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AI TUTOR-BASED LANGUAGE LEARNING: LINKING SERVICE QUALITY TO LEARNERS' CONTINUANCE INTENTION THROUGH A DUAL-PATHWAY MODEL

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ABSTRACT

Aim/Purpose	This study employs the Stimulus-Organism-Response (SOR) framework to investigate the psychological drivers of learners' continuance intention toward AI tutors. The study explores how five core service quality dimensions (aesthetics, control, personalization, responsiveness, and reliability) shape learners' internal states, conceptualized as a dual system consisting of rational attitude and experiential engagement. The study further examines how these internal states foster satisfaction and subsequently influence continuance intention, while also analyzing the asymmetrical moderating role of perceived risk on these psychological pathways.
Background	AI tutors are increasingly adopted in language education due to their capacity to deliver scalable, adaptive, and personalized instruction, an especially relevant development in settings such as Vietnam, where language proficiency gaps persist. Despite their rapid integration into everyday learning, the mechanisms that sustain learners' long-term use remain insufficiently understood. Existing research largely relies on broad technology acceptance models that conceptualize AI systems as uniform delivery tools, overlooking their highly interactive and adaptive nature. Consequently, limited attention has been given to which specific service quality dimensions most strongly shape learners' evaluations and sustained engagement. Moreover, prior studies often assume a direct relationship between system features and continuance intention, neglecting the cognitive and experi-

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ential states that emerge as learners interact with AI tutors. These gaps are particularly salient in Vietnam's fast-growing digital learning environment, where high demand for effective language education converges with increasing public interest in AI-based solutions. Yet, empirical evidence on how learners assess the quality of AI tutor services remains scarce. This underscores the need for a more fine-grained examination of how distinct service characteristics influence learners' internal evaluations and their intention to continue using AI tutors, providing both theoretical precision and practical guidance for enhancing AI-supported language learning.

Methodology	This study utilized a quantitative, cross-sectional design via a structured online questionnaire. Data were collected through purposive sampling from 771 experienced users of AI language tutors (including high school students, university students, and working professionals) in Vietnam. The data was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 3.0 software to test the complex research model, including the proposed moderation effects.
Contribution	This study advances technology acceptance theory by applying a nuanced SOR framework to the AI tutor domain, deconstructing service quality into five specific, actionable dimensions. Its primary theoretical contribution is the validation of a "dual-engine" retention model (distinguishing between a rational attitude path and an experiential engagement path) and the introduction of the resilience of flow phenomenon, demonstrating that the engagement-based pathway is uniquely resilient to the negative impacts of perceived risk. The study also provides crucial empirical evidence from the under-researched context of Vietnam's emerging market.
Findings	The results reveal that all five service quality dimensions (aesthetics, control, personalization, responsiveness, and reliability) significantly and positively influence both learner attitude and engagement. These two internal states, in turn, cultivate satisfaction and drive continuance intention. Crucially, perceived risk demonstrates an asymmetrical moderating effect: it significantly weakens the influence of the rational pathway (attitude → continuance intention) and the summative judgment (satisfaction → continuance intention), but it does not weaken the influence of the "hot" experiential pathway (engagement → continuance intention).
Recommendations for Practitioners	Developers and educators should adopt a dual defensive-offensive strategy. Defensively, they must mitigate perceived risk by ensuring pedagogical accuracy (reliability) and data transparency. Offensively, they should prioritize investments in features that drive deep, resilient engagement, as this pathway is robust to risk. Enhancing aesthetics, learner control, personalization, and responsiveness are all critical levers for building both positive attitudes and strong engagement.
Recommendations for Researchers	Researchers should validate this model across specific linguistic cohorts to test for variance. Studies should also test the model's generalizability in other cultural or educational contexts beyond the specific emerging market of Vietnam.
Impact on Society	By providing a strategic blueprint for designing more effective and engaging AI tutors, this study helps educational technology providers create tools that foster long-term learner commitment. This can help close persistent language proficiency gaps in emerging economies, support economic globalization, and enable transformative, scalable language acquisition for learners at all stages.

Future Research	Future research should employ longitudinal designs to track the evolution of engagement and satisfaction beyond the initial novelty period. Subsequent studies must also connect these service quality factors and psychological constructs to objective, tangible learning outcomes, such as measured proficiency gains, to ascertain the AI tutor's true pedagogical efficacy.
Keywords	AI tutors, continuance intention, service quality, Stimulus-Organism-Response (SOR), engagement, perceived risk

INTRODUCTION

The educational technology (EdTech) industry has become a transformative force in the global learning landscape, with recent advances in information and communication technology profoundly changing language education (Adeoye & Otemuyiwa, 2024). Mobile platforms and AI-powered "tutors," including sophisticated chatbots and intelligent apps, now offer personalized, on-demand support, enabling learners to learn at any time and from anywhere (Guo et al., 2025). Within this global trend, Vietnam has emerged as one of Southeast Asia's most vibrant markets for these technologies. This dynamism, propelled by strong government support for digital transformation and high public trust in AI, converges with a significant societal demand (Pham et al., 2024). In an increasingly globalized economy, effective foreign language skills are paramount; however, despite long-term investment in language education, achieving widespread proficiency remains a persistent national challenge (Alvakili, 2024). This enduring gap underscores the urgent need for effective, scalable, and engaging language learning solutions, an area where AI tutors are increasingly viewed not merely as innovative tools but as transformative enablers of language acquisition.

However, while the pedagogical potential of AI tutors is widely recognized, their long-term success depends critically on learners' continuance intention to use, a behavioral outcome that remains insufficiently understood in current literature. Most existing studies on e-learning adoption have relied heavily on generalized technology acceptance frameworks, such as the Technology Acceptance Model (TAM), which treat educational platforms as monolithic systems for content delivery (Bin et al., 2024). These models often fall short because they fail to capture the unique pedagogical nature of AI tutors, which function not as static repositories but as dynamic, interactive learning partners. Consequently, broad constructs such as system quality, information quality, or ease of use are insufficient to explain the user experience (Khine, 2024). The true drivers of a learner's decision to continue using an AI tutor likely lie in specific, granular service dimensions that define the interactive experience: the adaptive tailoring of content (personalization), the immediacy of feedback (responsiveness), the degree of learner autonomy (control), and the system's dependability (reliability) (Bauer et al., 2025; Tan et al., 2025; L. Wang & Li, 2024). Without deconstructing service quality into these core interactive components, the key factors that foster sustained engagement remain obscured (R. Liu et al., 2025).

Furthermore, the psychological pathway from initial use to long-term commitment is often oversimplified in current literature. Many studies model a direct leap from perceived quality to ultimate outcomes like satisfaction or continuance intention, treating the learner's internal state as a single event rather than a developmental process (Y. M. Cheng, 2023; Rajeh et al., 2021). This overlooks the nuanced psychological journey of a learner. A user first forms a cognitive and affective evaluation and then immerses themselves in the learning process through active use (Ismail & Aljabr, 2025). It is the quality of this ongoing interaction that culminates in a deeper, more stable state of overall satisfaction, which in turn becomes a powerful predictor of the will to continue. This sequential progression from initial attitude and engagement to eventual satisfaction is a critical but largely unexplored mechanism (Chopra et al., 2025). Compounding this gap, the majority of technology acceptance research originates from developed markets, whose findings may not be transferable to the unique socio-technical context of emerging economies like Vietnam, where digital infrastructure and pedagogical expectations differ significantly (Manfreda & Mijač, 2024).

Given these theoretical and contextual gaps, this study employs the Stimulus–Organism–Response (SOR) framework (Mehrabian & Russell, 1974) to explore how the service quality of AI tutors influences learners' continuance intention to use. The SOR model posits that external stimuli (S) trigger changes in an organism's internal states (O), which in turn produce observable responses (R). This framework is particularly well-suited for examining human-computer interaction in educational contexts (Bai et al., 2025). Applying this framework to this study's context, the stimulus is defined by five key dimensions of AI tutor service quality (AISQ): aesthetics (interface design), control (learner's ability to guide pace), personalization (tailoring to individual needs), responsiveness (speed of feedback), and reliability (consistency and correctness). These stimuli are expected to influence the learner's organism variables, or internal states, which are conceptualized as a sequential process. The service quality dimensions are posited to first influence the primary organism variables: attitude toward the AI tutor (a cognitive and affective evaluation) and engagement with the learning process (behavioral immersion). These initial states, in turn, are expected to cultivate the higher-order organism variable, satisfaction, which represents a cumulative affective judgment. This causal chain is consistent with educational service research, arguing that service quality enhances satisfaction (Q. Chen et al., 2022). The final response in the model is the learner's continuance intention to use the AI tutor. This reflects a decision-making process to persist with the tool, which is strongly influenced by user satisfaction (Li et al., 2022). Finally, this study introduces perceived risk as a critical moderating factor, recognizing that the path from positive internal states to sustained use is not frictionless. In the AI context, these risks include tangible concerns about content accuracy, data privacy, or an over-reliance on technology (Zhao & Khaliq, 2024). This study proposes that high perceived risk will weaken the positive influence of internal states on continuance intention to use. This reflects a practical reality: even a satisfied learner may hesitate to fully commit to a tool if they perceive significant underlying risks.

Building on this framework, the overarching objective of the study is to elucidate how AI tutor service quality influences Vietnamese language learners' continuance intention through a structured set of psychological mechanisms. To this end, the research pursues four interrelated aims. First, it examines the effects of five AI tutor service quality dimensions, including aesthetics, control, personalization, responsiveness, and reliability, on key organismic states, namely learners' attitude and engagement. Second, it investigates the interrelationships among these organismic variables, with particular emphasis on their respective contributions to learner satisfaction. Third, the study assesses how attitude, engagement, and satisfaction subsequently shape learners' continuance intention toward AI tutors for language learning. Finally, it explores the moderating role of perceived risk in the relationships between organismic states and continuance intention. To enhance the robustness and generalizability of the findings, the study draws on a heterogeneous sample comprising high school students, university students, and working professionals. This sampling strategy enables the examination of continuance intention across major stages of the contemporary learner lifecycle in Vietnam.

This research makes several significant contributions. First, it applies a nuanced SOR model to the novel domain of AI language tutors, extending technology acceptance theories into the rapidly evolving field of generative AI in education. Second, by deconstructing service quality into its constituent dimensions, it offers a more granular framework for understanding their individual impacts on the learner's psychological state and behavioral intentions. Third, the study provides valuable empirical evidence from Vietnam, an under-researched and fast-growing emerging market, offering cross-cultural insights that enrich a field largely dominated by studies from developed nations. From a practical standpoint, this research provides educational technology developers with actionable strategies for designing AI tutors that foster user loyalty. For educators and institutions, it offers a diagnostic framework to evaluate and implement technologies that enhance learner engagement and satisfaction, ultimately contributing to more effective language acquisition outcomes.

LITERATURE REVIEW

THEORETICAL BACKGROUND

AI tutor service quality

AI tutor service quality (AISQ) has emerged as a foundational construct for understanding learner satisfaction, engagement, and long-term system use within AI-supported educational environments (Vieriu & Petrea, 2025). Conceptually, AISQ represents a specialized extension of traditional e-learning service quality frameworks, which are themselves adaptations of the foundational SERVQUAL model (Y. Lu & Khan, 2024). However, while traditional e-learning quality models emphasize human instruction, course materials, and administrative support, AISQ restructures these dimensions for an autonomous, algorithm-driven system where the "service provider" is an intelligent pedagogical agent rather than a human instructor (Sumi & Kabir, 2021).

Early e-learning service quality frameworks typically revolve around three core components: system quality, information quality, and service quality (Akter et al., 2023; Cohen et al., 2022). These constructs remain relevant for AI tutors, yet they no longer capture the full nature of learner–AI interaction. AISQ is distinct from generic e-learning quality because its core value proposition is not static content delivery; rather, it is a dynamic, interactive, and personalized pedagogical partnership (Benkhalfallah et al., 2024). Accordingly, AISQ must be understood not merely as the quality of platform performance, but as the quality of an ongoing, dynamic learning partnership between the learner and the AI.

In the rapidly expanding field of AI-powered language learning, AISQ has become the primary competitive differentiator. Learners' expectations have shifted; they now demand sophisticated, personalized learning paths, adaptive, real-time feedback on complex tasks such as pronunciation and grammar, and high levels of interactive engagement (Alhusaiyan, 2025; Shemshack & Spector, 2020; Zhai et al., 2021). However, this context is also fraught with specific challenges that threaten the service experience. These include the potential for algorithmic bias in feedback, significant data privacy concerns, and a lack of human-centric, nuanced understanding in the AI's responses (Holmes & Porayska-Pomsta, 2023; Lawasi et al., 2024). These challenges are not merely technical issues; they are potent service failures that directly map to AISQ dimensions. Algorithmic bias, for instance, represents a fundamental failure in reliability (Chopra et al., 2025). Privacy concerns amplify the perceived risk that this study investigates as a moderator (Holmes & Porayska-Pomsta, 2023). A lack of nuanced feedback constitutes a failure in both personalization and responsiveness (Benkhalfallah et al., 2024; Gokce et al., 2024).

