness in AI-generated content contribute to this trust by assuring learners that the information they receive is objective, unbiased, and socially responsible (Đerić et al., 2025). Platforms that deliver high-quality information consistently are more likely to foster student confidence in both their educational effectiveness and overall reliability (Akpen et al., 2024; Enyoojo et al., 2024). Moreover, maintaining a consistent standard of information quality across various instructional contexts has been found to be a critical factor in building and sustaining student trust (Pitafi & Ali, 2023).

Based on this understanding, the hypotheses are proposed:

H7: Information quality has a positive effect on perceived value.

H8: Information quality has a positive effect on perceived trust.

System quality

System quality refers to the technical and functional attributes of AI-powered learning platforms that ensure efficient and effective platform performance (Hamzah et al., 2025). Key components of system quality include system reliability, accessibility, response time, user interface design, system stability, and overall technical performance (Alkhuwaylidee, 2025). The hallmark of high-quality learning systems lies in their seamless operation, intuitive navigation, consistent performance, and robust technical infrastructure that supports uninterrupted learning experiences (Sutiah & Supriyono, 2024). Beyond these technical aspects, system quality in AI-based learning also involves the ethical and pedagogical responsibility of ensuring data security, user privacy, and equitable access across diverse learner groups. Systems that handle user data transparently and provide inclusive interface design enhance not only usability but also learners' moral and psychological comfort (Ain et al., 2025).

In the field of educational technology, system quality has been recognized widely as a key determinant of perceived value. Platforms that exhibit high system performance such as reliable operation, fast response times, and intuitive interfaces, significantly influences students perceived value of their learning experience (J. Wang & Fan, 2025). Several studies confirm that students assign greater value to platforms that offer stable operation, smooth navigation, efficient load times, and consistent performance across different devices (Giday & Perumal, 2024). Technical reliability and system responsiveness directly impact on students' engagement with learning tasks and their overall evaluation of the platform's worth (Akpen et al., 2024). Furthermore, when platforms integrate culturally adaptive interface design and accessibility features that accommodate diverse learners, they reinforce perceptions of fairness and inclusivity, factors that are tied to perceived value in digital education (G. W. Choi & Seo, 2024). Consequently, high system quality contributes directly to perceived value by fostering a learning environment that is stable, efficient, user-friendly and aligned with students' educational goals (Feng et al., 2025).

The connection between system quality and trust formation represents a fundamental aspect of student acceptance of AI-powered learning platforms. Trust is more likely to emerge when learners perceive the platform as technically dependable, consistently operational, and capable of supporting their educational goals (Rittenberg et al., 2024). Research shows that students develop stronger trust in platforms that maintain stable performance, provide consistent access to learning resources, and offer smooth technical operations (Barz et al., 2024). Systems that deliver consistent high performance and reliability significantly strengthen students' perceptions of the platform's credibility and dependability (Chugh et al., 2023). Furthermore, ensuring stable technical quality across diverse learning contexts and usage conditions is critical for fostering and sustaining student trust (Nazaretsky et al., 2025).

Based on this understanding, the hypotheses are proposed:

H9: System quality has a positive effect on perceived value.
H10: System quality has a positive effect on perceived trust.

Perceived value

Perceived value in AI-powered learning environments refers to students' overall judgment of the benefits and utility offered by the system in relation to the time, effort, and resources they invest in the learning process. This term is complex and includes educational efficacy, time efficiency, personalization, and the perceived return on learning outcomes like academic achievement and skill development (Al-Abdullatif & Alsubaie, 2024). The perception of value is formed through students' cumulative experiences with the platform and their evaluation of its contribution to their learning goals (Maqbool et al., 2022). In addition to these functional aspects, perceived value in AI learning systems also reflects ethical and cultural dimensions, as learners tend to evaluate whether platforms provide equitable access, respect user data, and deliver culturally relevant and pedagogically sound content (Gerlich, 2023). Systems that align educational benefits with ethical transparency and inclusivity are therefore perceived as offering higher value to diverse learners.

A growing body of research has identified perceived value as a key driver of trust in educational technologies. According to Xin et al. (2025), when students perceive that a platform delivers educational content in an efficient and goal-oriented manner, they are more likely to view it as a competent and dependable learning assistant. This perceived utility forms the groundwork for more complex trust-based interactions. Extending this insight, Changwen et al. (2025) argue that perceived value catalyzes the formation of trust relationships by reinforcing the system's perceived integrity and alignment with students' long-term academic interests. Rather than being a passive outcome, trust emerges as a cumulative response to repeated value-driven experiences, strengthening students' willingness to rely on the platform over time.

In addition, perceived value has been acknowledged widely as a fundamental predictor of student learning performance. Learners who perceive high value in their educational experience tend to be more engaged, motivated, and committed to achieving their academic objectives (Bergdahl et al., 2024). Students who recognize high value in their learning experience demonstrate better academic achievement, knowledge retention, and skill development (Amado et al., 2023). This positive perception encourages the use of effective learning strategies, sustained effort, and deeper engagement with course content, which collectively contribute to enhanced performance outcomes (Gkintoni et al., 2025). For instance, in AI-powered learning environments, when students perceive high value from features such as real-time feedback, personalized learning pathways, and content aligned with their goals, they are more likely to stay motivated and overcome learning challenges, leading to measurable improvements in academic performance (Villegas-Ch et al., 2025).

Based on this understanding, the hypotheses are proposed:

H11: Perceived value has a positive effect on perceived trust.
H12: Perceived value has a positive effect on student learning performance.

Perceived trust

Perceived trust in AI-powered learning represents students' belief in the system's reliability, competence, and benevolence in supporting their educational journey (S. Choi et al., 2023). This factor comprises multiple dimensions, including trust in the system's educational guidance, confidence in data privacy and security, belief in the platform's commitment to student success, and faith in the accuracy of AI-generated recommendations (Raza et al., 2024). Trust does not emerge instantly; rather, it evolves progressively through repeated, positive interactions with the system, as students observe the platform's reliability, responsiveness, and alignment with their learning needs (Afroogh et al., 2024). In contemporary AI learning environments, trust also extends beyond technical reliability to encompass ethical transparency and cultural sensitivity. Learners tend to trust systems that demonstrate fairness in algorithmic decisions, protect user data responsibly, and respect cultural diversity in content delivery (Pasipamire & Muroyiwa, 2024). When students perceive that the system operates with ethical integrity and pedagogical fairness, their confidence in its guidance and decisions is reinforced even further.

Perceived trust plays an essential role in influencing student learning performance in AI-enhanced educational settings. When students develop strong trust in a learning platform, they are more inclined to explore its advanced functionalities, follow system recommendations, and remain persistent when facing academic challenges (Fuertes et al., 2023). High levels of trust lead to more effective utilization of platform resources, increased engagement with adaptive learning features, and better integration of AI-powered guidance into learning strategies (Yaseen et al., 2025). The relationship between trust and learning performance has been documented across various educational contexts, showing that students with higher trust levels demonstrate superior academic achievement and skill development (Kaya & Erdem, 2021). Trust has been identified as a crucial mediator between system characteristics and learning outcomes, facilitating more effective learning experiences and better academic results (Pitts & Motamedi, 2025).

Based on this understanding, the hypothesis is proposed:

H13: Perceived trust has a positive effect on student learning performance.

Self-efficacy

Self-efficacy in the context of AI-powered learning represents students' beliefs in their capabilities to effectively utilize the platform's features and achieve their learning objectives (Sari et al., 2025). This aspect highlights students' confidence in their ability to navigate technological challenges, manage their learning process, and integrate AI-powered support successfully into their educational journey (Bećirović et al., 2025). As a motivational and cognitive construct, self-efficacy influences how students approach challenges, persist through difficulties, and utilize available learning resources (Miao et al., 2025). In the context of AI-mediated education, self-efficacy also carries ethical and cultural dimensions: students' confidence can be influenced by their perceptions of algorithmic fairness, accessibility, and cultural inclusivity in system design. Learners from diverse cultural or linguistic backgrounds may experience varying levels of efficacy depending on how well the platform accommodates their needs and learning styles (M. P. Lin et al., 2024).

The moderating role of self-efficacy in the relationship between perceived value and student learning performance has been well-documented in educational technology research. Students with higher self-efficacy are not only more confident in their learning capabilities but also more proactive in applying perceived value to concrete academic efforts, such as setting learning goals, overcoming difficulties, and sustaining motivation (Basileo et al., 2024). Research demonstrates that self-efficacy enhances the positive effects of perceived value by enabling students to utilize platform features more effectively and maintain motivation through challenging learning tasks (Zhuofan et al., 2024). As a result, students with strong self-efficacy can transform perceived benefits into tangible academic improvements, including enhanced engagement, deeper knowledge acquisition, and better academic performance (Jeilani & Abubakar, 2025).

Similarly, self-efficacy has been shown to moderate the relationship between perceived trust and student learning performance. Research indicates that students with higher self-efficacy are able to leverage their trust in the platform more effectively to achieve superior learning outcomes (Aliño et al., 2024). Self-efficacy enhances the positive impact of trust by enabling students to act more confidently on system recommendations and effectively utilize AI-powered learning support (Ishan & Tan, 2025). The combination of high self-efficacy and strong trust has been shown to produce particularly positive learning outcomes, as students are both willing and able to engage fully with the platform's capabilities (Al-khresheh & Alkursheh, 2024).

Based on this understanding, the hypotheses are proposed:

H14: Self-efficacy positively moderates the relationship between perceived value and student learning performance.

H15: Self-efficacy positively moderates the relationship between perceived trust and student learning performance.

Conceptual Model

The conceptual model, illustrated in Figure 1, outlines the pathways through which key system characteristics of AI-powered learning platforms influence student learning performance through psychological mechanisms. This model is grounded in the S-O-R framework, where the stimulus (S) refers to external features of the learning environment, the organism (O) represents students' internal psychological processes, and the response (R) reflects their observable learning outcomes.