This study delves into how five specific AISQ dimensions influence the learner's internal cognitive and affective states. Aesthetics refers to the visual appeal, interface design, and perceived professionalism of the e-learning platform (Ghai & Tandon, 2022). A high-quality visual design simplifies the message, reduces extraneous cognitive load, and conveys credibility, which is posited to shape a positive learner attitude and foster initial engagement (Alshaykha, 2022). Control refers to the learner's perceived ability to direct their own learning progress, manage their pace, and choose their learning sequence (Li et al., 2022). This sense of agency is a key factor in e-learning satisfaction and is hypothesized to positively influence both learner attitude and cognitive engagement (Rajeh et al., 2021). Personalization involves the AI's capacity to adapt instructional content, feedback, and guidance to the unique needs, pace, and knowledge level of the individual learner (Qatawneh et al., 2024; Shemshack & Spector, 2020; Zhai et al., 2021). This adaptivity is the core function of an "intelligent" tutor and is expected to strongly enhance learner engagement and foster a positive attitude (Benkhalfallah et al., 2024; Vieriu & Petrea, 2025). Responsiveness is defined as the system's ability to provide prompt, clear, and meaningful feedback (Setiono & Hidayat, 2022). This creates a high sense of perceived interactivity, where the learner feels "heard" and "understood" by the AI, which is crucial for driving engagement and improving attitude (Al-Shafei, 2025). Finally, reliability ensures the AI tutor's performance is accurate, consistent, and trustworthy (Maia et al., 2024). A system that functions smoothly and provides factually correct language instruction builds essential trust, which is foundational to a positive attitude and sustained learner engagement (Dzakwan & Ubit, 2025). By examining these dimensions, this research provides valuable insights into enhancing AISQ to meet the expectations of a dynamic and demanding language-learning market.

Stimulus-Organism-Response (SOR) model

The SOR model, introduced by Mehrabian and Russell (1974), offers a comprehensive theoretical framework for understanding how external stimuli influence individuals' internal states and drive behavioral outcomes. The model is structured around three key components: stimulus (S), encompassing external environmental factors or cues; organism (O), representing individuals' internal cognitive and affective states; and response (R), denoting the resulting observable behaviors or intentions. This sequential structure enables a nuanced understanding of how external system characteristics translate into human behaviors, making the SOR model particularly suitable for research contexts involving human-computer interaction and technology-mediated learning.

Over the past decade, the SOR model has been increasingly applied in information systems and educational technology research due to its capacity to explain complex pathways linking system attributes to user behaviors. In e-learning contexts, the SOR framework has been used to explore the effects of diverse stimuli such as e-learning service quality, technology antecedents, and specific AI tool characteristics on learner behaviors. For example, Zheng et al. (2023) demonstrated that e-learning service quality dimensions positively affect learner satisfaction and perceived effectiveness, which in turn drive higher learning persistence. Duong (2024) applied the model to examine ChatGPT use and showed that technology acceptance factors act as stimuli that shape learners' trust and attitude (organism), which then predict continuance intention (response). Similarly, Chang (2022) demonstrated that technology-related stimuli influence learners' flow experiences and satisfaction, which in turn affect mobile learning continuance. Across these and other studies, the SOR model has proven effective in identifying the psychological mechanisms through which external technological features influence internal psychological states and subsequent learner behaviors.

The AI tutoring environment represents a highly interactive and psychologically rich learning setting in which learners continuously interpret system characteristics and adjust their behaviors accordingly. The SOR model is therefore well-suited to this context for several reasons. First, AISQ comprises a set of distinct, observable system features, such as interface design, personalization capability, and feedback responsiveness, that naturally function as external stimuli in the SOR framework. These stimuli elicit users' internal cognitive and affective appraisals, which ultimately determine their willingness to continue using the system. Second, learning with an AI tutor involves a progressive psychological journey rather than a single evaluative reaction. This aligns with the SOR model's capacity to incorporate multi-stage organismic processes, offering a structured way to capture both immediate and cumulative internal states.

In this study, the SOR model is adapted to examine how AISQ shapes Vietnamese learners' continuance intention to use AI tutors in language learning. The five AISQ dimensions, including aesthetics, control, personalization, responsiveness, and reliability, are conceptualized as stimuli that learners perceive during their interaction with the AI tutor. These dimensions shape the learners' internal psychological states. This study proposes a two-stage organismic process where stimuli first influence foundational first-order states of attitude and engagement (organism 1), which in turn culminate in the summative, second-order judgment of learner satisfaction (organism 2). This complex internal state then drives the final behavioral outcome: the intention to continue using. Furthermore, this study extends the framework by incorporating perceived risk as a critical moderator, examining how it conditions the relationship between the organismic states and the final behavioral response. By employing this adapted SOR model, this study aims to unravel the mechanisms through which AISQ influences key psychological and behavioral outcomes, offering nuanced insights into the dynamics of the AI-driven language-learning experience.

HYPOTHESIS DEVELOPMENT

Aesthetics

In the context of human–computer interaction, aesthetics represents the visual allure and perceived elegance of a system's interface (Silvennoinen, 2021). This construct is typically categorized into two dimensions: classical aesthetics, which values order, symmetry, and clarity; and expressive aesthetics, which reflects creativity, originality, and visual complexity (Cunningham et al., 2023). Within AI-driven language tutoring platforms, visual design functions as a primary heuristic because the interface is the first point of contact for the learner (Jingxiu, 2024). Rather than being a surface-level attribute, empirical evidence suggests that high-quality visuals trigger instantaneous positive emotional reactions (Karim et al., 2022). This "general positivity" serves as the affective foundation upon which a learner builds a comprehensive evaluative stance, or attitude, toward the educational technology (Mohamed & Kamel, 2024). Specifically, while a professional (classical) layout fosters credibility, a vibrant and unique (expressive) design enhances the system's overall appeal (Xie, 2023). Consequently, the aesthetic dimension is expected to underpin the formation of favorable attitudes toward AI tutors. Based on these findings, the following hypothesis is proposed:

> **H1:** Aesthetics have a significant positive influence on attitude.

Parallel to its role in shaping attitudes, aesthetic quality acts as a powerful catalyst for learner engagement. This influence is largely channeled through the system's hedonic value, the degree to which an interface provides intrinsic pleasure, excitement, and sensory stimulation, beyond its purely pragmatic functions (Starr, 2023). Educational technology literature indicates that such hedonic traits, characterized by visually rich and imaginative content, are robust predictors of a learner's drive to invest time and energy into their studies (Nikolopoulou et al., 2021). An immersive visual environment can spark "situational interest," a temporary affective state that narrows a learner's focus and encourages deeper cognitive processing (Ruf et al., 2022). When the interface design aligns with the concept of "learning through entertainment," the interaction ceases to be a mandatory task. It becomes a rewarding experience, thereby intensifying the cognitive, emotional, and behavioral involvement known as engagement (Yang, 2025). Accordingly, the visual sophistication of an AI tutor is essential for mobilizing and maintaining active participation. Based on these findings, the following hypothesis is proposed:

> **H2:** Aesthetics have a significant positive influence on engagement.

Control

Control refers to the extent to which an AI-driven language-learning system enables learners to exercise authentic agency over their learning experience, including regulating pace, selecting content, and choosing interaction modalities (Mohebbi, 2025). In AI-mediated learning environments, such agency is theorized to shape learners' downstream psychological states and affective responses. From the perspective of self-determination theory (SDT), supporting the basic psychological need for autonomy is foundational to intrinsic motivation, well-being, and sustained engagement in learning activities (Autin et al., 2021). Accordingly, when learners perceive an AI tutor as adaptable and responsive to their preferences, rather than prescriptive, it is more likely to satisfy autonomy needs and promote more favorable evaluative judgments (Tanchuk & Taylor, 2025). This logic is consistent with technology acceptance principles: systems that confer a sense of user control typically strengthen perceived ease of use and mitigate anxiety, which, in turn, contributes to more positive attitudes toward the technology (Tran et al., 2025). In computer-assisted language learning (CALL), attitude is widely recognized as a key antecedent of both adoption and continued use (Bessadok & Hersi, 2025). By contrast, highly rigid or predetermined learning pathways may undermine perceived autonomy, weaken motivation, and elicit negative evaluations. Based on these findings, the following hypothesis is proposed:

H3: Control has a significant positive influence on attitude.

Control is also a key determinant of learner engagement, which encompasses cognitive, affective, and behavioral involvement in the learning process (L. Wang et al., 2025). The autonomy granted by system control features is identified as a critical factor for ensuring learners remain psychologically and behaviorally invested in their studies (Guay, 2022). When AI tutors endow learners with control, it fosters a sense of ownership that transforms them from passive recipients of information. Empirical evidence in the domain of AI instructional agents demonstrates that greater perceived control leads to more frequent interactions and more efficient learning behaviors, reflecting heightened behavioral engagement (Dai et al., 2024). Moreover, control plays a central role in facilitating cognitive engagement. It requires learners to move beyond passive consumption and actively utilize self-regulation strategies, such as goal-setting, strategic planning, and monitoring progress (Kharroubi & ElMediouni, 2024). This self-directed and metacognitive involvement reflects a deeper and more sustained form of engagement that is essential for successful language acquisition (Mitschelen & Kauffeld, 2025). By strengthening both behavioral participation and cognitive self-regulation, systems that offer meaningful control effectively support comprehensive, long-term engagement in learning. Based on these findings, the following hypothesis is proposed:

H4: Control has a significant positive influence on engagement.

Personalization

Personalization signifies the AI tutor's capability to dynamically tailor the learning experience, adapting educational content, instructional pace, and feedback mechanisms to the distinct learning styles, knowledge levels, and individual learning objectives (Kaswan et al., 2024). Within AI-driven language education, such adaptive capability represents a pivotal determinant of learners' psychological responses, particularly their overall attitude toward the technology. Language acquisition, in particular, is often associated with high levels of anxiety (Russell, 2020). AI-driven personalization directly mitigates this anxiety by modulating task difficulty to align with the learner's current competence, thereby fostering a critical sense of self-efficacy (Yan et al., 2025). When learners perceive that the content is calibrated for their success and relevant to their specific needs, their confidence in their own abilities increases, which is a core component of a positive affective state toward the technology and the learning domain (Gottlieb et al., 2022). Conversely, non-adaptive "one-size-fits-all" platforms disregard this crucial learner heterogeneity (Verstraete et al., 2025). Such systems risk generating frustration and disengagement in learners who struggle to keep pace, while simultaneously inducing boredom and reduced motivation in those who find the content insufficiently challenging (Hamamra & Qabaha, 2024). As a result, personalization functions as a core service component that addresses individual learner needs, enhancing perceived value and fostering the positive psychological states required for sustained learning. Based on these findings, the following hypothesis is proposed:

H5: Personalization has a significant positive influence on attitude.

In addition to influencing attitudes, personalization is theorized to stimulate learner engagement, which encompasses cognitive, behavioral, and affective participation in learning activities (Selvakumar et al., 2025). Because adaptive systems can continually recalibrate learning experiences, they are particularly well-suited to sustaining such multidimensional involvement (Strielkowski et al., 2025). By maintaining alignment between instructional materials and learners' evolving competence, the system preserves relevance, a condition that helps sustain attention and facilitates deeper mastery (Carroll et al., 2021; Vaghela & Parsana, 2024). Empirical evidence from AI language learning contexts supports this view. Personalized curriculum recommendations have been shown to increase learner engagement, and conversational agents that adjust to user preferences are associated with substantially greater time on task (Dogan et al., 2025; Tan et al., 2025). By comparison, static systems that do not adapt can quickly drift out of sync with learners' skill levels, producing boredom when tasks are too easy or cognitive overload when tasks are too difficult (Ali et al., 2025). Both outcomes undermine the sustained cognitive and behavioral investment characteristic of meaningful engagement. Accordingly, personalization can be viewed as a foundational mechanism for maintaining focused, continued participation in AI-mediated language learning. Based on these findings, the following hypothesis is proposed:

H6: Personalization has a significant positive influence on engagement.

Responsiveness

Responsiveness captures an AI tutor's capacity to provide timely, accurate, and appropriate support to the learner's immediate context, and it is widely viewed as a core antecedent of learners' attitudes toward AI-enabled instruction (W. Wang, 2025). Attitude, in turn, reflects a composite evaluation that combines cognitive judgments with affective reactions to the learning experience (Svenningsson et al., 2022). This service attribute becomes especially salient in language acquisition, where learners regularly confront uncertainty, complex grammatical patterns, and substantial cognitive processing demands. When intelligent tutoring systems deliver guidance that is both immediate and context-sensitive, they can better accommodate learners' moment-to-moment needs while reducing cognitive strain (C. C. Lin et al., 2023). Learners' favorable perceptions of AI tutors have been attributed, in part, to the availability of instant and individualized assistance (J. Kim et al., 2020). Such immediacy reduces ambiguity, clarifies linguistic problems, and enables learners to resolve difficulties without prolonged interruptions. In addition, real-time, hierarchical feedback is often interpreted as both convenient and pedagogically valuable (Bernius et al., 2022), thereby strengthening the cognitive and affective bases of positive attitude formation. Overall, a tutor that responds quickly and correctly signals reliability and instructional usefulness, which can lessen frustration and cultivate a more favorable orientation toward continued use. Based on these findings, the following hypothesis is proposed:

H7: Responsiveness has a significant positive influence on attitude.