In this context, five essential system characteristics: intelligence, anthropomorphism, personalization, information quality, and system quality, function as stimuli. These technological and interactive features shape how students perceive and interact with the AI-powered platform. As stimuli, they influence two critical psychological responses: perceived value and perceived trust. These organismic variables capture students' cognitive and emotional appraisals of the platform's usefulness, reliability, and supportiveness in their learning journey. These psychological responses are proposed to have a direct and positive effect on student learning performance, the ultimate behavioral response in the model. Students who perceive high value and trust in the platform are more likely to engage meaningfully with its features and achieve stronger academic outcomes.

Furthermore, the model introduces self-efficacy as a key moderating variable, emphasizing its role in strengthening or weakening the effects of perceived value and trust on learning outcomes. Students with higher self-efficacy are more confident in their ability to navigate the platform and are thus better positioned to translate their positive perceptions into actual learning success.

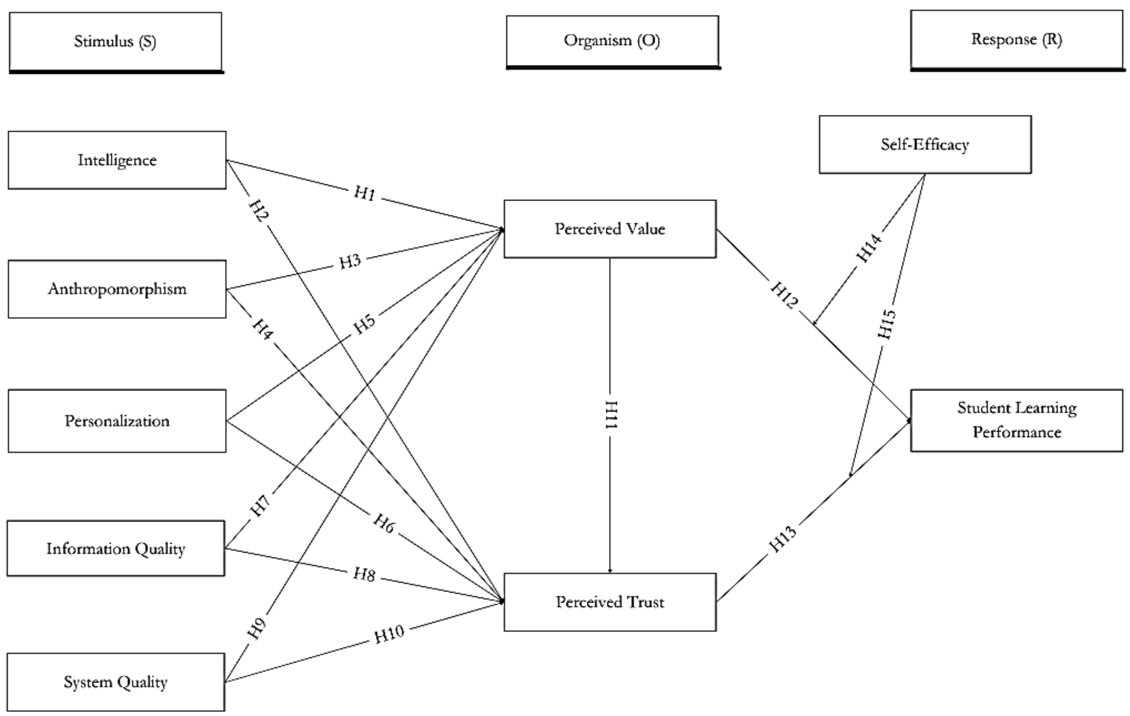

Figure 1. Conceptual model

METHODOLOGY

RESEARCH DESIGN AND INSTRUMENTS

This study takes a quantitative approach, employing a cross-sectional survey design to investigate the links among system characteristics of AI-powered learning platforms, students' psychological responses, and learning performance. The research is grounded in a conceptual framework based on the S-O-R model, aiming to test a series of hypothesized structural relationships. A confirmatory research strategy was employed to validate the theoretical model and assess interrelationships among constructs. The unit of analysis is individual students with prior experience using AI-enabled personalized learning platforms.

The measurement instrument comprised a structured questionnaire developed by incorporating items from established, validated scales. These measurement items were adapted to ensure both reliability and validity for the current research context. The questionnaire was organized into three main sections. The first section of the survey consisted of preliminary screening questions to confirm the eligibility of respondents. Participants were required to have prior experience with AI-powered learning platforms and be actively involved in online learning environments. To assess this, respondents were asked two closed-ended questions: "Have you used any AI-powered personalized learning platform such as Duolingo, Coursera, edX, or Knewton Alta?" and "Are you currently engaged in online learning activities that utilize AI-powered learning platforms?" Only those who answered "Yes" to both questions were considered eligible to proceed with the survey. Additionally, to ensure ethical compliance, only individuals aged 18 years or older were eligible to participate in the study. This screening process ensured that the responses were relevant and rooted in actual user experience, thereby enhancing the accuracy and applicability of the results. The second section collected data on participants' background, including gender, age, education level, and frequency of using AI-powered learning platforms. These demographic variables were used to contextualize the findings and explore how different student groups interact with AI-powered learning systems within the educational technology landscape.

The third section focused on measuring the key constructs of the research model using validated items adapted from previous studies. All measurement items were adapted from validated scales in previous literature and modified to fit the context of AI-based personalized learning platforms. All items were measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Specifically, Intelligence is measured using five items adapted from Moussawi and Koufaris (2019), evaluating the platform's learning, adaptation, and decision-making capabilities. Anthropomorphism is assessed with five items, also from Moussawi and Koufaris (2019), measuring the human-like characteristics of the platform. Personalization is evaluated using four items from Baek and Morimoto (2012), examining the platform's ability to provide customized learning experiences. Information quality is measured using four items adapted from Alfaki (2021), assessing the relevance and accuracy of content. System quality is evaluated using three items from H. Y. Lin et al. (2006), capturing the technical performance, stability, and ease of use of the platform. For psychological responses, perceived value is measured using four items adapted from Akdim and Casaló (2023), reflecting students' assessment of the benefits offered by the platform. Perceived trust is assessed using four items from Helal et al. (2023), examining students' confidence in the platform. Self-efficacy is evaluated using three items from Shengyao et al. (2024), focusing on students' belief in their capacity to utilize the platform effectively. Student learning performance is measured using five items adapted from W.-T. Wang and Lin (2021), capturing dimensions of academic achievement, critical thinking, and skill development.

To ensure the validity and clarity of the instrument, a pilot study was conducted with a sample of 50 students who met the inclusion criteria. The pilot aimed to identify potential issues related to wording, cultural relevance, and measurement reliability (Presser et al., 2004). Based on participant feedback, minor modifications were made to enhance item clarity and contextual alignment (Hertzog, 2008). The results demonstrated satisfactory internal consistency, with Cronbach's alpha values for all constructs ranging from 0.765 to 0.931, exceeding the recommended threshold of 0.70 (Taber, 2018), supporting the readiness of the instrument for large-scale data collection. To mitigate common method bias (CMB), the questionnaire included a marker variable that was unrelated to the main constructs theoretically. This allowed for statistical control of CMB during the data analysis phase and helped ensure that the observed relationships were not influenced unduly by the data collection method.

DATA COLLECTION AND SAMPLING

This study employed an online survey to collect data from Vietnamese students with prior experience using AI-powered learning platforms in educational settings. Google Forms was selected as the data collection tool due to its intuitive interface, cross-device compatibility, and real-time data processing capabilities (Vasantha Raju & Harinarayana, 2016). A non-probability convenience sampling method was utilized, focusing on participants who were accessible and willing to participate. The survey was disseminated through diverse channels such as digital learning communities, educational networks, and academic institutions across multiple levels of education. Participants were recruited primarily through university mailing lists, online student forums, and social media groups dedicated to higher education in Vietnam, ensuring access to a broad pool of students who were engaged actively in digital learning environments. Reminder notifications were issued periodically to boost participation. The data collection phase spanned three months, allowing adequate time to accommodate academic schedules and increase response rates. Prior to participation, respondents were provided with clear information regarding the voluntary nature of the study, data confidentiality, and privacy protections. Participation required informed consent, and data was used solely for academic research purposes.

The survey instrument consisted of 37 items designed to measure the key constructs in the research model, including intelligence, anthropomorphism, personalization, information quality, system quality, perceived value, perceived trust, self-efficacy, and student learning performance. All items were adapted from validated scales to ensure content validity and measurement reliability. Following Hair et al. (2014), for reflective measurement models, a rule of thumb commonly accepted is to have a minimum sample size equal to ten times the number of observed variables. With 37 items in total, this guideline suggested a minimum of 370 respondents (37 × 10). This more conservative approach was adopted to ensure adequate statistical power and reliable parameter estimation. As a result, the study aimed for a sample size of at least 370 participants to enhance the robustness and generalizability of the results.

To ensure the relevance of responses, participants were required to use AI-powered learning platforms consistently for at least three months. Screening questions at the beginning of the survey verified this experience. Respondents who failed to meet this minimum usage criterion were disqualified and excluded from further participation. During the data cleaning process, responses with incomplete answers or inconsistent demographic information were also removed. A total of 548 responses were collected initially. After applying the screening and validation procedures, 462 valid and complete responses remained for analysis.

Demographic characteristics of the final sample are presented in Table 1.

Table 1. Participant demographics

Variable	Category	Frequency (n=462)	Percentage (%)
Gender	Male	202	43.7
	Female	245	53.0
	Not to specify	15	3.3
Age	18–22 years old	211	45.7
	23–26 years old	156	33.8
	27–29 years old	58	12.6
	30 years old and above	37	8.0
Education Level	Intermediate	43	9.3
	College	124	26.8
	Undergraduate	236	51.1
	Postgraduate	59	12.8
Platform usage frequency	Daily	122	26.4
	3–4 times/week	143	31.0
	1–2 times/week	129	27.9
	Less than once/week	68	14.7

Among the respondents, 245 (53.0%) identified as female, 202 (43.7%) as male, and 15 (3.3%) preferred not to disclose their gender. In terms of age, 211 respondents (45.7%) were aged 18–22, 156 (33.8%) were 23–26, 58 (12.6%) were 27–29, and 37 (8.0%) were 30 or older. Regarding educational background, 43 participants (9.3%) held intermediate qualifications, 124 (26.8%) had completed college, 236 (51.1%) were pursuing undergraduate degrees, and 59 (12.8%) were postgraduate learners. Usage frequency of AI-based platforms varied: 122 (26.4%) used them daily, 143 (31.0%) used them 3–4 times per week, 129 (27.9%) used them 1–2 times per week, and 68 (14.7%) used them less than once per week. This diverse and representative sample enhances the external validity of the study and ensures that insights reflect a broad spectrum of learners' experiences in AI-supported educational environments.