Responsiveness is also central to sustaining learner engagement, a multifaceted construct encompassing cognitive, behavioral, and emotional participation in the learning task (Wong & Liem, 2022). Interactive learning environments rely heavily on timely system feedback to maintain the learner's momentum and focus. A responsive AI tutor enhances engagement by providing real-time, context-specific explanations that promote active cognitive processing and prevent the accumulation of uncorrected misunderstandings (Sajja et al., 2025). Immediate feedback enables learners to identify, interpret, and correct errors as they occur, which prevents the build-up of frustration and supports ongoing task involvement. Empirical findings demonstrate that students who use responsive AI tutors report significantly higher engagement and motivation than those in traditional, less interactive learning settings (Chiu et al., 2024). By delivering instant, personalized, and easily accessible feedback, the AI tutor creates a continuous interaction loop (Sarshartehrani et al., 2024). This loop encourages continued behavioral interaction and deepens cognitive investment, as the learner perceives the interaction as productive and supportive (C. C. Lin et al., 2023). Consequently, responsiveness acts as a key mechanism for maintaining a learner's active involvement. Based on these findings, the following hypothesis is proposed:

H8: Responsiveness has a significant positive influence on engagement.

Reliability

The reliability of AI tutors is a fundamental factor in shaping a learner's attitude towards language learning technology. This reliability extends beyond simple system uptime to include the consistency and accuracy of the educational content and feedback provided by the AI tutor (Ghosh, 2025). When learners perceive the AI tutor as a dependable and credible source of linguistic guidance, this perception shapes a more favorable evaluative attitude toward the technology. Previous research in e-learning environments consistently showed that system reliability is highly correlated with positive user attitudes (Sandiwarno et al., 2024). Similarly, evidence from broader digital contexts shows that the perceived credibility of online platforms enhances user satisfaction and positive appraisal (Lillo, 2023). These findings imply that learners who believe in the accuracy and correctness of an AI tutor's explanations and corrections are more likely to view the system positively. Conversely, a commonly expressed concern among students is the possibility of receiving incorrect, inconsistent, or misleading responses from AI systems. Such inaccuracies can undermine trust and foster unfavorable attitudes toward the technology, diminishing its perceived educational value (H. Lin & Chen, 2024). A reliable AI tutor that consistently delivers accurate guidance aligns with learner expectations and reinforces perceptions of usefulness, mirroring established relationships between perceived usefulness, ease of use, and positive attitudes toward e-learning (Maphalala et al., 2025). Based on these findings, the following hypothesis is proposed:

H9: Reliability has a significant positive influence on attitude.

Moreover, reliability is a key antecedent of learner engagement, which encompasses the cognitive and behavioral investment students make in the learning process. A dependable AI tutor facilitates this engagement by offering accurate real-time feedback and generating personalized learning pathways that remain aligned with the learner's evolving skill level (Kaswan et al., 2024). Research on intelligent tutoring systems highlights that providing tailored guidance and support based on individual learning patterns, a key function of reliable AI, is a driver of engagement (Kumar et al., 2025). For instance, when an AI reliably analyzes a student's skills and provides a specific, personalized curriculum, a significant increase in engagement is observed (Huang et al., 2023). This functional reliability ensures that the interaction is productive, encouraging learners to spend more time actively using the system, as seen in conversational chatbots. This pattern has been observed in conversational AI applications, where dependable system performance correlates closely with higher levels of learner engagement (Fazil et al., 2024). In this way, reliability acts as a stabilizing mechanism that maintains focus, supports continuous participation, and prevents disengagement resulting from system errors or inconsistencies. Therefore, reliable delivery of educational feedback is essential to fostering an immersive and effective AI-mediated learning environment. Based on these findings, the following hypothesis is proposed:

H10: Reliability has a significant positive influence on engagement.

Attitude

Attitude, defined as an individual's overall affective response and evaluative judgment toward a particular technology, serves as a fundamental antecedent to user satisfaction within technology-mediated learning environments (J. Chen et al., 2025). In the context of AI tutors, attitude reflects learners' general favorability or unfavorability toward interacting with the AI tutor. Theoretically, this affective judgment precedes and shapes the more cognitively grounded evaluation of satisfaction. Information systems research conceptualizes user satisfaction as an "object-based attitude," meaning that satisfaction represents an accumulated evaluative outcome shaped by users' prior affective orientations (Zhi & Wang, 2024). This conceptual linkage is consistently validated across e-learning contexts. For instance, empirical evidence shows that a positive learner attitude significantly predicts their satisfaction with e-learning courses (Sokro et al., 2025). This relationship is further amplified in AI-driven systems, where the technology's capacity to adapt and respond effectively is crucial for maintaining a positive learner attitude (Strielkowski et al., 2025). Research confirms that in such advanced learning environments, the user's attitude exerts a powerful, direct influence on their resulting experience satisfaction (Idkhan & Idris, 2023). As such, learners who approach the AI tutor with a favorable attitude are more likely to interpret their interactions and cumulative experience positively. Based on these findings, the following hypothesis is proposed:

H11: Attitude has a significant positive influence on satisfaction.

In addition, attitude plays a critical role in shaping future behavioral intentions. This relationship is a central proposition of established behavioral theories, including the theory of reasoned action and the technology acceptance model, which posit that an individual's positive or negative feelings toward a behavior are the most proximal determinants of their intention to engage in that behavior (Sapry & Ahmad, 2024). This principle holds robustly in digital learning contexts, where learners' attitudes toward e-learning systems significantly and directly influence their intention to use and continue using the technology (Humida et al., 2022). A favorable attitude, which reflects a positive perception of the learning experience and its effectiveness, fosters greater motivation and reinforces the cognitive decision to continue using the technology (Wu et al., 2022). This mechanism is even more pronounced in AI-driven language learning systems. Empirical evidence shows that learners' positive attitudes toward AI-based tools significantly predict both intention to use and actual continued adoption (Jo, 2023). Thus, a favorable affective evaluation of the AI tutor is considered a necessary prerequisite for their willingness to adopt it as a long-term component of their language learning process. Based on these findings, the following hypothesis is proposed:

H12: Attitude has a significant positive influence on continuance intention to use.

Engagement

Within the landscape of AI-mediated instruction, learner engagement serves as a pivotal catalyst for user satisfaction. Rather than a singular metric, engagement is understood as an integrative phenomenon wherein cognitive, affective, and behavioral resources are synergistically invested in the educational process (X. Xu et al., 2023). In the specific context of AI-driven tutoring, this construct distinguishes itself by prioritizing proactive participation and sustained mental focus over the unidirectional intake of information (Ding et al., 2025). Such active involvement fosters a sense of personal agency and perceptible academic advancement. When students become cognitively immersed and behaviorally dedicated to their interactions with an AI tutor, the resulting experience is perceived as inherently rewarding and efficacious (S. Chen, 2025). This is exemplified in the work of S. Wang et al. (2024), who demonstrated that the iterative, interactive dialogues facilitated by AI language agents significantly bolster learner gratification by providing a high degree of system responsiveness to idiosyncratic needs. Unlike traditional, static e-learning frameworks, the dynamic interactivity inherent in AI tutoring ensures that engagement acts as a primary barometer for service quality. Thus, satisfaction is derived not merely from the final attainment of learning objectives but from the stimulating nature of the instructional journey itself. This correlation is well-supported in current literature, which consistently identifies highly engaged learners as reporting superior levels of fulfillment (Fang et al., 2023; Rajabalee & Santally, 2021). Based on these findings, the following hypothesis is proposed:

H13: Engagement has a significant positive influence on satisfaction.

Extending beyond immediate contentment, learner engagement functions as a fundamental precursor to the sustained use of AI tutoring systems. The transition from initial adoption to long-term habituation is largely mediated by the depth of a user's involvement with the platform (Goh & Yang, 2021). This behavioral trajectory is frequently analyzed through the lens of Flow Theory, which characterizes a psychological state of profound, effortless absorption in a task (Dmello et al., 2024). When an AI tutor calibrates its interactions to be optimally challenging and highly immersive, it facilitates the emergence of this flow state (A. Lu et al., 2022).

Because such experiences are intrinsically reinforcing, the learning activity evolves into a self-sustaining source of motivation. Supporting this view, Bekteshi (2025) argued that deep immersion with AI tools promotes the formation of resilient learning habits, thereby minimizing the cognitive friction usually required to initiate subsequent study sessions. This internal reward mechanism is vital for longitudinal commitment; users who encounter such profound engagement are psychologically driven to revisit the platform to recapture that positive experience (Dmello et al., 2024). Ultimately, engagement cultivates behavioral loyalty, transforming the use of the AI tutor from a necessitated task into a self-selected preference (Ahmed et al., 2024). Given the competitive nature of the language learning application market, establishing this level of deep-seated commitment is essential for ensuring user retention. Based on these findings, the following hypothesis is proposed:

H14: Engagement has a significant positive influence on continuance intention to use.

Satisfaction

Learner satisfaction is conceptualized as the individual's overall affective and cognitive evaluation of their cumulative learning experience, which arises from a comparison between the AI tutor's perceived performance and the learner's initial expectations and goals (Ling et al., 2022). This affective judgment is a cornerstone of the expectation-confirmation model (ECM), which posits that satisfaction is the most direct and powerful antecedent of a user's continuance intention (Obeid et al., 2024). Extensive empirical research in the broader e-learning domain confirms this critical linkage, frequently identifying learner satisfaction as the single most significant factor driving the intention to continue using a digital learning system (Yunusa & Umar, 2021). This relationship is equally robust in the context of AI-driven educational tools. Studies on AI-powered tutoring systems report a strong positive association between student satisfaction and their expectancy or intention for future use (Ni & Cheung, 2023). Similarly, research on generative AI for learning confirms that students' continuance intention is significantly influenced by satisfaction (Jung & Jo, 2025). The pattern remains consistent within language learning applications: empirical investigations of platforms such as Duolingo demonstrate that satisfaction exerts a direct, positive, and significant impact on continuance usage intention (Ulfiah et al., 2025). These findings suggest that when learners perceive that the AI tutor has met or exceeded their expectations, this positive confirmation produces a favorable affective response (satisfaction). This response then becomes the primary psychological mechanism driving their willingness to continue using the system over time. Based on these findings, the following hypothesis is proposed:

H15: Satisfaction has a significant positive influence on continuance intention to use.

Perceived risk

As learners evaluate the uncertainty and potential harms associated with using an AI tutor, perceived risk emerges as a significant influence on whether they adopt and continue using educational technologies (Wu et al., 2022). In the context of AI-based language learning, perceived risk encompasses multiple dimensions, including performance risk (e.g., receiving inaccurate feedback), privacy risk (e.g., concerns over data collection and use), and psychological risk (e.g., anxiety about interacting with AI) (X. Xu et al., 2025). Although attitude is widely acknowledged as a central driver of intention within technology acceptance frameworks, its predictive power is not unconditional. Prior research in technology acceptance demonstrates that perceived risk negatively moderates the link between performance expectancy (a construct analogous to attitude) and behavioral intention (Kaur & Arora, 2021). Habib et al. (2025) further highlighted that even when learners hold positive attitudes toward the pedagogical benefits of an AI tool, high perceived privacy risks can create a cognitive dissonance that suppresses their willingness to commit to long-term use. This reflects a broader cognitive conflict in which learners simultaneously perceive the AI tutor as beneficial (a positive attitude) while harboring apprehensions about potential harm. This apprehension functions as a significant psychological barrier, introducing hesitation that attenuates the positive influence of their attitude on the ultimate decision to continue using the service (Yin, 2025). Based on these findings, the following hypothesis is proposed:

H16: Attitude drives continuance intention to use, moderated by the learner's perceived risk.

The moderating role of perceived risk is likewise theorized for the association between learner engagement and continuance intention, as engagement denotes intensive cognitive, affective, and behavioral involvement with the platform (Xiao & Hew, 2024). However, empirical studies within e-learning contexts have found that the direct relationship between learner engagement and continuance intention is often weak or non-significant, suggesting it is highly conditional upon other factors

(S. Xu et al., 2024). Perceived risk offers a critical explanation for this fragile connection. Supporting this view, DeVos et al. (2022) found that highly engaged users, due to their deeper interaction with the system, are often more sensitive to potential data breaches or algorithmic biases, which can rapidly erode their intention to continue using the system despite their initial high involvement. High engagement inherently involves greater exposure to the system's functionalities and, consequently, its potential vulnerabilities or flaws. If a highly engaged learner perceives significant privacy concerns or performance inconsistencies, this can induce negative emotions, such as anxiety, which may discourage further use (Yang & Rui, 2025). Thus, when perceived risk is high, it can override the positive momentum of engagement, weakening the progression from active use to a long-term continuance intention. Based on these findings, the following hypothesis is proposed:

H17: Engagement drives continuance intention to use, moderated by the learner's perceived risk.

Finally, the effect of learner satisfaction on continuance intention is expected to be diminished when perceived risk is high. Satisfaction, an affective state that emerges from the positive confirmation of a learner's expectations, is widely regarded as a primary antecedent of technology continuance (Ye et al., 2023). However, this established relationship can be destabilized in high-risk contexts. A robust body of evidence confirms that perceived risk significantly weakens the predictive power of satisfaction on continuous-use intention (Y. Liu et al., 2024). Specifically, studies find that the higher the perceived risk, the weaker the positive effect of satisfaction on continuance intention becomes (Ha et al., 2024). In line with this, Altrichter and Benoit (2025) demonstrated that satisfied users might still discontinue a service if they perceive future risks, such as escalating costs or potential obsolescence of their learning data, outweigh the current benefits. This creates a temporal conflict between a positive, past-oriented evaluation (satisfaction) and a negative, future-oriented apprehension (risk). Even a highly satisfied learner may defect if they perceive unresolved risks, as the uncertainty of future negative outcomes diminishes the influence of their past positive experiences (Englund et al., 2023). Based on these findings, the following hypothesis is proposed:

H18: Satisfaction drives continuance intention to use, moderated by the learner's perceived risk.

Theoretical Framework

The theoretical framework for this study, illustrated in Figure 1, is grounded in the SOR paradigm to delineate the relationships between AISQ, learners' internal states, and their behavioral intentions. Within this model, the stimulus is conceptualized as a multidimensional construct of AISQ, encompassing five key dimensions: aesthetics, control, personalization, responsiveness, and reliability. These stimuli are hypothesized to directly influence the organism block, which represents the learner's internal psychological states. This organismic component is structured hierarchically, with attitude and engagement serving as first-order internal states. These initial states are then hypothesized to collectively form the second-order construct, learner satisfaction.

Finally, the response, or the primary dependent variable, is the learner's continuance intention to use the AI tutor. This framework suggests a sequential path wherein the service quality dimensions influence these organismic factors, which in turn affect the final continuance intention. Additionally, perceived risk is integrated as a critical moderating variable, posited to attenuate the relationships between the organismic states and the final usage intention.

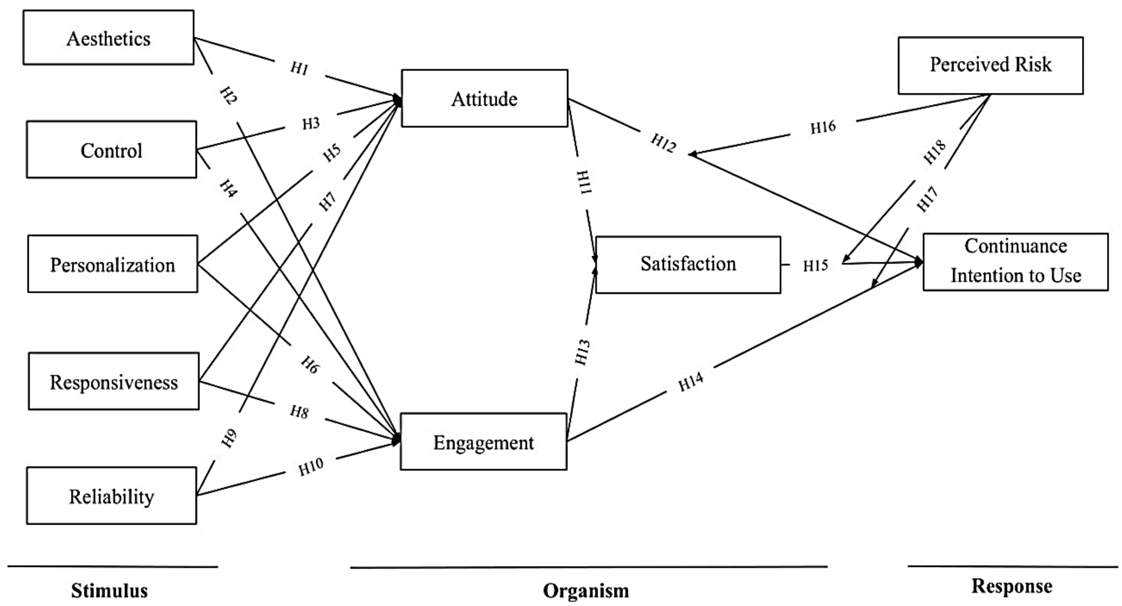

Figure 1. Theoretical framework

METHODOLOGY

PARTICIPANTS

This study investigates the influence of AI tutors on learners' language learning experiences, focusing on the role of AISQ in shaping continuance intention. With the increasing adoption of AI technologies in educational contexts, learners across diverse age groups and educational backgrounds are engaging with intelligent learning tools (Sanusi et al., 2022). To capture a comprehensive understanding of AISQ effects, this research targeted three learner segments: high school students, university students, and adult learners.

An initial pool of 804 survey responses was collected from individuals who had previously used AI tutors for learning purposes. According to Arndt et al. (2022), to ensure the reliability of the data, a screening process was implemented to filter out incomplete submissions and respondents without relevant experience. This screening process resulted in a final sample of 771 valid responses for analysis.

The demographic profile of the participants revealed that the largest cohort consisted of high school students aged 15–17, representing 31.4% of the sample, followed by university students aged 18–22 at 28.9%. Adult learners also formed a significant portion, with those aged 23–28 accounting for 23.0% and individuals over 28 making up 16.7%. The gender distribution was composed of 54.1% males and 45.9% females. In terms of income, nearly half of the participants (49.3%) reported a monthly income below 5 million VND, while the remainder were distributed across higher income brackets.

Behavioral data highlighted high engagement with AI tutors, as a significant majority of participants used these tools either daily (41.8%) or frequently (37.1%). The most common duration for a usage session was between 30 and 60 minutes (32.9%) or one to two hours (31.0%). The primary purpose for using AI tutors was to practice foreign languages and soft skills (28.0%), followed by completing assignments and essays (25.0%). These demographic and behavioral characteristics confirm that the sample is appropriate and representative for investigating the factors, such as service quality, that shape learners' continuance intention to use AI tutors within their language learning process.

Table 1. Respondents' profile

Demographic information (N = 771)		Frequency	Percentage
Gender	Male	417	54.1%
	Female	354	45.9%
Age	15 to 17 years old	242	31.4%
	18 to 22 years old	223	28.9%
	23 to 28 years old	177	23.0%
	Above 28 years old	129	16.7%
Education level	High School or Equivalent	343	44.5%
	College	139	18.0%
	University	153	19.8%
	Postgraduate	136	17.6%
Occupation	Students	445	57.7%
	Office workers	94	12.2%
	Businessmen	85	11.0%
	Freelancers	75	9.7%
	Laborers	72	9.3%
Monthly income	Below 5 million VND	380	49.3%
	From 5 to below 10 million VND	146	18.9%
	From 10 to below 20 million VND	135	17.5%
	Above 20 million VND	110	14.3%
Usage frequency	Rarely	8	1.0%
	Occasionally	27	3.5%
	Moderately	128	16.6%
	Frequently	286	37.1%
	Daily	322	41.8%
Usage time	Less than 30 minutes	107	13.9%
	From 30 to 60 minutes	254	32.9%
	From 1 to 2 hours	239	31.0%
	More than 2 hours	171	22.2%
Usage purpose	To explain lessons/concepts	138	17.9%
	To complete assignments/essays	193	25.0%
	To practice foreign languages/soft skills	216	28.0%
	To plan study schedules/search for materials	124	16.1%
	For quick Q&A/revision	100	13.0%

INSTRUMENTS

This study employed a quantitative survey instrument, administered through an online questionnaire, as the primary method for data collection. The instrument was developed based on established literature and previous empirical studies, as summarized in Table 2, to ensure content validity and theoretical alignment. Clear and simple language was used throughout the questionnaire to enhance participant understanding, minimize ambiguity, and improve response reliability (Koo & Yang, 2025).

The questionnaire comprised three main sections. The first section contained screening questions to verify that respondents met the study's inclusion criteria (e.g., individuals who have used or are currently using an AI tutor for language learning). This ensured that the collected data were relevant and representative of the target population (Tawfik et al., 2019). The second section collected participants' demographic and background information, such as gender, year of birth, education level, occupation, monthly income, frequency of use, duration of use, and purpose of use. These variables provided contextual information for interpreting the main findings. The final section was designed to measure the key constructs of the theoretical model using multi-item scales, a common approach for enhancing measurement accuracy and reliability (Cheah et al., 2018).

The final section consisted of 40 closed-ended items used to assess 10 latent constructs within the theoretical framework. All constructs were measured using a five-point Likert scale ranging from "1 = Strongly Disagree" to "5 = Strongly Agree." The service quality dimensions, including aesthetics (AES), control (CON), personalization (PER), responsiveness (RES), and reliability (REL), were adapted from J.-S. Chen et al. (2021); Q. Chen et al. (2022); Q. Chen et al. (2023); Lee and Koubek (2010); Sumi and Kabir (2021); S. Wang et al. (2021); and Xia et al. (2023). The organism-related constructs attitude (ATT), engagement (ENG), and satisfaction (SAT) were adapted from Almulla (2024), Foroughi et al. (2025), Ji et al. (2024), K. Kim et al. (2014), Park et al. (2012), and Read et al. (2019). The response-related construct continuance intention to use (CIU) was adapted from Ashfaq et al. (2020), Bhattacherjee (2001), and Ji et al. (2024). The moderating variable, perceived risk (PRI), was adapted from Tao et al. (2024) and Zuo et al. (2025).

Prior to the main data collection phase, a pilot study was conducted with a small sample of 50 participants. The purpose of this pre-test was to assess the questionnaire's clarity, item comprehension, technical functionality, and overall flow (Kunselman, 2024). Feedback from this group was used to refine the wording of several items to eliminate potential ambiguity. Furthermore, this initial data was analyzed for internal consistency. The results were positive, showing strong reliability, with Cronbach's alpha coefficients for all constructs surpassing the 0.7 threshold and confirming construct validity, as factor loadings were all above 0.5 (Cheung et al., 2024). This preliminary validation process affirmed that the instrument was well-suited and effective for deployment in the main study.

Table 2. Constructs' items

Factor	Measure items	Source
Aesthetics (AES)	AES1. "I feel the design of the AI tutor is clear."	Lee and Koubek (2010)
	AES2. "I feel the design of the AI tutor is systematic."	
	AES3. "I feel the design of the AI tutor is creative."	
	AES4. "I feel the design of the AI tutor is sophisticated."	
Control (CON)	CON1. "I feel like I have a lot of input in deciding how I use the AI Tutor in my learning."	Xia et al. (2023)
	CON2. "I feel a sense of freedom when using the AI tutor."	
	CON3. "I have many opportunities with the AI tutor to decide for myself how to learn."	
	CON4. "I have a say regarding what input I want to learn with the AI tutor."	
Personalization (PER)	PER1. "The personalized learning content recommended by the AI tutor is what I am interested in."	S. Wang et al. (2021)
	PER2. "The personalized learning content recommended by the AI tutor is what I like to learn."	
	PER3. "The personalized learning content recommended by the AI tutor is based on my needs."	
	PER4. "The personalized learning content recommended by the AI tutor is tailored to my situation."	