DATA ANALYSIS

The collected data were analyzed using SmartPLS 3.0, applying partial least squares structural equation modeling (PLS-SEM). This analysis method was selected due to its suitability in handling complex models that involve multiple mediating and moderating effects (Hair et al., 2019), particularly in examining the relationships among system characteristics, user perceptions, and learning performance in AI-powered learning platforms. PLS-SEM was deemed appropriate due to the complexity of the research model, which includes several latent constructs and interaction terms, as well as the exploratory nature of the study, which seeks to extend existing theoretical frameworks into the context of AI-enhanced educational environments. The analysis was conducted in two main stages.

The first stage focused on evaluating the measurement model to ensure the reliability and validity of the constructs. Internal consistency reliability was assessed using both Cronbach's Alpha (CA) and Composite Reliability (CR), with acceptable thresholds set at 0.70 (Nunnally & Bernstein, 1994). Convergent validity was examined by analyzing item loadings, with acceptable values above 0.70 (Hair et al., 2022) and Average Variance Extracted (AVE), which needed to exceed 0.50 (Fornell & Larcker, 1981). Discriminant validity was assessed using the Fornell-Larcker criterion, which requires that the square root of each construct's AVE exceeds its correlations with other constructs (Fornell & Larcker, 1981), and the Heterotrait-Monotrait ratio (HTMT), which should be below 0.85 (Henseler et al., 2015). To detect potential multicollinearity, Variance Inflation Factor (VIF) values were examined, ensuring all values were below the conservative threshold of 5.0 (Hair et al., 2011). Additionally, the study addressed the possibility of common method bias using the marker variable technique (Lindell & Whitney, 2001), analyzing whether the inclusion of the marker variable significantly altered the relationships among key constructs.

The second stage involved evaluating the structural model to test the hypothesized relationships. This included analyzing the path coefficients, their significance levels, and effect sizes. Statistical significance was assessed using a bootstrapping procedure with 5,000 resamples, meaning that the software drew 5,000 random subsamples (with replacement) from the original dataset to estimate the stability and precision of the path coefficients. This large number of resamples increases the robustness and reliability of the estimated standard errors and confidence intervals (Hair et al., 2022). The model's explanatory power was determined by examining the R^2 values for the endogenous variables, with thresholds of 0.25, 0.50, and 0.75 representing weak, moderate, and substantial explanatory power, respectively (Hair et al., 2022). Predictive relevance was assessed using the blindfolding procedure to generate Q^2 values, where values greater than zero indicated that the model possessed predictive capability (Hair et al., 2019).

RESULT

MEASUREMENT MODEL ASSESSMENT

Measurement model robustness

A comprehensive assessment of the measurement model was carried out to evaluate its robustness, focusing on indicator reliability, internal consistency reliability, and multicollinearity. This evaluation was essential to confirm that the constructs and their associated indicators represented the intended latent variables accurately and consistently, thereby ensuring both empirical soundness and conceptual validity. These results, as presented in Table 2, provided a solid foundation for the subsequent analysis of the structural model.

The analysis of indicator reliability was conducted by examining the outer loadings of each item. All item loadings exceeded the recommended threshold of 0.70 (Hair et al., 2022), demonstrating strong individual item reliability across all constructs. Specifically, the loadings ranged from 0.843 to 0.861 for intelligence, 0.891 to 0.906 for anthropomorphism, 0.826 to 0.858 for personalization, 0.862 to 0.882 for information quality, 0.882 to 0.897 for system quality, 0.858 to 0.888 for perceived value, 0.857 to 0.873 for perceived trust, 0.826 to 1.000 for self-efficacy, and 0.819 to 0.885 for student learning performance. These consistently high values across all constructs provide strong evidence of reliable item measurement.

Internal consistency reliability was assessed using both Cronbach's alpha and composite reliability (CR). The results were well above the conventional threshold of 0.70 suggested by Nunnally and Bernstein (1994), with Cronbach's alpha values ranging from 0.867 to 0.940. Composite reliability values ranged from 0.909 to 0.954, further confirming the high internal consistency of each measurement scale. These findings indicate that the items within each construct are highly consistent in measuring their respective underlying concepts.

Multicollinearity was examined using variance inflation factor (VIF) values, which ranged from 1.000 to 3.950. These values are well below the critical threshold of 5.0 recommended by Hair et al. (2011), suggesting that multicollinearity is not a concern in this model. The absence of multicollinearity strengthens confidence in the stability of the parameter estimates and affirms that the predictor variables are distinct and independently contributing to the model.

Table 2. Construct reliability and validity

Constructs	Item code	Measurement items	Loadings	Cronbach's Alpha	Composite reliability	VIF
Intelligence (IN)	IN1	"This AI-powered personalized learning platform can complete tasks efficiently."	0.857	0.906	0.930	2.623
	IN2	"This AI-powered personalized learning platform can understand my commands."	0.843			2.258
	IN3	"This AI-powered personalized learning platform communicates with me in an understandable manner."	0.861			2.713
	IN4	"This AI-powered personalized learning platform can find and process the necessary information to assist my learning."	0.845			2.546

Constructs	Item code	Measurement items	Load-ings	Cronbach's Alpha	Composite reliability	VIF
	IN5	"This AI-powered personalized learning platform provides me with useful responses."	0.852			2.270
Anthropo-morphism (AN)	AN1	"This AI-powered personalized learning platform is able to communicate like a human."	0.901	0.940	0.954	3.469
	AN2	"This AI-powered personalized learning platform can express happiness in its responses."	0.897			3.451
	AN3	"This AI-powered personalized learning platform feels friendly when I interact with it."	0.894			3.230
	AN4	"This AI-powered personalized learning platform demonstrates respect in the way it communicates with me."	0.891			3.265
	AN5	"This AI-powered personalized learning platform shows care for my learning needs."	0.906			3.459
Personaliza-tion (PE)	PE1	"This AI-powered personalized learning platform provides recommendations that match my learning needs."	0.856	0.867	0.909	2.587
	PE2	"The course suggestions on this AI-powered personalized learning platform are tailored to my preferences."	0.858			2.577
	PE3	"This AI-powered personalized learning platform makes me feel like my learning experience is unique."	0.826			1.993
	PE4	"This AI-powered personalized learning platform personalizes its content to fit my needs."	0.841			2.041
Information Quality (IQ)	IQ1	"This AI-powered personalized learning platform provides accurate information needed to complete my learning tasks."	0.867	0.894	0.926	2.424
	IQ2	"The information on this AI-powered personalized learning platform is well-organized."	0.872			2.411
	IQ3	"This AI-powered personalized learning platform ensures that the provided information is up to date"	0.882			2.665
	IQ4	"The content recommended by this AI-powered personalized learning platform is relevant and reliable for my learning needs."	0.862			2.260

Constructs	Item code	Measurement items	Load-ings	Cronbach's Alpha	Composite reliability	VIF
System Quality (SQ)	SQ1	"This AI-powered personalized learning platform's user interface can be easily adapted to one's personal approach."	0.882	0.872	0.921	2.363
	SQ2	"This AI-powered personalized learning platform responds quickly enough."	0.897			2.246
	SQ3	"This AI-powered personalized learning platform is always up and running as necessary."	0.896			2.352
Perceived Value (PV)	PV1	"I believe that using this AI-powered personalized learning platform is valuable."	0.879	0.900	0.930	2.637
	PV2	"I believe that using this AI-powered personalized learning platform is beneficial."	0.858			2.230
	PV3	"I believe that using this AI-powered personalized learning platform is worthwhile."	0.882			2.674
	PV4	"Overall, using this AI-powered personalized learning platform delivers high value."	0.888			2.664
Perceived Trust (PT)	PT1	"This AI-powered personalized learning platform has integrity."	0.871	0.889	0.923	2.437
	PT2	"This AI-powered personalized learning platform is reliable."	0.873			2.381
	PT3	"This AI-powered personalized learning platform is trustworthy."	0.864			2.325
	PT4	"I can trust this AI-powered personalized learning platform."	0.857			2.236
Self-Efficacy (SE)	SE1	"I am convinced that I am able to successfully learn all relevant course content even if it is difficult."	0.828	0.926	0.918	3.481
	SE2	"When I try really hard, I am able to learn even the most difficult content."	0.826			3.422
	SE3	"I am convinced that, over time, I will become increasingly capable of learning the content on this AI-powered personalized learning platform."	1			3.950
Student Learning	SP1	"Using this AI-powered personalized learning platform improves my study efficiency."	0.863	0.914	0.936	3.061

Constructs	Item code	Measurement items	Load-ings	Cronbach's Alpha	Composite reliability	VIF
Perfor-mance (SP)	SP2	"This AI-powered personalized learning platform enhances my learning productivity."	0.819			2.363
	SP3	"By using this AI-powered personalized platform, I do my assignments and tests more skillfully."	0.885			3.043
	SP4	"By using this AI-powered personalized platform, my academic performance has improved."	0.865			3.055
	SP5	"By using this AI-powered personalized platform, I achieved better grades as compared to other students."	0.884			3.336

Convergent validity and discriminant validity

The measurement model's validity was examined through a systematic two-phase validation process. The assessment of convergent validity relied on the Average Variance Extracted (AVE) values, while discriminant validity was confirmed using two methods: the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio analysis.

Convergent validity results, summarized in Table 3, were conducted using Average Variance Extracted (AVE) and demonstrated exceptional results across all constructs, with values exceeding the recommended 0.50 threshold (Fornell & Larcker, 1981). Specifically, intelligence demonstrated robust convergent validity with an AVE of 0.725, while anthropomorphism achieved a particularly strong AVE of 0.806. Similarly, personalization and information quality showed strong results with AVEs of 0.714 and 0.758, respectively. System quality exhibited strong convergent validity with an AVE of 0.795. The psychological constructs of perceived value and perceived trust demonstrated excellent convergent validity with AVEs of 0.769 and 0.750, respectively. Self-efficacy and student learning performance also demonstrated strong convergent validity, with AVEs of 0.789 and 0.746. These results confirm that the indicators for each construct are highly correlated and represent their underlying dimensions effectively.