Factor	Measure items	Source
Responsiveness (RES)	RES1. "The AI tutor replies quickly."	J.-S. Chen et al. (2021); Q. Chen et al. (2022)
	RES2. "Getting in contact with the AI tutor is easy."	
	RES3. "The AI tutor is always ready to assist me."	
	RES4. "Every time I interact with the AI tutor, I receive a timely response."	
Reliability (REL)	REL1. "The AI tutor can accurately understand what I say."	Q. Chen et al. (2023); Sumi and Kabir (2021)
	REL2. "The responses from the AI tutor are accurate."	
	REL3. "The answers from the AI tutor meet my expectations."	
	REL4. "The AI tutor fulfills its promises."	
Attitude (ATT)	ATT1. "Learning with the AI tutor is a good idea."	Foroughi et al. (2025); Park et al. (2012)
	ATT2. "I think using the AI tutor is a helpful way to study."	
	ATT3. "Learning with the AI tutor is worth trying."	
	ATT4. "I have a positive attitude toward learning with the AI tutor."	
Engagement (ENG)	ENG1. "My interaction with the AI tutor makes me feel valued."	Read et al. (2019)
	ENG2. "I feel that I have a special connection with the AI tutor during learning."	
	ENG3. "If the AI tutor were a person, I would consider it a supportive friend in learning."	
	ENG4. "Seeing messages or feedback from the AI tutor feels like hearing from a helpful friend."	
Satisfaction (SAT)	SAT1. "The learning opportunities provided by the AI tutor contribute to my overall satisfaction."	Almulla (2024); Ji et al. (2024); K. Kim et al. (2014)
	SAT2. "I am highly satisfied with the learning outcomes facilitated by the AI tutor."	
	SAT3. "I have no complaints about using the AI tutor for learning."	
	SAT4. "I am satisfied with my overall experience of learning with the AI tutor."	
Perceived risk (PRI)	PER1. "There is a possibility that the AI tutor may malfunction or perform poorly, so they may provide inaccurate information that could mislead my study."	Tao et al. (2024); Zuo et al. (2025)
	PER2. "There is a probability that I will need extra time to handle errors or odd behaviors from the AI tutor."	
	PER3. "I am worried that the AI tutor will reveal my personal/private information."	
	PER4. "I am concerned that the AI tutor may introduce unexpected problems in my learning process."	
Continuance intention to use (CIU)	CIU1. "I intend to continue using the AI tutor in the future."	Ashfaq et al. (2020); Bhattach-erjee (2001); Ji et al. (2024)
	CIU2. "I will choose to use the AI tutor more often for my learning in the future."	
	CIU3. "I will always try to use the AI tutor in my daily learning activities."	
	CIU4. "My intention is to continue using the AI tutor rather than switching to other learning tools."	

DATA COLLECTION

This study employed a quantitative research approach, utilizing a structured questionnaire with predefined response items to empirically test the proposed hypotheses and examine the relationships among the constructs in the research model (Morgan, 2015). A cross-sectional study design was implemented, gathering all data within a specific timeframe to provide a snapshot of learners' experiences and behaviors regarding AI tutor usage (Yousef et al., 2025). The survey instrument was deployed via Google Forms, chosen for its high accessibility, ease of use for participants, and compatibility with various devices (Muley et al., 2021). To ensure broad coverage, the questionnaire link was distributed through online educational forums, social media platforms, and learning communities. Primary data was gathered from individuals who had experience using AI-powered tutors for language learning; these individuals constituted the study's unit of analysis. Given the undefined total population of AI tutor users, a non-probability sampling strategy was adopted. Specifically, purposive sampling was employed to ensure that all respondents met the key eligibility criterion of having used AI tutors, thereby enhancing the relevance and applicability of the collected data (Campbell et al., 2020).

The target sample size was determined based on established guidelines for survey-based research, which recommend a minimum of ten respondents per questionnaire item to ensure statistical robustness (Hair et al., 2017). With 40 items in the research model, a minimum of 400 valid responses was deemed necessary. The data collection period ran from October 15 to November 8, 2025. This process initially yielded 804 responses. Following the data cleaning protocols suggested by Hair et al. (2021), the initial dataset was refined by excluding responses that failed the screening questions, exhibited straight-lining patterns (invariant answers across all items), or contained incomplete information. As a result, the final dataset was free of missing values and comprised only valid responses. This final sample size of 771 comfortably exceeds the minimum requirement, providing a solid foundation for the subsequent statistical analysis and enhancing the reliability and generalizability of the study's conclusions.

All procedures involving human participants were conducted in strict accordance with ethical guidelines. The principles of informed consent, voluntary participation, anonymity, and data confidentiality were prioritized throughout the research (A. Xu et al., 2020). Participants were presented with an informed consent statement at the beginning of the survey and were required to actively provide consent via a checkbox, confirming their understanding of the study's purpose and voluntary participation. The survey introduction clearly explained the research objectives, and all data collected was processed anonymously to ensure participant confidentiality was maintained (Petrova et al., 2016).

DATA ANALYSIS

This study utilized Structural Equation Modeling (SEM), a sophisticated multivariate technique, to comprehensively test the proposed research model (S. Wang et al., 2024). SEM is highly suitable for examining intricate networks of relationships simultaneously. Specifically, the Partial Least Squares (PLS) approach (PLS-SEM) was chosen over traditional covariance-based SEM (CB-SEM) (Dash & Paul, 2021). This selection was motivated by PLS-SEM's effectiveness in handling complex models that include many constructs, its flexibility with data distribution assumptions, and its strong capability for prediction-oriented research (Legate et al., 2023). The model was estimated using PLS-SEM, and significance testing was conducted via bootstrapping with 5,000 subsamples (Streukens & Leroi-Werelds, 2016). All statistical analyses were performed using the SmartPLS 3.0 software, a leading application renowned for its robust and user-friendly execution of PLS-SEM (Kapoor, 2025).

Prior to model estimation, the data analysis followed a preparatory screening stage to ensure data quality and suitability for subsequent analysis. IBM SPSS Statistics 27.0 was used to perform initial data screening procedures, including the examination of missing values and outliers. Descriptive statistics were also computed to summarize participants' demographic profiles and to inspect the distribution patterns of the study variables. These preliminary procedures helped verify the adequacy of the dataset before proceeding with PLS-SEM analysis.

Following data screening, the analysis was conducted using a widely accepted two-stage procedure. The first stage involved a thorough assessment of the measurement model. This critical step was performed to ensure that all constructs in the study possessed adequate reliability and validity (Lambert & Newman, 2023). Before evaluating reliability and validity, indicator distributions were examined using skewness and kurtosis indices as a diagnostic check for extreme non-normality; the results are reported in Section "Normality assessment". Although PLS-SEM does not impose normality assumptions, this diagnostic check was performed to identify potential extreme non-normality that could affect estimation stability. Consistent with conventional guidelines, skewness and kurtosis values within the range of −2 to +2 were considered acceptable, indicating no serious departures from normality (Sharma & Aggarwal, 2025). Internal consistency was evaluated using both Cronbach's Alpha (CA) and Composite Reliability (CR) (Hair & Alamer, 2022). Convergent validity was then confirmed by examining the factor loadings of all items and the Average Variance Extracted (AVE) for each construct (Fornell & Larcker, 1981). Subsequently, discriminant validity was established by applying both the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio (HTMT), ensuring that each variable was empirically distinct (Fornell & Larcker, 1981; Henseler et al., 2015).

After confirming the adequacy of the measurement model, the second stage focuses on evaluating the structural model to test the proposed hypotheses. The significance and strength of the hypothesized relationships were assessed using a non-parametric bootstrapping procedure with 5,000 resamples, generating path coefficients (β), t-values, and p-values (He et al., 2024). To ensure the model's robustness, Variance Inflation Factors (VIF) were calculated. This step served a dual purpose: to detect any problematic levels of multicollinearity among predictor variables and to assess potential Common Method Bias (CMB) (Hair & Alamer, 2022; Kock, 2015). The model's explanatory power was judged by its coefficient of determination (R^2) values, while its predictive relevance was assessed using the Stone-Geisser Q^2 statistic (Hair & Alamer, 2022; Henseler et al., 2009).

Through this rigorous and structured analytical approach, this study provides reliable and empirically grounded insights. The findings clarify how various dimensions of AISQ interact to influence learners' attitude, engagement, and satisfaction, from which these positive learning experiences collectively shape their continuance intention to use AI tutors within the expanding field of language education technology.

RESULTS

MEASUREMENT MODEL ASSESSMENT

Normality assessment

Prior to examining the structural model, we evaluated the distributional properties of the dataset to ensure the validity of statistical inferences. While PLS-SEM is recognized for its robustness in handling non-normal data compared to covariance-based SEM, verifying the absence of extreme deviations remains a critical prerequisite (Hair et al., 2021). Following the guidelines proposed by Sharma and Aggarwal (2025), skewness and kurtosis indices falling within the range of ±2 are considered indicative of an acceptable normal distribution.

As presented in Table 3, the results show that Skewness values fluctuated between −0.721 (PRI4) and −0.143 (AES2), while Kurtosis values ranged from −1.142 (AES2) to 0.295 (RES3). Since all indicators strictly adhered to the recommended thresholds, the data demonstrate sufficient normality for subsequent analysis using the PLS-SEM approach.

Measurement model robustness

Assessing the measurement model's quality is a fundamental step to confirm the reliability and validity of the constructs. This evaluation process involves a thorough examination of the model's reliability, convergent validity, and discriminant validity. As an initial check, the outer loadings for all individual items were inspected. These loadings represent the amount of variance an item shares with its intended latent construct, with values of 0.70 or higher considered acceptable (Hair et al., 2017). As detailed in Table 3, all item loadings in this study were found to be within the strong range of 0.714 (REL3) to 0.839 (PER4). This confirms that all indicators are appropriate and share a high degree of variance with their respective constructs.

To ensure the consistency and stability of the measures, construct reliability was evaluated. This was accomplished using two primary metrics: CA and CR. Both of these statistics are used to appraise the internal consistency of the set of items representing each latent variable. A widely accepted standard for demonstrating reliability is a value of 0.70 or greater for both CA and CR (Hair & Alamer, 2022). The results from this analysis, shown in the table, indicate that all CA values ranged from 0.742 (AES) to 0.833 (CON & PER), while all CR values ranged from 0.838 (AES) to 0.889 (CON & PER). Since all of these values comfortably exceed the recommended threshold, the measurement model demonstrates a high degree of internal consistency and reliability.

Table 3. Construct reliability and validity

Constructs	Items	Loadings	CA	CR	AVE	Skewness	Kurtosis
Aesthetics (AES)	AES1	0.740	0.742	0.838	0.563	-0.437	-0.768
	AES2	0.770				-0.143	-1.142
	AES3	0.755				-0.492	-0.671
	AES4	0.736				-0.274	-1.121
Control (CON)	CON1	0.828	0.833	0.889	0.666	-0.528	-0.065
	CON2	0.825				-0.463	-0.354
	CON3	0.792				-0.401	-0.648
	CON4	0.820				-0.429	-0.262
Personalization (PER)	PER1	0.782	0.833	0.889	0.666	-0.442	-0.584
	PER2	0.819				-0.672	0.137
	PER3	0.823				-0.435	-0.392
	PER4	0.839				-0.662	0.215
Responsibility (RES)	RES1	0.761	0.797	0.867	0.621	-0.478	-0.247
	RES2	0.821				-0.413	-0.658
	RES3	0.770				-0.641	0.295
	RES4	0.799				-0.552	-0.335
Reliability (REL)	REL1	0.790	0.755	0.845	0.577	-0.498	-0.511
	REL2	0.742				-0.304	-0.746
	REL3	0.714				-0.327	-1.022
	REL4	0.790				-0.398	-0.723
Attitude (ATT)	ATT1	0.783	0.801	0.870	0.627	-0.580	0.050
	ATT2	0.835				-0.365	-0.421
	ATT3	0.760				-0.453	-0.314
	ATT4	0.787				-0.395	-0.573

Constructs	Items	Loadings	CA	CR	AVE	Skewness	Kurtosis
Engagement (ENG)	ENG1	0.793	0.813	0.877	0.641	-0.440	-0.678
	ENG2	0.810				-0.472	-0.440
	ENG3	0.821				-0.328	-0.991
	ENG4	0.780				-0.440	-0.673
Satisfaction (SAT)	SAT1	0.802	0.818	0.880	0.647	-0.494	-0.387
	SAT2	0.805				-0.351	-0.477
	SAT3	0.798				-0.347	-0.793
	SAT4	0.812				-0.493	-0.261
Perceived Risk (PRI)	PRI1	0.818	0.797	0.868	0.622	-0.496	-0.641
	PRI2	0.791				-0.467	-0.316
	PRI3	0.795				-0.653	0.099
	PRI4	0.750				-0.721	0.273
Continuance Intention to Use (CIU)	CIU1	0.768	0.793	0.866	0.617	-0.484	-0.350
	CIU2	0.775				-0.426	-0.103
	CIU3	0.799				-0.417	-0.603
	CIU4	0.799				-0.546	-0.300

Note: CA = Cronbach's Alpha; CR = Composite Reliability; AVE = Average Variance Extracted

Convergent validity

Convergent validity confirms that the indicators for a specific latent construct are highly correlated and effectively measure the same underlying concept (Hair & Alamer, 2022). This is primarily assessed using the AVE, which represents the average proportion of variance in the indicators that is explained by the latent construct. According to the criterion established by Fornell and Larcker (1981), an AVE value should be 0.50 or higher. This threshold indicates that the latent variable explains, on average, at least half of the variance in its associated items. As presented in Table 3, the findings from this study demonstrate that all constructs met this requirement. The AVE values for all ten constructs ranged from 0.563 (AES) to 0.666 (CON & PER), all of which are comfortably above the 0.50 benchmark. This result confirms that strong convergent validity was achieved for the measurement model.

Discriminant validity

Discriminant validity ensures that a latent construct is empirically unique and does not overly overlap with other constructs within the research model (Hair et al., 2017). This was evaluated using two established methods: the Fornell-Larcker criterion and the HTMT ratio. The Fornell-Larcker criterion requires that the square root of each construct's AVE be larger than its correlation with any other construct. As detailed in Table 4, the value on the diagonal for each construct (the square root of its AVE) is greater than all other values in the corresponding row and column, thereby satisfying this condition.

In addition, the HTMT ratio was calculated as a more stringent assessment (Henseler et al., 2015). This approach suggests that values should ideally be below 0.85, or at a maximum, below 0.90, to confirm distinctness. As presented in Table 5, all HTMT values were within the acceptable range. The highest value recorded was 0.853 (between CIU and CON), which is below the 0.90 threshold. The successful results from both the Fornell-Larcker criterion and the HTMT analysis provide strong support for the discriminant validity of all measurement scales used in this study.

Table 4. Fornell-Larcker criterion

	AES	ATT	CIU	CON	ENG	PER	PRI	REL	RES	SAT
AES	0.750									
ATT	0.576	0.792								
CIU	0.563	0.670	0.785							
CON	0.527	0.582	0.696	0.816						
ENG	0.585	0.662	0.665	0.609	0.801					
PER	0.519	0.670	0.627	0.584	0.629	0.816				
PRI	0.517	0.617	0.592	0.582	0.544	0.649	0.789			
REL	0.628	0.479	0.483	0.450	0.520	0.420	0.426	0.760		
RES	0.525	0.603	0.620	0.650	0.590	0.618	0.593	0.481	0.788	
SAT	0.548	0.672	0.645	0.618	0.687	0.595	0.571	0.483	0.598	0.804

Note: AES = Aesthetics; CON = Control; PER = Personalization; RES = Responsiveness; REL = Reliability; ATT = Attitude; ENG = Engagement; SAT = Satisfaction; PRI = Perceived Risk; CIU = Continuance Intention to Use

Table 5. Heterotrait-Monotrait (HTMT) Ratio

	AES	ATT	CIU	CON	ENG	PER	PRI	REL	RES	SAT
AES										
ATT	0.745									
CIU	0.732	0.841								
CON	0.671	0.709	0.853							
ENG	0.750	0.821	0.827	0.736						
PER	0.657	0.820	0.770	0.702	0.764					
PRI	0.671	0.772	0.743	0.713	0.675	0.796				
REL	0.834	0.614	0.623	0.567	0.660	0.528	0.546			
RES	0.677	0.745	0.777	0.799	0.723	0.753	0.741	0.617		
SAT	0.701	0.829	0.799	0.748	0.840	0.720	0.706	0.613	0.736	

Note: AES = Aesthetics; CON = Control; PER = Personalization; RES = Responsiveness; REL = Reliability; ATT = Attitude; ENG = Engagement; SAT = Satisfaction; PRI = Perceived Risk; CIU = Continuance Intention to Use

Structural Model Assessment

Assessment of common method bias (CMB)

An evaluation of the inner VIF values was conducted as a crucial step in assessing the structural model. This procedure is designed to detect potential multicollinearity among the predictor variables and, concurrently, to diagnose the potential presence of CMB. Both of these issues can significantly skew the estimation of path coefficients in a PLS-SEM analysis (Kock, 2015). This diagnostic is particularly important in studies, such as this one, that rely on self-reported data from a single questionnaire, where shared method variance (e.g., from item wording or response styles) rather than the true theoretical relationships could inflate the correlations between constructs (Hair et al., 2021).

To ensure the statistical validity of the model, established thresholds were applied. According to Hair et al. (2017), VIF values should remain below the 5.0 threshold to indicate an absence of critical collinearity. A more conservative threshold of 3.3 has also been suggested, above which CMB might be considered a potential issue (Kock, 2015). As presented in Table 6, the inner VIF values for all constructs in this study were found to be well within these acceptable limits. The recorded values ranged from a low of 1.751 (for the "REL → ATT and REL → ENG" path) to a high of 2.562 (for the "SAT*PRI → CIU" interaction path). Because all VIF values are substantially below both the 3.3 and 5.0 benchmarks, it is concluded that neither multicollinearity nor common method bias is a concern for this study. This result supports the robustness of the structural model, indicating that the findings are not significantly affected by measurement artifacts and that the subsequent hypothesis tests are reliable.

Hypothesis testing

The structural model was evaluated using PLS-SEM to test the hypothesized relationships among AISQ dimensions, learner attitudes, and continuance intention to use. SmartPLS software was utilized, applying a bootstrapping procedure with 5,000 resamples to assess the stability and significance of path coefficients. Following Hair et al. (2017), hypotheses were accepted when p-values were below 0.05 ($p < 0.05$), indicating statistically significant relationships. As presented in Table 6, most hypotheses were supported, except for H17, which was found to be non-significant ($p > 0.05$) and therefore rejected.

Examining the antecedents of learner attitude (ATT) and engagement (ENG), aesthetics (AES) and control (CON) demonstrated significant positive relationships with both attitude (H1: $\beta = 0.188$, $p = 0.000$; H3: $\beta = 0.135$, $p = 0.002$) and engagement (H2: $\beta = 0.179$, $p = 0.000$; H4: $\beta = 0.212$, $p = 0.000$). These results highlight that visually appealing and well-structured AI tutor systems enhance both learners' affective attitudes and active engagement. Similarly, personalization (PER) showed a strong positive impact on both attitude (H5: $\beta = 0.369$, $p = 0.000$) and engagement (H6: $\beta = 0.281$, $p = 0.000$), emphasizing the importance of customized learning experiences in fostering user involvement.

Responsiveness (RES) and reliability (REL) also played significant roles in shaping learner perceptions. Responsiveness positively influenced both attitude (H7: $\beta = 0.154$, $p = 0.005$) and engagement (H8: $\beta = 0.118$, $p = 0.005$), while reliability had weaker but still significant effects on attitude (H9: $\beta = 0.072$, $p = 0.037$) and engagement (H10: $\beta = 0.097$, $p = 0.038$). These findings suggest that timely and dependable AI tutor interactions contribute to users' favorable impressions and involvement in the learning process.

Regarding the internal relationships among organism variables, both attitude and engagement significantly influenced satisfaction (SAT) (H11: $\beta = 0.386$, $p = 0.000$; H13: $\beta = 0.432$, $p = 0.000$). Furthermore, attitude, engagement, and satisfaction each positively predicted continuance intention to use (CIU) (H12: $\beta = 0.247$, $p = 0.000$; H14: $\beta = 0.291$, $p = 0.000$; H15: $\beta = 0.155$, $p = 0.013$). These results confirm that positive attitudes, strong engagement, and satisfaction collectively enhance learners' willingness to continue using AI tutors.

In terms of moderation effects, perceived risk (PRI) was examined as a moderator in the relationships between the organism variables and continuance intention to use. The moderating effect of perceived risk on the relationship between attitude and continuance intention was negative and significant (H16: $\beta = -0.075$, $p = 0.021$), indicating that higher perceived risk weakens the positive influence of attitude on continuance intention. However, the moderating effect of perceived risk on the relationship between engagement and continuance intention to use was not statistically significant (H17: $\beta = 0.088$, $p = 0.063$), suggesting that perceived risk does not significantly alter the impact of engagement on continuance intention. Finally, the moderation between satisfaction and continuance intention (H18: $\beta = -0.096$, $p = 0.022$) was significant and negative, implying that as perceived risk increases, the effect of satisfaction on continuance intention decreases.

Overall, these findings provide empirical support for the theoretical model, demonstrating that AISQ dimensions substantially influence learners' attitudes, engagement, and satisfaction, which in turn drive continuance intention to use. Moreover, perceived risk plays a crucial moderating role, particularly by dampening the positive effects of key psychological variables on continuance intention.

Table 6. Hypothesis testing result

H	Paths	Coefficient (β)	Sample mean	Standard deviation	T statistic	P values	VIF	Results
H1	AES → ATT	0.188	0.187	0.036	5.174	0.000	2.011	Accepted
H2	AES → ENG	0.179	0.179	0.039	4.623	0.000	2.011	Accepted
H3	CON → ATT	0.135	0.134	0.043	3.112	0.002	2.013	Accepted
H4	CON → ENG	0.212	0.213	0.044	4.809	0.000	2.013	Accepted
H5	PER → ATT	0.369	0.366	0.047	7.870	0.000	1.878	Accepted
H6	PER → ENG	0.281	0.279	0.041	6.939	0.000	1.878	Accepted
H7	RES → ATT	0.154	0.156	0.045	3.448	0.001	2.153	Accepted
H8	RES → ENG	0.118	0.120	0.042	2.789	0.005	2.153	Accepted
H9	REL → ATT	0.072	0.073	0.035	2.078	0.038	1.751	Accepted
H10	REL → ENG	0.137	0.137	0.037	3.709	0.000	1.751	Accepted
H11	ATT → SAT	0.386	0.386	0.043	8.983	0.000	1.780	Accepted
H12	ATT → CIU	0.247	0.248	0.043	5.724	0.000	2.378	Accepted
H13	ENG → SAT	0.432	0.433	0.045	9.578	0.000	1.780	Accepted
H14	ENG → CIU	0.291	0.292	0.043	6.829	0.000	2.323	Accepted
H15	SAT → CIU	0.155	0.153	0.040	3.878	0.000	2.446	Accepted
H16	ATT*PRI → CIU	-0.075	-0.072	0.037	2.033	0.042	2.119	Accepted
H17	ENG*PRI → CIU	0.088	0.081	0.047	1.861	0.063	2.528	Rejected
H18	SAT*PRI → CIU	-0.096	-0.09	0.042	2.293	0.022	2.562	Accepted

Note: AES = Aesthetics; CON = Control; PER = Personalization; RES = Responsiveness; REL = Reliability; ATT = Attitude; ENG = Engagement; SAT = Satisfaction; PRI = Perceived Risk; CIU = Continuance Intention to Use

Model fit and predictive power

The explanatory strength and predictive accuracy of the structural model were assessed using the coefficient of determination (R^2), adjusted R^2, and the Q^2 predictive relevance statistic. These indices evaluate how well the model explains variance in the endogenous constructs and its ability to predict unseen data.

The R^2 value indicates the proportion of variance in each endogenous construct that is explained by its antecedent variables. According to Hair and Alamer (2022), R^2 values of 0.50 represent moderate explanatory power, whereas values of 0.75 or higher are considered substantial. As presented in Table 7, the model demonstrated moderate to substantial explanatory strength across all endogenous variables. Specifically, attitude exhibited an R^2 of 0.561, suggesting that 56.1% of its variance was explained by the stimulus factors (aesthetics, control, personalization, responsiveness, and reliability). Engagement recorded an R^2 of 0.552, while satisfaction had an R^2 of 0.556, indicating strong influence from both attitude and engagement. Finally, continuance intention to use achieved an R^2 of

0.590, confirming that 59.0% of its variance was explained by satisfaction, attitude, and the moderating effect of perceived risk. The adjusted R^2 values were closely aligned, ranging from 0.549 to 0.587, supporting the model's strong internal consistency and explanatory capacity.

The predictive relevance of the model was examined using the Stone-Geisser Q^2 statistic obtained through blindfolding. A Q^2 value greater than zero indicates that the model has predictive relevance for a specific endogenous construct (Henseler et al., 2009). The analysis revealed Q^2 values of 0.552 for attitude, 0.543 for engagement, 0.498 for satisfaction, and 0.566 for continuance intention to use. As all Q^2 values are well above the zero threshold, the model demonstrates strong predictive validity and confirms its capacity to generalize beyond the sample data.