Discriminant validity was verified using two complementary methods. First, the Fornell-Larcker criterion was applied by comparing the square root of each construct's AVE with its correlations with other constructs. As detailed in Table 4, the results confirmed strong discriminant validity, with the square root of AVE for each construct exceeding its correlations with all other constructs (Fornell & Larcker, 1981). For example, the square root of AVE for intelligence (0.851), anthropomorphism (0.898), and personalization (0.845) exceeded their correlations with other constructs, which ranged between 0.534 and 0.623. Similarly, information quality (0.871), system quality (0.892), perceived value (0.877), perceived trust (0.866), self-efficacy (0.888), and student learning performance (0.864) each demonstrated clear discriminant validity, as their inter-construct correlations were consistently lower than their respective AVE square roots.

To further validate the discriminant validity of the constructs, the Heterotrait-Monotrait (HTMT) ratio analysis was conducted as a more stringent criterion. Table 5 shows that all HTMT values were below the conservative threshold of 0.85 (Henseler et al., 2015). The highest observed HTMT value was 0.735, occurring between perceived value and perceived trust, while most other ratios were substantially lower. This indicates a strong distinction between constructs and reinforces their theoretical uniqueness.

The comprehensive evaluation of the measurement model confirms strong reliability and validity across all constructs and indicators. The findings indicate that the model not only meets but surpasses established thresholds for reliability and validity, offering a solid empirical foundation for the forthcoming hypothesis testing and structural model analysis. This assurance in the model's measurement quality enhances confidence in the robustness and credibility of the subsequent structural results.

Table 3. Construct convergent validity

Constructs	Average Variance Extracted (AVE)
IN	0.725
AN	0.806
PE	0.714
IQ	0.758
SQ	0.795
PV	0.769
PT	0.750
SE	0.789
SP	0.746

Note: IN = Intelligence; AN = Anthropomorphism; PE = Personalization; IQ = Information Quality; SQ = System Quality; PV = Perceived Value; PT = Perceived Trust; SE = Self-Efficacy; SP = Student Learning Performance

Table 4. Fornell-Larcker criterion

	AN	IN	IQ	PE	PT	PV	SE	SP	SQ
AN	0.898								
IN	-0.011	0.852							
IQ	-0.077	0.095	0.871						
PE	0.007	0.051	0.096	0.845					
PT	0.122	0.299	0.421	0.387	0.866				
PV	0.308	0.344	0.363	0.402	0.658	0.877			
SE	-0.045	-0.006	0.048	0.060	0.074	0.087	0.888		
SP	0.126	0.174	0.278	0.271	0.490	0.524	0.045	0.864	
SQ	0.035	0.109	0.113	0.091	0.371	0.387	0.105	0.201	0.892

Note: IN = Intelligence; AN = Anthropomorphism; PE = Personalization; IQ = Information Quality; SQ = System Quality; PV = Perceived Value; PT = Perceived Trust; SE = Self-Efficacy; SP = Student Learning Performance

Table 5. Heterotrait-Monotrait (HTMT) Ratio

	AN	IN	IQ	PE	PT	PV	SE	SP	SQ
AN									
IN	0.045								
IQ	0.086	0.105							
PE	0.043	0.101	0.110						
PT	0.134	0.329	0.472	0.441					
PV	0.334	0.375	0.404	0.453	0.735				
SE	0.041	0.023	0.049	0.065	0.059	0.074			
SP	0.135	0.187	0.307	0.305	0.543	0.576	0.050		
SQ	0.046	0.126	0.128	0.105	0.417	0.436	0.092	0.225	

Note: IN = Intelligence; AN = Anthropomorphism; PE = Personalization; IQ = Information Quality; SQ = System Quality; PV = Perceived Value; PT = Perceived Trust; SE = Self-Efficacy; SP = Student Learning Performance

Common method bias assessment using marker variable

To evaluate the potential influence of common method bias (CMB) in this study, the marker variable technique was applied in accordance with the recommendations of Lindell and Whitney (2001). A theoretically unrelated marker variable was incorporated into the survey instrument to statistically control for CMB. This variable was selected carefully based on its conceptual irrelevance to the main constructs of the research model, ensuring its appropriateness for this analysis.

The initial assessment involved examining the correlations between the marker variable and all substantive constructs in the model, including intelligence, anthropomorphism, personalization, information quality, system quality, perceived value, perceived trust, self-efficacy, and student learning performance. The results indicated that the marker variable exhibited low and non-significant correlations with all major constructs, with coefficients ranging from -0.090 to 0.094 (all $p > 0.05$), suggesting minimal risk of CMB at the bivariate level.

To assess the impact of common method variance more fully, the marker variable was introduced into the structural model as a control variable. Upon re-estimation, the path coefficients among the primary constructs remained consistent, and the significance of the hypothesized relationships was unaffected. Additionally, the explanatory power of the model, as reflected by the R^2 values for perceived value, perceived trust, and student learning performance, changed only minimally after the inclusion of the marker variable ($\Delta R^2 < 0.1$). Specifically, the R^2 for perceived value increased from 0.543 to 0.548, for perceived trust from 0.525 to 0.527, and for student learning performance from 0.501 to 0.522. All changes in R^2 values fell beneath the 10% threshold suggested by Rönkkö and Ylitalo (2011), indicating that common method bias did not substantially affect the study's results.

These findings provide strong evidence that common method variance does not significantly bias the relationships observed in this study. The stability of the model estimates and explanatory power after controlling for the marker variable reinforces the validity and reliability of the findings. Therefore, the relationships among system characteristics, psychological factors, and student learning performance, as proposed in the conceptual framework, can be interpreted with a high degree of confidence.

Structural Model Assessment

Hypothesis testing

The structural model was evaluated using path coefficients (β) and significance levels to test the proposed hypotheses. The results, as summarized in Table 6 and illustrated in Figure 2, offer strong empirical support for the hypothesized relationships and validate the study's conceptual framework.

The analysis showed that intelligence significantly positively influenced both perceived value (H1: $\beta = 0.272$, $p < 0.001$) and perceived trust (H2: $\beta = 0.115$, $p = 0.003$). This means that when AI-powered platforms demonstrate intelligent capabilities, such as efficiently handling tasks and providing relevant responses, students not only perceive the platform as more valuable but also begin to trust it more. In practical terms, smarter systems build confidence and demonstrate usefulness, which is critical for sustained usage.

The findings further established that anthropomorphism exhibited no significant influence on perceived trust (H4: $\beta = 0.014$, $p = 0.697$), indicating that the human-like features of AI-powered learning platforms do not directly influence students' trust toward the system. However, anthropomorphism exhibited a significant positive effect on perceived value (H3: $\beta = 0.322$, $p < 0.001$). This suggests that while "human-like" features, such as friendliness or empathy, do not necessarily convince students to trust the system, they do make students feel that the platform experience is more enjoyable and worthwhile, thereby increasing its perceived value.

Personalization was also found to significantly enhance both perceived value (H5: $\beta = 0.332$, $p < 0.001$) and perceived trust (H6: $\beta = 0.187$, $p < 0.001$). This highlights that tailored recommendations and adaptive content delivery are powerful drivers of student confidence and satisfaction. Students interpret personalization not only as an added functional benefit but also as a sign that the platform understands their needs, thereby building stronger trust.

Information quality demonstrated significant positive effects on perceived value (H7: $\beta = 0.298$, $p < 0.001$) and perceived trust (H8: $\beta = 0.233$, $p < 0.001$). This underscores the importance of accurate, relevant, and up-to-date content in fostering student reliance on AI systems. If the information provided is dependable, students both value the system more and are more inclined to trust its recommendations.

System quality also exhibited a significant positive impact on both perceived value (H9: $\beta = 0.282$, $p < 0.001$) and perceived trust (H10: $\beta = 0.163$, $p < 0.001$). This means that a reliable, user-friendly platform interface is not just a technical requirement but a psychological enabler of trust and value perception. Smooth, efficient system performance strengthens students' willingness to use the tool consistently.

Regarding outcomes, perceived value exerted a significant positive influence on both perceived trust (H11: $\beta = 0.392$, $p < 0.001$) and student learning performance (H12: $\beta = 0.357$, $p < 0.001$). This indicates that when students perceive the system as beneficial and worthwhile, they are more likely to trust it and also achieve better learning results. In other words, value perception acts as a bridge between platform design and tangible performance improvement. Among all tested relationships, perceived value → perceived trust ($\beta = 0.392$) emerged as the strongest path in the model, highlighting that students' sense of value is the most powerful driver of trust in AI-powered learning environments.

Furthermore, perceived trust demonstrated a significant positive effect on student learning performance (H13: $\beta = 0.263$, $p < 0.001$). This suggests that students who trust the system are more engaged and motivated to apply its recommendations, leading to improved academic outcomes.

Finally, the moderating role of self-efficacy was supported: the influence of perceived value on learning performance was stronger for students with higher levels of self-efficacy (H14: $\beta = 0.235$, $p < 0.001$), and the same was true for perceived trust (H15: $\beta = 0.219$, $p = 0.001$). This means confident learners extract more benefits from AI systems; they translate trust and value into real performance gains more effectively than those with lower self-efficacy. Practically, this finding suggests that training interventions to boost student confidence can maximize the impact of AI learning tools.

These findings, while statistically robust, also require interpretation within the cultural context. In Vietnam, where AI-mediated learning is still emerging, students may emphasize system reliability, fairness, and transparency as prerequisites for trust more than anthropomorphic or surface-level features. This suggests that cultural expectations around education, such as high regard for credibility, teacher-like authority, and equitable treatment, play a critical role in shaping how trust dynamics develop in AI-powered learning platforms.

Table 6. Hypothesis testing result

Hypothesis	Paths	Path coefficient (β)	Sample mean (M)	Standard deviation (SD)	T statistics	P-values	f^2	Results
H1	IN → PV	0.272	0.274	0.032	8.419	0.000	0.158	Accepted
H2	IN → PT	0.115	0.118	0.039	2.965	0.003	0.024	Accepted
H3	AN → PV	0.322	0.323	0.035	9.294	0.000	0.225	Accepted
H4	AN → PT	0.014	0.014	0.035	0.390	0.697	0.000	Rejected
H5	PE → PV	0.332	0.332	0.031	10.701	0.000	0.237	Accepted
H6	PE → PT	0.187	0.188	0.039	4.779	0.000	0.058	Accepted
H7	IQ → PV	0.298	0.296	0.035	8.610	0.000	0.188	Accepted
H8	IQ → PT	0.233	0.233	0.037	6.300	0.000	0.093	Accepted
H9	SQ → PV	0.282	0.281	0.032	8.848	0.000	0.169	Accepted
H10	SQ → PT	0.163	0.163	0.037	4.360	0.000	0.046	Accepted
H11	PV → PT	0.392	0.389	0.048	8.235	0.000	0.148	Accepted
H12	PV → SP	0.357	0.357	0.044	8.200	0.000	0.144	Accepted
H13	PT → SP	0.263	0.259	0.045	5.850	0.000	0.078	Accepted
H14	SE*PV → SP	0.235	0.225	0.066	3.584	0.000	0.061	Accepted
H15	SE*PT → SP	0.219	0.230	0.064	3.418	0.001	0.058	Accepted

Note: IN = Intelligence; AN = Anthropomorphism; PE = Personalization; IQ = Information Quality; SQ = System Quality; PV = Perceived Value; PT = Perceived Trust; SE = Self-Efficacy; SP = Student Learning Performance

Predictive power and relevance

The structural model demonstrated solid explanatory capability based on the coefficient of determination (R^2). According to Hair et al. (2022), R^2 values of 0.25, 0.50, and 0.75 are interpreted as indicating weak, moderate, and substantial explanatory power, respectively. As detailed in Table 7, the R^2 values for perceived trust (0.525), perceived value (0.543), and student learning performance (0.501) indicate a moderate level of explanatory power. These results suggest that the independent variables in the model collectively account for a considerable portion of the variance in the core dependent constructs.

In addition to explanatory power, the model's predictive relevance was examined using Stone-Geisser's Q^2 values obtained through the blindfolding procedure. In line with Hair et al. (2019), Q^2 values greater than zero indicate that the model has predictive relevance for a given endogenous construct. The results demonstrate that perceived trust ($Q^2 = 0.388$), perceived value ($Q^2 = 0.412$), and student learning performance ($Q^2 = 0.364$) all exceed this threshold, confirming the model's strong predictive relevance.

The comprehensive structural model assessment reveals a theoretically sound and empirically validated framework for understanding the complex relationships between system characteristics, psychological factors, and learning outcomes in AI-powered personalized learning environments. The findings strongly validate the proposed theoretical model while offering valuable insights that can benefit both academic researchers and educational technology practitioners.

Table 7. R-squared and Q-squared results

Constructs	R-squared	Q-squared
PT	0.525	0.388
PV	0.543	0.412
SP	0.501	0.364

Note: PT = Perceived Trust; PV = Perceived Value;
SP = Student Learning Performance

Effect size

To gain a deeper assessment of the practical significance of the hypothesized relationships, effect size values were calculated for each structural path. According to Hair et al. (2022), f^2 values of 0.02, 0.15, and 0.35 are interpreted as indicating small, medium, and large effects, respectively. The results are summarized in Table 6.

The findings reveal that the strongest effects on perceived value (PV) are exerted by personalization (PE → PV, $f^2 = 0.237$) and anthropomorphism (AN → PV, $f^2 = 0.225$), both of which represent medium-to-large effects. This highlights that when AI-powered platforms personalize learning content and incorporate human-like features, students perceive them as substantially more valuable. In addition, intelligence (IN → PV, $f^2 = 0.158$), information quality (IQ → PV, $f^2 = 0.188$), and system quality (SQ → PV, $f^2 = 0.169$) also show medium effects on perceived value, reinforcing its role as a central construct within the model.

The paths from perceived value to trust (PV → PT, $f^2 = 0.148$) and from perceived value to student learning performance (PV → SP, $f^2 = 0.144$) are also of medium strength, underscoring PV as the primary driver that translates system design features into psychological and performance outcomes. By contrast, the direct effect of trust on student performance (PT → SP, $f^2 = 0.078$) is relatively small, suggesting that students derive stronger benefits from perceiving the system as valuable rather than solely trustworthy.

Smaller effects were observed in the paths linking system characteristics to trust, including intelligence (IN → PT, $f^2 = 0.024$), personalization (PE → PT, $f^2 = 0.058$), information quality (IQ → PT, $f^2 = 0.093$), and system quality (SQ → PT, $f^2 = 0.046$). These results indicate that while system features do contribute to building trust, their impact is modest compared to their influence on perceived value. The moderating role of self-efficacy (SE) also showed small but significant effects on the links between perceived value and performance (SE*PV → SP, $f^2 = 0.061$) and between trust and performance (SE*PT → SP, $f^2 = 0.058$). This suggests that students with higher SE amplify the benefits of PV and PT, but the magnitude of this moderation remains limited.

Finally, anthropomorphism had no effect on trust (AN → PT, $f^2 = 0.000$), confirming that while human-like attributes enhance perceived value, they are not sufficient to increase student trust in the platform.

Overall, the effect size analysis demonstrates that perceived value (PV) is the pivotal construct in the model, mediating the influence of key platform characteristics and exerting a stronger impact on student learning performance (SP) than perceived trust (PT). For practitioners, this implies that design efforts should prioritize enhancing personalization (PE), anthropomorphism (AN), and information quality (IQ) to maximize PV, while complementary interventions such as building students' self-efficacy (SE) can further strengthen performance outcomes.

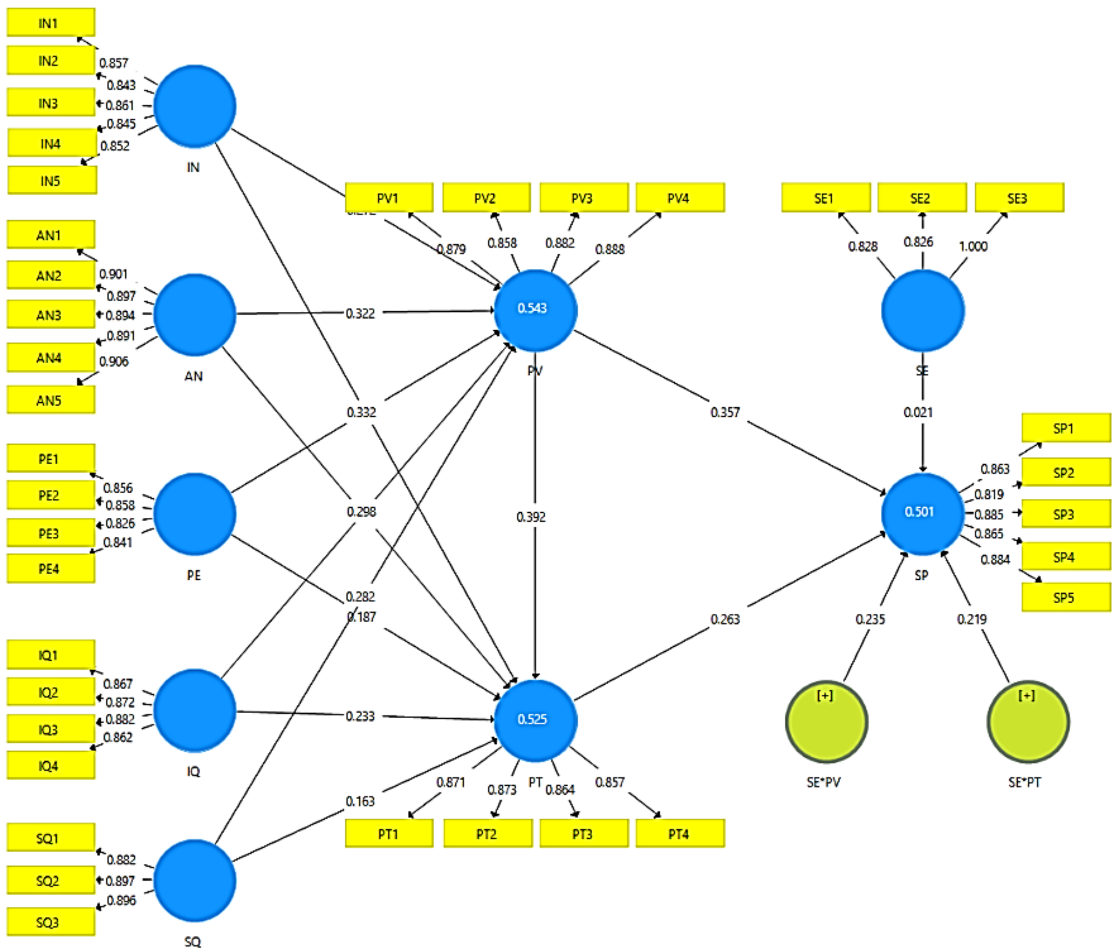

Figure 2. Results of PLS-SEM analysis

DISCUSSION

INTELLIGENCE: A CATALYST FOR PERCEIVED VALUE AND PERCEIVED TRUST

The findings of this study reaffirm the pivotal role of intelligence in AI-driven learning systems as a key determinant of both perceived value and trust (H1, H2). Specifically, students who perceive the platform as intelligent, meaning that it can adapt to their individual progress, preferences, and learning needs, are more likely to regard it as both useful and trustworthy. This finding aligns with previous research by Luo (2023), who emphasized that intelligent features such as adaptive feedback, content personalization, and real-time support enhance users' perceptions of a system's utility substantially. In our study context, where digital learning adoption is expanding in response to growing demands for flexible and individualized education in Vietnam, intelligence acts not merely as a technical feature but as a personalized learning enabler. For instance, intelligent functionalities like automated assessment, dynamic learning paths, and progress tracking tools provide timely, relevant interventions that help optimize learning outcomes. These align with Merino-Campos (2025), who noted that intelligent systems streamline learning by tailoring resources to learners' evolving needs, enhancing both efficiency and satisfaction. Furthermore, the implementation of real-time analytics and automated formative assessments ensures that students are challenged appropriately, which reduces cognitive overload and increases engagement (du Plooy et al., 2024). These intelligent mechanisms not only improve learning outcomes but also reinforce the perception that the platform is a reliable partner in students' academic journeys. This finding contributes to the growing literature on human–AI trust by emphasizing that intelligence-related transparency and responsiveness can trigger both cognitive and affective forms of trust. In line with Sajja et al. (2023) and Nazaretsky et al. (2025), the perception that an AI system "understands" and adapts to users' needs establishes not only functional reliability but also a sense of psychological safety, which is central to trust formation.