Table 7. Model performance metrics

Constructs	R square	R square adjusted	Q square
ATT	0.561	0.558	0.552
ENG	0.552	0.549	0.543
SAT	0.556	0.555	0.498
CIU	0.590	0.587	0.566

Note: ATT = Attitude; ENG = Engagement; SAT = Satisfaction; PRI = Perceived Risk; CIU = Continuance Intention to Use

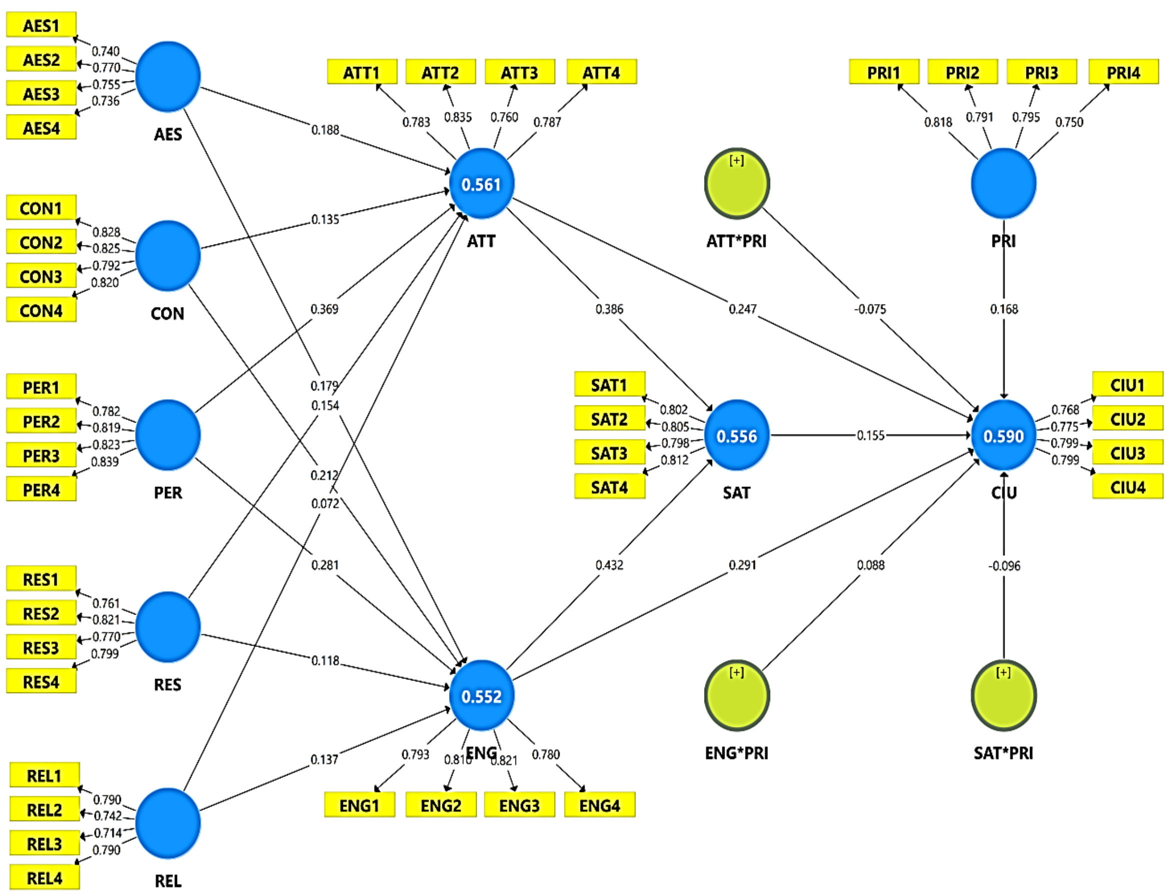

Figure 2. Results of PLS-SEM analysis

DISCUSSION

The empirical results provide strong support for the theoretical model and offer several important contributions to the literature on AI-mediated learning, service quality, and technology adoption. Across all dimensions of AISQ, the findings reveal both expected patterns consistent with prior scholarship and several context-specific insights that advance our understanding of learner behavior, particularly within Vietnam's rapidly evolving digital education ecosystem.

DESIGN-RELATED SERVICE QUALITY AS DRIVERS OF LEARNER ATTITUDE AND ENGAGEMENT

The findings provide strong empirical support for the proposed relationships, confirming that design-related service quality dimensions, namely aesthetics and control, are fundamental drivers of both learner attitude and engagement. Specifically, hypotheses H1 and H3, which examine the impact of these factors on attitude, and H2 and H4, which evaluate their influence on engagement, are all supported. These results indicate that the visual interface and the degree of agency afforded by an AI tutor are not peripheral features but central stimuli shaping learners' internal psychological responses of language learners.

The validation of H1 indicates that the visual appeal of an AI tutor functions as more than a superficial design attribute; rather, it operates as an affective heuristic that shapes learners' initial interpretations of the system. Consistent with prior research, aesthetically refined interfaces evoke immediate positive emotional responses, which subsequently anchor more favorable evaluative attitudes, even within utilitarian learning contexts (Karim et al., 2022; Mohamed & Kamel, 2024). The concurrent support for H2 further extends this logic by showing that aesthetics also serves as a catalyst for engagement. This aligns with the concept of situational interest, whereby hedonic and expressive design elements stimulate curiosity and motivational arousal, encouraging learners to invest sustained cognitive and behavioral effort (Ruf et al., 2022; Yang, 2025). Together, these findings reinforce the notion that aesthetics acts as an entry point through which learners become psychologically receptive to AI-mediated learning experiences.

Similarly, the support for H3 and H4 underscores the centrality of learner control in shaping both attitudinal and behavioral responses. The positive effect of control on attitude suggests that granting learners agency over pacing, content sequencing, and timing enhances their evaluative orientation toward the AI tutor. This finding is consistent with self-determination theory (SDT), which posits that autonomy satisfaction fosters intrinsic motivation and more positive cognitive appraisals (Autin et al., 2021; Mitschelen & Kauffeld, 2025). In parallel, the effect of control on engagement indicates that autonomy-supportive system features promote deeper involvement and self-regulated interaction, echoing prior evidence from digital and adaptive learning environments (Dai et al., 2024; Guay, 2022). These results suggest that learner control transforms interaction with an AI tutor from a passive consumption process into an active, self-directed learning experience.

When interpreted within the Vietnamese context, these relationships acquire additional explanatory depth. Formal education in Vietnam has traditionally emphasized structured curricula, teacher-centered instruction, and limited learner autonomy, reflecting broader high power-distance cultural norms. Against this backdrop, an AI tutor characterized by modern interface aesthetics and high degrees of learner control represents a pronounced departure from learners' habitual educational experiences. This contrast may heighten learners' sensitivity to design-related service quality, thereby amplifying its psychological effects on both attitude and engagement. In this sense, aesthetics and control function not only as general design stimuli, but also as culturally salient cues that reframe learners' roles – from passive recipients of instruction to active participants in their own learning trajectories.

Interaction-Related Service Quality as Drivers of Learner Attitude and Engagement

The structural results provide strong empirical support for the interaction-related dimensions of service quality, confirming that personalization, responsiveness, and reliability each exert significant positive effects on learner attitude and engagement. Accordingly, hypotheses H5 through H10 are all supported. These findings indicate that learners develop more favorable evaluations and remain more actively involved when AI tutors adapt to individual proficiency levels, respond promptly and contextually, and deliver feedback that is sufficiently consistent to be trusted during routine learning activities. Together, these dimensions extend the stimulus–organism logic by demonstrating that interaction quality, beyond interface design, plays a decisive role in shaping learners' internal psychological responses.

Among these dimensions, personalization emerged as a particularly salient driver. This result reinforces prior research suggesting that adaptive calibration reduces language learning anxiety and enhances perceived competence, thereby fostering more positive affective evaluations and sustained effort (Dogan et al., 2025; Yan et al., 2025). However, the contribution of this study lies in reframing personalization not merely as an efficiency-enhancing mechanism, but as a source of psychological safety. While personalization in Western, individualistic contexts is often valued for optimizing learning speed or performance outcomes (Ali et al., 2025), its role appears qualitatively different in the Vietnamese context. Vietnam's collectivist orientation and strong face-saving norms may heighten learners' sensitivity to public error, negative evaluation, and perceived incompetence. In this setting, personalized interaction with an AI tutor—delivered privately and without social judgment—creates a low-stakes learning environment in which experimentation, error-making, and linguistic risk-taking become psychologically acceptable. This interpretation helps explain why personalization exerts a particularly strong influence on both affective evaluation and engagement intensity in this study.

Responsiveness also demonstrates a robust positive association with learner attitude and engagement, reinforcing the importance of immediate and context-aware feedback in AI-mediated learning. Consistent with prior literature, timely responses help reduce cognitive load, clarify uncertainty, and sustain learning momentum, thereby preventing frustration from escalating into disengagement (Bernius et al., 2022; Chiu et al., 2024). Importantly, the present findings help conceptually distinguish responsiveness from personalization, two constructs that are often conflated under the broader notion of "AI intelligence." Personalization operates at a strategic level by shaping the long-term learning trajectory based on learner profiles and prior performance. Responsiveness, by contrast, functions at a tactical level, providing moment-to-moment guidance, clarification, and conversational support during active learning episodes. The independent significance of both constructs suggests that learners value not only tailored learning pathways but also the immediacy and conversational fluency of real-time interaction. This distinction clarifies why systems that excel in one dimension but neglect the other may fail to sustain positive psychological responses.

Reliability further exhibited a positive association with both attitude and engagement, although its effect was comparatively weaker than those of personalization and responsiveness. This relatively modest influence does not undermine its role; instead, it suggests that reliability operates as a baseline condition in contemporary AI tutoring environments. Once acceptable levels of accuracy and consistency are achieved, learners appear to place greater weight on interactive features when forming evaluative judgments and experiential responses. This interpretation partially diverges from earlier studies that position reliability as the primary determinant of favorable perceptions and sustained involvement (Huang et al., 2023; Sandiwarno et al., 2024), implying that the relative importance of reliability may shift as learners gain familiarity with AI-driven learning systems. Such divergence may reflect the evolving maturity of AI-enabled learning systems, in which heightened awareness of hallucination risks has led learners to treat reliability as a prerequisite rather than a source of added value. In this sense, reliability enables engagement but does not actively generate it beyond an acceptable standard.

Collectively, these findings underscore that interaction-related service quality shapes learner attitude and engagement through complementary psychological mechanisms. Personalization contributes to emotional safety and self-efficacy, responsiveness sustains cognitive flow and interactional continuity, and reliability provides the necessary epistemic foundation upon which these processes operate. In the Vietnamese context, where AI tutoring adoption is expanding alongside persistent concerns about accuracy, exam-oriented outcomes, and learner confidence, the differentiated roles of these interactional attributes become particularly salient. Rather than functioning as interchangeable indicators of system quality, personalization, responsiveness, and reliability jointly structure the psychological conditions under which learners evaluate, engage with, and persist in AI-driven language learning.

From Organism States to Continuance: The Roles of Attitude, Engagement, and Satisfaction

The statistical analysis strongly supports the hypotheses regarding the internal dynamics of the organism phase, confirming that both attitude and engagement act as powerful precursors to learner satisfaction (H11 and H13). This outcome demonstrates that satisfaction with AI-based language learning systems is jointly shaped by evaluative judgments and experiential involvement. Learners who hold favorable attitudes toward the AI tutor and who actively invest cognitive and behavioral effort during interaction are more likely to report higher overall fulfillment. This pattern is consistent with prior studies showing that attitude frames how users interpret their learning experiences (Idkhan & Idris, 2023) and that deeper behavioral immersion is associated with stronger feelings of gratification (Fang et al., 2023). Together, these results reinforce the view that satisfaction is not solely a function of system performance but emerges from the interaction between user evaluation and engagement intensity. The convergence between the present results and existing literature highlights that the perceived value of AI tutors is co-created through positive user sentiment and active participation. This insight is particularly salient in the Vietnamese context, where educational practices have traditionally favored passive knowledge reception. The findings indicate that learner satisfaction with digital tools is closely associated with the extent to which learners adopt more active and engaged roles during interaction. In this setting, satisfaction appears to emerge not merely from content delivery but from experiences that encourage sustained participation and repeated interaction, thereby challenging entrenched teacher-centered learning norms.

The structural results further confirm that attitude, engagement, and satisfaction each exert significant positive effects on continuance intention (H12, H14, and H15). This emphasizes that learners' decisions to persist with AI-based language learning are shaped by multiple, complementary psychological mechanisms. Favorable attitudes support continuance through evaluative judgments of usefulness and value, whereas engagement promotes persistence through experiential immersion. Satisfaction functions as the most proximal predictor, reflecting the cognitive confirmation of expectations derived from prior interactions. This finding corroborates recent studies identifying attitude as a key determinant of long-term adoption in generative AI contexts (Jo, 2023), the role of deep engagement in reducing re-engagement costs through immersive task involvement (Dmello et al., 2024), and the dominant influence of satisfaction in preventing discontinuance in mobile learning environments (Ulfiah et al., 2025). The alignment of these results with global studies confirms that the psychological mechanisms driving retention are robust across different educational technologies. In the Vietnamese context, where strong societal expectations regarding foreign language proficiency coexist with high discontinuance rates in self-directed learning applications, these findings offer an important interpretive insight. They indicate that sustained use of AI-based language learning tools is closely tied to learners' subjective experiences of enjoyment, immersion, and overall fulfillment. Rather than being driven solely by external pressure or functional incentives, continuance intention appears to emerge when learners perceive the learning process itself as intrinsically rewarding and psychologically satisfying.

ASYMMETRICAL MODERATING EFFECTS OF PERCEIVED RISK

The most novel and theoretically significant findings emerge from the asymmetrical moderation effects of perceived risk. The study found support for H16 and H18, confirming that perceived risk acts as a powerful "cognitive veto" on the evaluative pathways to retention. This indicates that a learner's subjective assessment of uncertainty (e.g., regarding data privacy, performance accuracy, or even wasted time) creates a "cognitive conflict" (Kaur & Arora, 2021; X. Xu et al., 2025). This result strongly aligns with prior research (Ha et al., 2024; Y. Liu et al., 2024), which demonstrates that high apprehension can sever the link between positive evaluations and future intentions. Essentially, even if a learner thinks the tool is good (attitude) or was satisfied in the past (satisfaction), a high perceived risk introduces a rational "but …" ("… is it safe?" "… is it really accurate?") that stops them from committing to future use. This is the "cool," rational part of the brain weighing pros and cons. This finding, while not novel, is the essential "control" that sets the stage for the real novel finding of this study.