Moreover, the findings reveal that intelligence plays a dual role, not only enhancing perceived value but also serving as a critical driver of trust in AI-driven platforms. Students are more likely to trust platforms that deliver accurate, context-sensitive, and responsive learning experiences consistently, reinforcing prior evidence from Nazaretsky et al. (2025). When intelligent platforms demonstrate an ability to understand learning behaviors and adapt accordingly, students interpret this as a sign of the system's reliability and capability (Sajja et al., 2023). This perception of reliability is further strengthened when students view the system as transparent in its decision-making and equitable in assessments, reducing anxiety about algorithmic bias or system errors (Khalil et al., 2023). Such trust fosters a more committed and confident user experience, where students are more likely to engage deeply with the platform and rely on it for personalized guidance, timely feedback, and academic support (Bergdahl et al., 2024).

In the Vietnamese higher education context, where students may be new to AI-mediated learning environments, such perceptions are crucial in reducing skepticism and encouraging adoption. Compared to previous studies conducted in Western contexts, the findings of this study suggest a similar pattern, but with some contextual nuances. In Vietnam, where digital transformation in education is still maturing, students may place even greater emphasis on a system's intelligence to compensate for the lack of one-on-one instruction or traditional classroom interaction. Therefore, trust and value derived from intelligent features are not only important but essential for the successful implementation of AI in personalized learning.

Anthropomorphism: Enhancing Perceived Value Without Guaranteeing Trust

The results indicate that anthropomorphic features significantly enhance students' perceived value of AI-based personalized learning systems (H3), but do not have a corresponding effect on perceived trust (H4). These human-like elements can make digital interactions feel more natural and engaging, which proves highly beneficial in remote or self-directed learning contexts where direct human support is minimal (Mamun et al., 2022). By introducing elements of familiarity, warmth, and emotional resonance, anthropomorphic cues help reduce feelings of isolation, increase learner motivation, and create a sense of companionship with the system (Christoforakos & Diefenbach, 2023). Students may perceive these features as indicators that the platform is attentive to their needs, thereby enhancing the perceived usefulness and encouraging more consistent use (Ackermann et al., 2025). This supports prior research suggesting that anthropomorphism in educational technologies can increase user satisfaction by fostering a more relatable and interactive learning environment (Wu et al., 2024).

However, while these features enrich the user's experience and perceived value, they may not influence trust in this context directly. This lack of a significant effect on perceived trust diverges from some earlier studies, which have proposed that anthropomorphism increases trust by making systems seem more emotionally intelligent and approachable (Y. Li et al., 2024; N. Ma et al., 2025). This contrast may reflect a growing critical awareness among students, especially in academic settings where expectations for performance, accuracy, and fairness are high. In such environments, students may perceive anthropomorphic features as surface-level enhancements unless they are accompanied by consistent, transparent, and contextually appropriate system behavior. Trust, as the current findings suggest, hinges more on functional attributes such as the system's accuracy in assessment, reliability in recommendations, and ethical handling of user data, rather than on its ability to mimic human interaction (A. Nguyen et al., 2024). This distinction may also be influenced by cultural expectations and previous experiences with digital agents, which can moderate how anthropomorphic features are received and interpreted (Bui et al., 2025; Payadnya et al., 2024). These insights highlight the importance of thoughtful design: while anthropomorphism can enhance engagement and perceived value, it must be supported by transparent and consistent system behavior to generate genuine trust. This reinforces emerging evidence that human-like cues alone do not ensure trust unless they demonstrate reliability and fairness, reflecting a cognitive rather than emotional basis of human–AI trust.

PERSONALIZATION: DRIVING VALUE AND DEEPENING TRUST

The findings reveal that personalization serves as a critical driver in enhancing both perceived value and perceived trust in AI-powered learning platforms (H5, H6). When students engage with systems that dynamically adjust content, pace, and feedback based on their individual preferences, abilities, and progress, they develop a stronger sense of being understood and supported (Ayeni et al., 2024). By tailoring lessons, recommending resources, and modifying assessments in real time, the platform shifts the learning experience from a generic format to one that is highly relevant and individualized, which not only increases engagement but also boosts intrinsic motivation and satisfaction (Inthanon & Wised, 2024). The ability to accommodate diverse learning styles and academic needs signals to students that the platform demonstrates genuine investment in their personal academic journey and success (Qu, 2025), thereby encouraging sustained use and deeper commitment to learning. As a result, students are more likely to remain committed to their studies and utilize the platform's features to their fullest potential. Within the Vietnamese educational context, where students often face high academic pressure and large class sizes with limited one-on-one instructor support, the value of personalized platforms is even more pronounced. The ability of AI to provide individualized attention and support, previously difficult to scale in traditional classrooms, is likely to be valued by students navigating self-paced or hybrid learning environments.

Moreover, this study confirms that personalization contributes directly to building trust in the system. When students receive consistently tailored recommendations, feedback, and learning pathways aligned with their specific needs, they develop a stronger belief in the platform's reliability and competence (Tan et al., 2025). Crucially, this trust does not stem solely from the presence of adaptive features but from the system's demonstrated ability to monitor evolving learning patterns, identify gaps, and deliver timely and relevant support (Guerrero-Roldán et al., 2021). When students perceive that the platform "knows" them, understanding their strengths, weaknesses, and preferences, they are more confident in its capacity to guide them effectively through academic challenges and toward their goals (Alshammary & Alhalafawy, 2023). This result contrasts with the finding on anthropomorphism, showing that while human-like features may emotionally appeal to users, personalized intelligence builds trust through demonstrated competence. Trust, in this sense, stems from the AI's ability to consistently act in students' best interests, reinforcing its reliability and ethical alignment rather than its friendliness.

This perception of the system as an attentive and responsive partner is essential for cultivating long-term engagement and positive learning outcomes in AI-enhanced educational settings. In the Vietnamese educational context, where students are in the process of gradually adopting digital tools while still valuing traditional teacher-led instruction, effective personalization can serve as a meaningful bridge. By replicating the individualized attention typically provided by human educators and scaling it through technology, AI systems can offer a balanced solution. As a result, the trust nurtured through personalization not only strengthens system credibility but also increases students' willingness to integrate AI platforms as essential components of their academic journey.

Information Quality: The Cornerstone of Value and Trust

High information quality stands out as a fundamental driver of both perceived value and trust in AI-driven personalized learning environments (H7, H8). The empirical results show that when students perceive the information provided by these platforms as accurate, up-to-date, well-structured, and directly aligned with their learning goals, they are more likely to regard the system as valuable (Simon & Zeng, 2024). This strong alignment between information provided and individual learning needs enhances the platform's perceived utility and effectiveness, making it an indispensable educational resource (Al-Abdullatif, 2023). In academic contexts, where the consequences of misinformation can be particularly severe, students rely on these platforms to deliver reliable explanations, credible sources, and clear, goal-oriented learning trajectories (Yaseen et al., 2025).

While earlier studies have often focused on the technical functionality or aesthetic design of educational technologies, our study underscores the critical role of content quality. As Gkintoni et al. (2025) argue, access to trustworthy and high-quality material reduces cognitive burden, enabling students to devote more attention to comprehension and skill acquisition rather than verifying the reliability of the content. Consequently, platforms that deliver superior information are perceived not just as tools, but as valued partners in the learning journey—promoting greater satisfaction, engagement, and academic success. These findings are relevant in the context of self-directed and AI-supported learning, where the quality of information becomes the cornerstone of student confidence and learning efficacy.

Furthermore, information quality significantly contributes to the formation of trust in these systems. Students are more likely to trust platforms that deliver trustworthy, logically organized, and evidence-based content consistently (Pan et al., 2024). This echoes the findings of Henrique and Santos (2024), who emphasized that trust in educational platforms stems from their perceived epistemic reliability; students must believe the system is competent, fact-based, and aligned with academic integrity standards. Interestingly, the results of this study also suggest that trust develops not just from a single instance of quality content but through repeated interactions where students observe consistent accuracy, well-cited sources, and up-to-date knowledge. This cumulative experience fosters a dependable relationship with the platform, encouraging sustained usage and deeper engagement. This long-term trust development echoes theoretical models of human–AI trust that emphasize epistemic reliability as the foundation of users' confidence. Students build trust not from single positive interactions but through repeated experiences of consistent accuracy and integrity, confirming that informational credibility is a necessary precondition for stable trust in intelligent systems. Balalle (2024) supports this notion by noting that continuous informational credibility leads to habitual use and reliance, especially among university students who face complex and evolving academic tasks. This trust further encourages students to explore advanced features, seek help through the platform, and rely on its recommendations for further learning, solidifying the platform's role as a trusted and authoritative educational tool (M. B. Garcia et al., 2025).

This study situates these findings in the specific context of Vietnamese higher education, where students often seek additional support tools to supplement traditional classroom instruction. The demand for trustworthy, locally relevant, and pedagogically sound AI tools is particularly strong due to limitations in faculty availability or personalized support. Hence, platforms that excel in delivering high-quality information are not only more likely to be valued and trusted but also positioned better to support academic success in this environment.

System Quality: Enhancing Value and Trust

System quality, encompassing the platform's stability, usability, responsiveness, and technical reliability, was found to be a fundamental driver of students' perceived value and trust in AI-powered personalized learning environments (H9, H10). When students interact with systems that are intuitively designed, aesthetically coherent, and technically stable, they are more likely to perceive the platform as a valuable educational tool (X. Li & Zhu, 2022). This study supports and extends the work of

Suryani et al. (2025), emphasizing that intuitive interface design and logical feature arrangement reduce cognitive load and frustration, thereby improving user satisfaction. This seamlessness not only minimizes frustration but also enhances satisfaction and promotes sustained engagement with the platform (Strielkowski et al., 2025). High system quality removes barriers to learning, making the platform a more attractive and effective tool for academic achievement. This is relevant especially in the context of personalized learning, where continuous interaction with the system is key to tailoring educational pathways. Compared to platforms that require steep learning curves or are prone to glitches, those with high system quality foster smoother learning journeys and amplify the perceived academic value they deliver.

A positive relationship was also established between system quality and perceived trust. Students who encountered minimal technical issues, experienced fast load times, and found the platform available consistently developed a stronger sense of trust in its dependability and professionalism (Kuluşaklı, 2025). Reliable system performance signals to students that the platform is well-maintained and that their data and learning progress are secure, which is crucial for building long-term trust (Brugliera, 2024). When students feel confident that the platform will not fail them during critical learning moments, such as assessments or deadlines, they are more likely to integrate it into their daily academic routines and rely on it for ongoing support (Noor et al., 2022). This sense of reliability and technical excellence solidifies the platform's role as a trusted partner in students' educational pursuits. This study highlights that in the Vietnamese context, where digital learning adoption has surged post-pandemic, technical reliability and usability are not merely conveniences but essential elements in building student confidence and commitment to AI-based learning tools. As students rely more on these platforms for both self-directed learning and institutional instruction, high system quality becomes a prerequisite for trust formation and sustained usage.

Perceived Value and Perceived Trust: Pathways to Learning Performance

The results of this study reveal that perceived value significantly influences students' trust in AI-powered personalized learning platforms (H11). When students perceive clear academic benefits, such as tailored content delivery, timely feedback, and alignment with their personal learning goals, they are more likely to trust the platform's ability to support their academic success (Akpen et al., 2024; Al-Abdullatif, 2023). The results align with Stiggins (2025), who highlights the dynamic interplay between cognitive appraisals of usefulness and affective trust responses: as students experience tangible advantages and satisfaction, their confidence in the platform's reliability and intentions is strengthened. This relationship holds particular significance in the context of Vietnamese higher education, where students are navigating increasing digitalization in post-pandemic learning environments. In such a transitional context, platforms that offer not just features but clearly demonstrable value, such as adaptive learning paths or goal-aligned recommendations, serve as strong anchors for building trust in AI-assisted education. This underscores the necessity for educational technology designers to prioritize features and experiences that deliver concrete, student-centered value, as these directly foster a climate of trust and openness to new digital learning methods.

Moreover, both perceived value and perceived trust were found to have direct and significant effects on learning performance (H12, H13). These findings reinforce the theoretical argument that value and trust function as motivational drivers in technology-enhanced learning environments. When students recognize value, they are more likely to engage actively with the system, take initiative, and persist through academic challenges, ultimately taking ownership of their learning process and leading to improved academic outcomes (Alnaeem et al., 2024; Castro et al., 2024). Likewise, trust in the platform deepens engagement even further, reduces resistance to adopting innovative learning strategies, and encourages students to explore advanced functionalities with confidence (Yahiaoui et al., 2022).

Compared to prior research, this study contributes further by highlighting a synergistic relationship between perceived value and trust in driving learning performance. While earlier studies have often examined these constructs in isolation, the current findings suggest a reinforcing loop: perceived value boosts trust, and both together enhance students' academic outcomes significantly. This reciprocal mechanism reflects the dual cognitive–affective nature of human–AI trust: cognitive trust is developed through consistent value delivery, while affective trust evolves as students perceive fairness and reliability in system interactions. Together, these trust dimensions motivate sustained engagement and deeper learning outcomes. This dual-pathway model emphasizes the importance of designing AI-driven learning platforms that are both functionally effective and emotionally trustworthy. In the Vietnamese educational context, where many students are still acclimating to emerging technologies, it suggests that institutions should not only invest in technically sophisticated systems but also in communicating their tangible benefits and reliability to students. When students believe a platform is both valuable and dependable, they are more likely to integrate it into their learning routines, thereby optimizing academic performance in digitally mediated environments.

Self-Efficacy: Strengthening the Value–Performance and Trust–Performance Links

This study reveals that self-efficacy significantly moderates the effects of both perceived value and perceived trust on students' learning performance. Students with high self-efficacy, those who believe in their capacity to manage and succeed in academic tasks, are better positioned to leverage the advantages offered by intelligent learning platforms (Lyu & Salam, 2025). When these students recognize the platform's value, they are more likely to engage deeply with its features, utilize adaptive resources, and persist through challenges, thereby maximizing the positive impact on their academic outcomes (K. F. Garcia et al., 2025). This interaction suggests that perceived value alone may not be sufficient for driving performance outcomes across all learners. Without internal motivation and belief in their ability to succeed, students may not act fully on the opportunities a personalized learning platform provides. Platforms that incorporate features to build and support self-efficacy, such as goal-setting tools, progress tracking, and personalized encouragement, can help ensure that all users, not only those with pre-existing confidence, can benefit fully from personalized learning environments (Poh & Lee, 2025). Within the context of Vietnamese higher education, this result highlights the importance of developing platforms that not only deliver value but also support and nurture student confidence. Features such as personalized goal-setting, progress dashboards, and motivational feedback can play a crucial role in fostering a sense of self-efficacy, especially for students with lower initial confidence.

A parallel moderating effect was observed for the relationship between perceived trust and learning performance. Students with high self-efficacy are more likely to transform their trust in the platform into effective learning behaviors, such as actively seeking feedback, experimenting with new learning strategies, and taking initiative in their studies (Chen et al., 2024; Payadnya et al., 2024). This synergy between psychological readiness and technological trust amplifies the overall educational impact of AI-powered platforms. Consistent with emerging trust theories, this indicates that user characteristics such as self-efficacy shape the trajectory of human–AI trust in dynamic ways. Students who feel confident in their abilities are more likely to transition from initial cognitive trust to sustained affective trust, which in turn translates into higher engagement and performance. In contrast, students with lower self-efficacy may hesitate to rely on or fully engage with the system, even if they trust its capabilities (Y. Wang & Zhang, 2024). Therefore, fostering self-efficacy should be a strategic priority for educators and technology designers aiming to maximize the benefits of AI-driven personalized learning, ensuring equitable and meaningful learning gains across diverse student populations.

Taken together, these findings contribute to theoretical advancement by demonstrating how the integration of ISSM and S-O-R provides a holistic lens to link system characteristics, psychological responses, and learning performance. The study clarifies further the dual role of perceived value and trust as reinforcing mechanisms in AI-mediated education, while also showing that self-efficacy functions as a boundary condition that shapes these pathways. This integrated perspective enriches existing theories of human–AI interaction by emphasizing the combined influence of technological features and learner characteristics in driving educational outcomes.

IMPLICATIONS

THEORETICAL IMPLICATIONS

This study provides significant theoretical contributions by extending and integrating the S–O–R framework and the ISSM in the context of AI-driven personalized learning. By conceptualizing five key system characteristics, including intelligence, anthropomorphism, personalization, information quality, and system quality, as external stimuli, the research delineates how technological and design features elicit internal psychological responses, namely perceived value and perceived trust, which in turn shape learning performance. This conceptual advancement clarifies the underlying mechanisms through which AI-enabled systems influence learning outcomes, thereby refining the S–O–R model's application in technology-enhanced education. Moreover, the integration of cognitive and affective constructs within this framework bridges insights from technology acceptance theory and educational psychology, offering a unified theoretical lens for understanding learner–AI interactions.

In addition, by incorporating information and system quality into the S–O–R paradigm, this study extends the ISSM framework to emphasize that perceived value and trust act as pivotal psychological mediators connecting system success dimensions to user performance outcomes. The model contributes further to the emerging discourse on human–AI trust formation by demonstrating that trust in educational AI systems operates through both cognitive (competence-based) and affective (emotional assurance) pathways. This dual-path conceptualization advances a theoretical understanding of how learners interpret and internalize the reliability and benevolence of AI-driven platforms.

An important theoretical insight emerging from this study is the differential influence of system characteristics on users' psychological responses. The empirical findings underscore that AI intelligence features such as adaptability, responsiveness, and analytical capacity have a particularly strong influence on both perceived value and perceived trust. This highlights a critical shift in user-system dynamics, suggesting that beyond basic usability, the intelligent behavior of AI systems plays a transformative role in shaping learners' cognitive and affective evaluations. This insight extends traditional ISSM assumptions by illustrating how the intelligent behavior of AI systems acts as a critical determinant of perceived system success and user satisfaction in learning contexts.

Another notable theoretical contribution involves the reexamination of anthropomorphism in learning systems. Contrary to assumptions in some previous literature, the results indicate that while anthropomorphic cues enhance perceived value, they do not significantly influence trust. This finding refines prior trust models by emphasizing that in educational contexts, where accountability and accuracy are prioritized, cognitive trust derived from functionality outweighs affective trust derived from human-like cues. The study thereby advances human–AI interaction theory by distinguishing between surface-level social attraction and deeper credibility-based trust. This finding challenges the generalizability of positive effects often attributed to human-like design elements, calling for a more context-sensitive theoretical approach. Specifically, in academic contexts where competence, fairness, and transparency are important, trust appears to rely more on functional reliability than on superficial resemblance to human behavior. Theoretically, this distinction enriches human–AI interaction and human–computer interaction (HCI) literature by differentiating between surface-level social attraction and deeper credibility-based trust. Such insight calls for a more context-sensitive theoretical perspective that accounts for domain-specific factors influencing trust formation in intelligent systems.