The rejection of H17, however, presents a novel insight. This finding indicates that the positive relationship between learner engagement and continuance intention is not weakened by perceived risk. This result is in contrast to the theoretical propositions of prior research, such as S. Xu et al. (2024) and Yang and Rui (2025), who posited that this pathway would be equally fragile. This divergence is not a statistical anomaly; it reveals a fundamental psychological boundary. Attitude and satisfaction are "cool" cognitive, evaluative judgments. When a learner is in this rational mindset, they are susceptible to other rational inputs like perceived risk. Engagement, by contrast, is a "hot," intrinsically rewarding state of immersion and "flow," an interpretation strongly supported by work on immersive states from Dmello et al. (2024) and A. Lu et al. (2022). The rejection of H17 strongly suggests that when learners are deeply engaged, they are focused on immediate task fulfillment, leaving little cognitive space for abstract concerns about future risk. This psychological boundary may be particularly pronounced in Vietnam, where English proficiency is closely tied to upward mobility, career prospects, and global competitiveness. High motivation makes engagement more absorbing and shields it from risk-related hesitations. This finding indicates that the experiential pathway is not simply parallel to the rational pathway; it is more robust and less susceptible to uncertainty.

IMPLICATIONS

THEORETICAL IMPLICATIONS

This study makes several significant theoretical contributions by applying and extending the SOR framework of Mehrabian and Russell (1974) to explain the AI language tutor continuance process in e-learning. The study conceptualizes AI tutor service quality as the external stimulus and advances the organism component by modeling learners' internal states as a dual-process mechanism. Specifically, attitude represents a cognitive–evaluative response, while engagement captures an experiential and behavioral response. The response, continuance intention, is subsequently theorized as the downstream outcome of these complementary internal states. This structured application of the SOR framework clarifies how technological service cues are translated into sustained usage intentions and enriches the psychological explanation of learner–technology interaction.

This research advances the field by moving beyond a monolithic treatment of "service quality" and adopting a multidimensional perspective. Extending established service and e-service quality frameworks and recent developments in e-learning research (Al-Fraihat et al., 2020; Kataria & Rajput, 2025), the study decomposes AI tutor service quality into five distinct dimensions: aesthetics, control, personalization, responsiveness, and reliability. The findings demonstrate that each dimension functions as a significant antecedent influencing both learners' evaluative judgments (attitude) and their active involvement in the learning process (engagement). These results challenge simplified assumptions that specific AI features affect only attitudinal or behavioral responses. Instead, they suggest that continuance in AI-assisted learning emerges from an integrated service experience that combines functional effectiveness, interactive support, and experiential appeal.

Furthermore, a central contribution of this work is the theorization and validation of a dual-engine model within the organism stage. Instead of conceptualizing the learner's internal state as a single construct, this study establishes two parallel psychological processes. It demonstrates that retention is driven simultaneously by a "cool" cognitive-evaluative engine (a positive attitude) and a "hot" experiential-affective engine (deep engagement). The findings confirm that both pathways are potent drivers of the learner's summative evaluation (satisfaction) and their ultimate continuance intention. This enriches existing behavioral models by proposing that learners are concurrently rational evaluators and immersive participants, and that loyalty can be formed through both dispassionate judgment and intrinsically rewarding experience.

The most significant theoretical contribution is the introduction of perceived risk as an asymmetrical moderator, which charts a complex interplay between rational calculation and experiential immersion. The findings reveal that risk functions as a "cognitive veto" that successfully attenuates the influence of the "cool" cognitive-evaluative path and the final summative judgment on retention. In stark contrast, the study finds that the "hot" experiential path (engagement) is uniquely resilient to the negative effects of perceived risk. This novel finding proposes a resilience of flow phenomenon, theorizing that a state of deep engagement may crowd out or render non-salient the abstract calculations of risk. This challenges the assumption that risk is a universal deterrent, suggesting instead that the engagement-based, experiential pathway is a more robust and durable driver of loyalty in high-uncertainty contexts, such as the adoption of nascent AI technologies.

Practical Implications

From a practical perspective, this study's validated framework provides a clear, evidence-based blueprint for ed-tech developers, instructional designers, product managers, and language education providers. The findings move beyond general recommendations, pinpointing specific, high-impact design levers that can be manipulated to foster the positive attitudes and deep engagement necessary for long-term learner retention. This model serves as an actionable guide for strategic investment in AI tutor development and pedagogical implementation.

The strong, confirmed influence of reliability and aesthetics translates into two non-negotiable, foundational investment areas. First, to enhance reliability, which underpins all learner trust, managers must prioritize pedagogical accuracy. This means allocating resources for rigorous content validation, such as using certified language professionals to audit AI-generated content and feedback. Implementing transparent features, such as confidence scores for AI-generated corrections or clear channels for human-expert escalation, can build trust and manage learner expectations. Second, to leverage aesthetics, managers must treat user interface and user experience (UI/UX) design not as a cosmetic afterthought but as a core functional driver of motivation. The findings mandate investment in professional visual and interaction design to create an inviting, intuitive, and non-intimidating learning environment. This design is not decoration; it is a crucial feature that lowers the initial affective barrier to learning and serves as the hook that pulls the learner into the educational process.

The findings regarding control and personalization underscore the importance of shifting AI tutor design away from rigid, opaque systems toward architectures that support learner agency. Consistent with Siebert et al. (2023), who emphasized the necessity of combining high automation with meaningful human control in reliable AI systems, this study extends their framework to the language learning context by operationalizing "control" through concrete, user-facing features. While the foundational strategy emphasizes the necessity of user oversight to prevent alienation, we specifically propose implementing interactive dashboards that allow learners to select topics, sliders to adjust the pace of new material, and clear options to skip or review modules. Such features transform the AI from a "rigid instructor" to a "flexible partner," effectively satisfying the learner's need for autonomy. With respect to personalization, the findings indicate that superficial customization is insufficient to sustain continued use. Effective personalization requires investment in adaptive algorithms capable of continuously assessing learners' proficiency and dynamically adjusting content difficulty. Such capability reduces language learning anxiety associated with standardized instruction and prevents disengagement caused by content that is either overly challenging or insufficiently stimulating.

The robust support for responsiveness highlights the critical importance of the tactical, in-the-moment interaction loop. While personalization represents the long-term learning strategy, responsiveness is the short-term tactic that keeps learners in a state of flow. Practically, this requires investment in AI models capable of providing immediate, contextual, and constructive feedback. For instance, when a learner makes a grammatical error, a responsive system provides an instant, non-judgmental correction and a brief, clear explanation, rather than ignoring the error or flagging it for later review. This extends to support systems as well; managers should invest in 24/7 AI-powered chatbots that can answer procedural or basic content questions instantly, preventing minor frustrations from escalating into reasons for abandoning the platform.

The validation of the dual-engine model provides a powerful strategic framework for learner retention. Managers should not rely on a single strategy but must develop a two-pronged approach to nurture both the "cool" rational and "hot" experiential pathways to loyalty. To nurture the "attitude" path (the learner's "inner reviewer"), platforms should implement features that appeal to cognitive, goal-oriented evaluation. This includes clear progress-tracking dashboards, "milestone" badges, shareable certificates of completion, and testimonials from other successful learners. To nurture the engagement path (the learner's "inner doer"), platforms must invest in features that foster intrinsic motivation and flow. This includes gamification (e.g., points, leaderboards), narrative-based lessons (e.g., solving a mystery using the new language), and immersive, interactive scenarios (e.g., AI-powered role-playing with a virtual native speaker). These features make the process of learning, not just the outcome, its own reward.

The study further reveals an asymmetric role of perceived risk, offering important implications for strategic resource allocation in AI-driven education services. The findings suggest the need for a dual strategic approach that balances risk mitigation with engagement enhancement. From a defensive perspective, perceived risk emerges as a strong inhibitor that can weaken the influence of favorable attitudes and prior satisfaction on continuance intention, thereby highlighting the importance of a risk-mitigation strategy. Accordingly, companies should prioritize transparent data governance practices, clearly articulated terms of service, and independent security audits to address concerns related to privacy and system reliability. At the same time, the relative resilience of engagement to perceived risk highlights the importance of a complementary offensive strategy focused on fostering deep user engagement. This suggests that users who experience high levels of immersion are more likely to sustain long-term use and display greater loyalty, even in the presence of residual risk concerns. While the defensive strategy (risk mitigation) prevents a company from losing users, the offensive strategy (engagement maximization) enables it to win and keep them. This offensive approach extends Beyari's (2025) strategic framework, which argues that, in an era of escalating privacy anxieties, sustainable loyalty cannot be achieved through functional safeguards alone but requires the cultivation of emotionally resonant, immersive user experiences. By prioritizing investments in features that strengthen engagement, firms can build a more durable user base whose commitment is less susceptible to abstract risk evaluations. In this regard, deeply engaged learners represent a platform's most valuable strategic asset, as their continued use is driven more by experiential value than by risk avoidance considerations.

LIMITATIONS AND RECOMMENDATIONS

While this study provides a foundational model, its limitations offer clear directions for future inquiry. First, the investigation treats language learning monolithically, without differentiating by the specific target language being studied. This general approach may mask significant variances, as the perceived importance of factors like aesthetics or responsiveness might differ substantially for learners of structurally distinct languages, such as Japanese versus French. Future work should test the model's validity across specific linguistic cohorts. Second, the reliance on a cross-sectional methodology captures only a single, static snapshot of learner perceptions. This method is insufficient for tracking the evolution of learner attitudes, as factors like engagement and satisfaction may shift dramatically after an initial novelty period. A longitudinal design is needed to map these dynamic trajectories and their impact on long-term use. Finally, the framework's terminal variable is continuance intention to use, not a direct measure of educational success. A satisfying and engaging user experience is valuable, but it does not guarantee that actual learning has occurred. Subsequent research must connect these system quality factors and learner perceptions to tangible learning outcomes, such as measured proficiency gains or task performance, to ascertain the AI tutor's true pedagogical efficacy.

CONCLUSION

This investigation offers an analysis of the factors driving long-term learner retention of AI language tutors, employing the SOR paradigm. The study presents a comprehensive model that deconstructs service quality into five key attributes (aesthetics, control, personalization, responsiveness, and reliability), examining their influence on learners' internal psychological states, which consequently shape their behavioral intentions. To test the research objectives, a quantitative approach was adopted, gathering survey data from 771 experienced users of AI-driven language applications. The proposed conceptual framework and its associated hypotheses were subsequently analyzed using PLS-SEM, yielding significant advancements in understanding the learner's psychological journey and providing an evidence-based blueprint for educational technology design.

The empirical results demonstrate that all five service quality dimensions function as critical stimuli, exerting significant positive effects on both learner attitude and engagement. Among these, personalization emerges as the most influential stimulus, exerting the strongest effects on both attitude and engagement, highlighting its central role in shaping learners' initial psychological responses. Within the organismic stage, the analysis reveals that engagement operates as the most powerful internal state, generating the strongest downstream impact on satisfaction and a robust influence on continuance intention, thereby confirming the dominance of the experiential pathway over the attitudinal one in sustaining long-term learner commitment. Furthermore, the study identifies perceived risk as the most consequential moderator, significantly weakening the effects of attitude and satisfaction on continuance intention, while leaving the engagement pathway unaffected. This asymmetric moderating pattern underscores both the vulnerability of evaluative judgments under conditions of uncertainty and the remarkable robustness of experiential engagement in driving learner retention.

Key theoretical contributions stemming from this research include the validation of a dual-engine model of retention and the introduction of the resilience of flow phenomenon. For practitioners, the findings advocate for a dual defensive-offensive strategy: simultaneously mitigating user risk (a defensive measure) while prioritizing investments in engagement-driving features (an offensive measure) to build a more resilient user base. Nevertheless, the study's conclusions must be considered in light of its limitations. The reliance on a cross-sectional design provides only a static snapshot of learner perceptions, and the use of monolithic constructs for "risk" and "language" limits specificity. Moreover, the focus on self-reported intentions, rather than objective learning outcomes, means that pedagogical efficacy was not directly measured. Subsequent inquiries should therefore employ longitudinal methodologies, disaggregate these complex variables, and, most critically, connect user perceptions to measured proficiency gains.

In summary, this research underscores that in the dynamic field of educational technology, sustained user loyalty is a complex outcome that transcends mere functional approval. The findings illuminate the critical and parallel roles of both cognitive-evaluative judgments (attitude) and affective-experiential states (engagement) in cultivating the satisfaction that leads to long-term use. By providing a clear framework, this study offers developers and educators a strategic guide. It emphasizes that while mitigating risk is necessary, the most durable competitive advantage in the AI tutor market will be secured by designing an intrinsically rewarding, flow-inducing learning experience that fosters a uniquely resilient form of learner engagement.

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