Furthermore, the research advances motivation and learning theories by validating the moderating role of self-efficacy. These insights also align with recent conceptualizations of dynamic trust formation, suggesting that trust in AI is not static but contingent on user traits such as confidence and perceived control. This adds a behavioral psychology dimension to existing S–O–R interpretations, reinforcing that learners' internal states continuously interact with external technological stimuli to co-shape trust and performance. The results show that students' confidence in their own learning abilities amplifies the positive effects of perceived value and trust on learning performance, underscoring the dynamic interplay between individual differences and technology-induced psychological states. Additionally, the confirmed mediating roles of perceived value and trust provide deeper theoretical insight into the psychological mechanisms by which technological characteristics ultimately drive educational outcomes. This dual-mediation model, combined with the moderating effect of self-efficacy, offers a comprehensive and realistic framework for understanding technology acceptance and effectiveness in contemporary educational settings.

Practical Implications

The practical implications derived from the theoretical model provide actionable insights for educators, AI developers, and institutional leaders. First, the significant influence of intelligence features on both perceived value and trust highlights the importance of integrating advanced capabilities such as adaptive learning algorithms, diagnostic tools, and real-time performance feedback. These features should not only streamline instructional delivery but also provide meaningful, individualized support that directly enhances student engagement and performance. Developers are encouraged to continuously refine these features through user testing and data-driven optimization to ensure their pedagogical relevance. From a trust-building perspective, transparency in how these intelligent systems make decisions, provide feedback, and use data should be clearly communicated to users. This practical transparency reinforces trust by demonstrating accountability and aligning with ethical standards in AI-supported education.

The study also shows that anthropomorphic features significantly contribute to perceived value but do not significantly enhance trust. This outcome suggests that developers should design human-like elements carefully to complement, rather than replace, the cognitive basis of trust. Providing reliable, explainable system responses and consistent performance can ensure that trust remains grounded in perceived competence rather than mere social familiarity. Therefore, such features should be implemented selectively and with a clear educational purpose. Rather than adding human-like traits arbitrarily, developers should focus on elements that support cognitive and emotional engagement such as empathetic virtual tutors or conversational agents that facilitate natural interactions. These anthropomorphic cues should be grounded in pedagogical value, serving to humanize the learning experience without compromising the system's perceived credibility.

Moreover, the strong effect of personalization on both perceived value and trust reinforces the need for platforms that can adapt to the unique needs and preferences of individual learners. Effective personalization not only improves user experience but also fosters long-term trust through continuous demonstration of understanding and reliability. As students see that the platform learns from their progress and adjusts responsively, their confidence and emotional attachment toward the system naturally deepen. Educational institutions should prioritize the deployment of learning systems that offer flexible content pathways, personalized feedback, and interfaces that cater to various learning styles. Personalization should be embedded throughout the learning journey, enabling students to adjust their goals, pace, and content format according to their evolving needs and preferences. Such tailored experiences not only increase engagement but also foster trust in the system's ability to support academic success.

Besides, the study reinforces the enduring importance of information and system quality, which remains a foundational factor in shaping user trust and satisfaction. Institutions must ensure their platforms deliver accurate, relevant, and up-to-date learning content while maintaining a technically robust and user-friendly experience. This includes minimizing technical issues, providing intuitive navigation, and ensuring platform stability. Regular content reviews, system updates, and prompt technical support are critical in maintaining high standards and avoiding disruptions that could undermine student trust.

The study also recognizes the importance of self-efficacy as a moderator in the relationship between perceptions and learning performance. To support students' confidence and competence in using AI-powered tools, platforms should incorporate features that help students track their progress, set achievable goals, and receive timely positive reinforcement. Building self-efficacy in this way not only enhances students' performance but also strengthens their trust trajectory, from initial adoption to habitual reliance, by giving them a sense of agency and co-control in the human–AI relationship. Additionally, educational institutions should offer comprehensive onboarding programs and digital literacy training to help students, especially those with low initial confidence, build the necessary skills and attitudes to fully engage with personalized learning technologies.

Finally, the central roles of perceived value and trust call for transparent and proactive communication from educational institutions. Students need to understand how the system works, what benefits it offers, and how their data is used and protected. Institutions should design onboarding experiences that clearly explain the capabilities and limitations of AI tools and maintain open channels for feedback and improvement. Continuous refinement of the platform based on user input not only enhances system effectiveness but also fosters a culture of trust, responsiveness, and shared ownership of the learning process. Ultimately, these strategies reflect a shift from designing technology "for" students to designing technology "with" students, a participatory approach that ensures trust, transparency, and pedagogical relevance remain central to AI integration in education.

LIMITATIONS AND RECOMMENDATIONS

This study, while offering valuable insights into the mechanisms through which AI-driven personalized learning systems influence student learning performance, is subject to several limitations that should be considered when interpreting the findings. First, the use of a cross-sectional survey design restricts the ability to draw causal inferences between system characteristics, psychological mediators, and learning outcomes. To address this, future research should employ longitudinal or experimental designs that can capture changes over time and provide stronger evidence for causality within the S–O–R framework depicted in the research model.

Another limitation lies in the reliance on self-reported measures for all key constructs, including perceived value, perceived trust, self-efficacy, and student learning performance. Self-reporting may introduce common method bias and social desirability effects, potentially inflating the relationships observed in the model. To mitigate this, subsequent studies should incorporate objective data sources such as system usage logs, academic records, or teacher assessments, and consider triangulating these with self-reported perceptions to enhance validity.

The generalizability of the findings is also limited by the sample, which was drawn from a specific educational and cultural context. The relationships identified among intelligence, anthropomorphism, personalization, information quality, system quality, and psychological mediators may not be held in other countries, educational levels, or institutional settings where cultural attitudes toward technology and learning differ. Expanding future research to include more diverse and comparative samples will help determine the universality of the model and uncover potential contextual moderators.

In addition, the study employed a non-probability convenience sampling approach, which, although common in educational technology research, introduces potential sampling bias and limits representativeness. Combined with the reliance on voluntary participation, this may have resulted in overrepresentation of students who are more technologically confident or motivated. Future studies should consider probability-based sampling methods or mixed approaches that enhance representativeness and reduce bias. Incorporating stratified or multi-institutional samples across different regions would further improve generalizability.

Finally, the model focused on selected system and psychological variables, omitting other potentially influential factors such as teacher support, peer collaboration, prior experience with digital learning, and institutional resources. Future research should broaden the scope to include these variables, as they may interact with or moderate the effects observed in the current framework. Qualitative research methods, such as interviews or focus groups, could also be employed to gain deeper insight into students' lived experiences and the nuanced ways in which they engage with AI-based personalized learning systems.

CONCLUSION

This study provides a comprehensive and empirically validated understanding of how AI-powered personalized learning platforms influence student learning performance, guided by the S–O–R framework integrating with the ISSM model. Drawing on data from 462 Vietnamese students with experience using AI-powered personalized learning platforms and applying PLS-SEM analysis, the research rigorously examined the relationships between platform characteristics, psychological factors, and learning outcomes.

The results indicate that intelligence, personalization, information quality, and system quality significantly enhance both perceived value and perceived trust, which in turn influences student learning performance positively. Interestingly, while anthropomorphic features contribute to perceived value, they do not significantly affect trust, suggesting that students place greater importance on system reliability and competence than on human-like traits in building trust with educational technologies. Additionally, the findings confirm that perceived value not only directly improves learning outcomes but also reinforces trust in the system. Furthermore, self-efficacy moderates the impact of both perceived value and trust on learning performance, underscoring the importance of student confidence in achieving successful educational outcomes. Among all relationships, the link between perceived value and perceived trust emerged as the strongest, emphasizing that students' evaluation of a system's usefulness and benefits is the most decisive factor shaping their trust in AI-powered learning platforms.

The study's implications are both theoretical and practical. Theoretically, it extends the S–O–R model by differentiating the effects of specific system features and integrating insights from technology acceptance and educational psychology. Furthermore, the study aligns with and extends the ISSM model by demonstrating how information and system quality, two central success dimensions, operate through perceived value and trust to influence user performance outcomes in AI-enhanced educational contexts. The empirical validation of dual mediation and moderation mechanisms offers a nuanced understanding of how students' perceptions and internal states shape their learning experiences with AI-powered platforms. Practically, the findings offer clear guidance for developers and educators: prioritize the development of intelligent, personalized, and high-quality systems; incorporate anthropomorphic elements only when they serve clear pedagogical purposes; and foster students' self-efficacy through structured support and training initiatives. These strategies are critical for maximizing the educational potential of AI-driven technologies.

Nevertheless, these contributions must be interpreted with caution, considering several limitations. The use of a cross-sectional design restricts causal inference, while reliance on self-reported data may introduce bias. Moreover, the focus on a specific cultural and educational context (Vietnamese students) limits the generalizability of the findings to broader populations. These constraints highlight the need for future research to adopt longitudinal or experimental designs to establish causality, incorporate objective indicators such as academic records or system log data to validate self-reports, and extend analysis to more diverse, cross-cultural settings. Comparative studies across different countries and educational levels would further clarify the universality and contextual sensitivity of the proposed model. Additionally, the use of a non-probability convenience sampling approach may have introduced sampling bias and limited representativeness, suggesting the need for future studies to employ probability-based or multi-institutional sampling methods to enhance generalizability.

Expanding the model to include additional contextual and individual factors, such as teacher support, peer collaboration, and institutional readiness, alongside qualitative approaches like interviews or focus groups, would also enrich the understanding of how intelligent learning systems can be optimized to meet diverse learner needs. Such efforts will not only address the current study's limitations but also provide actionable pathways for future research to advance the design and application of AI-driven education globally.

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AUTHORS

Gia Khuong An graduated with a Bachelor's degree in International Business from FPT University, Can Tho City, Vietnam. He has participated in several scientific research projects in different fields and has published articles in high-quality international journals. His research interests include artificial intelligence, emerging technologies, education, consumer behavior, innovative marketing, and logistics.

Thi Thuy An Ngo has a Master's degree in Economics and a Master's degree in Aquaculture from Ghent University, Belgium. She is a Lecturer in the Business field and currently serves as the Vice Director at FPT University, Can Tho City, Vietnam. She has been actively involved in numerous research projects across diverse disciplines and has published over 40 papers in reputable international journals. Her research interests include education, innovative marketing, consumer behavior, social sciences, artificial intelligence, entrepreneurship, and sustainable development.