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Artificial Intelligence Driven Personalized E-Learning Languages and Its Effects on User Engagement and Continuance Intention

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Abstract

This study explores the impacts of AI-based chatbots in personalized digital marketing in e-Learning languages platforms. Building on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), the study examines the effects of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit on users' continued use of AI chatbots. Satisfaction and engagement are also incorporated into the model to explain how technology-related perceptions translate into sustained interaction with AI-enabled learning services. A mixed-methods approach was adopted. Quantitative data were collected from 642 users and analyzed using PLS-SEM, including tests of reliability, validity, and mediation. The quantitative findings were complemented by semi-structured interviews with 20 practitioners and system usage data, which were analyzed thematically. The findings indicate that personalized and real-time chatbot interactions are associated with higher levels of engagement, satisfaction, and continuous usage intention. Satisfaction and habit have the strongest relationships with continuance, whereas engagement provides a weaker mediating pathway. The findings also suggest that cognitive and social acceptance factors do not consistently translate into continued use, while concerns about trust and privacy remain important considerations for sustained adoption. The study contributes to the literature by extending UTAUT2 beyond technology acceptance to include experiential and behavioral outcomes in AI-supported language learning. It also offers practical implications for developing chatbot-based marketing and learning services that are personalized, trustworthy, transparent, and responsive to users' needs.

Keywords: E- Learning languages; AI Chatbots; Digital marketing; UTAUT2; Engagement; Satisfaction; Continuous usage intention.

1 Introduction

AI is becoming a common aspect in the way in which companies interact with their consumers and offer them digital services. There is also an alteration in the expectations of users due to the growth in the number of digital platforms (Chatterjee et al., 2021; Matarazzo et al., 2021). Speed and convenience are still important aspects but the users also have new expectations in terms of tailoring to their personal requirements and offering relevant information during the interaction. Such developments have forced the organizations to look for other means apart from traditional ways of communication in order to interact with their customers through technology.

Conversational agents have evolved greatly since the creation of early chatbots which primarily responded to predefined questions. Conversational agents that are available now have the capacity to use Natural Leveraging Language Processing (NLLP), Machine Learning (ML), among other AI technologies, in understanding user queries and responding in a continuous conversation (Bavaresco et al., 2020; Feine et al., 2020). Therefore, their usefulness does not solely lie in automation. They can be used by organizations for providing information, guiding customers through their services, suggesting items, as well as keeping in touch following an interaction. Conversational agents research has broadened into fields such as retail, banking, tourism, healthcare, education, among others (Bavaresco et al., 2020; Mariani et al., 2023; Alkadi & Abed, 2025).

This point is especially interesting for digital marketing applications. A chatbot can be integrated into the user's experience, as it can answer questions, recommend products and services, offer personalized information, and provide assistance even after the purchase. The quality of such interactions may affect the user's perception of the technology itself and the company which developed it. As was proved by previous studies, communication attributes, such as responsiveness and other human-like behaviors in the conversation, may impact relational outcomes in conversations with conversational agents (Feine et al., 2020). On the

other hand, the emerging body of literature indicates that trust, quality of communication, the value provided to the user, and the utility of the interaction are key motivators of consumers' use of conversational technologies (Mariani et al., 2023).

One of the most fascinating contexts in which to examine these trends is that of education. Conversational technologies are becoming more common among digital language-learning services in addition to traditional means of learning. Chatbots, for instance, are capable of offering immediate feedback, conversation practice, tailored exercises based on the learner's progress, and assistance outside of the learning process (Huang & Rust, 2021; Jeon, 2024). In this context, an interaction could be seen to serve not only an educational but also a marketing purpose. While aiding a learner with their language practice, a chatbot could suggest supplementary materials or promote premium services.

Personalization plays an important role in this dynamic. The user will be more inclined to see the value of the digital solution if the content of the interaction is personalized to meet his or her requirements. This can be done using conversational AI solutions, which could make use of information gathered during past interactions and the present request to shape the conversation. Personalization of the service, however, cannot be the only criterion that can bring about a good user experience. Reliability, understandability, transparency and respect for privacy also need to be considered by the users when evaluating their experience. This point has been highlighted in the recent studies about conversational agents (Mariani et al., 2023).

One way that could be used to approach this problem is the theory of technology acceptance. Specifically, the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model was created to describe technology acceptance in terms of consumers. This model differs from the initial one because it takes into account hedonic motivation, price value, and habit besides the factors included in the original UTAUT (Venkatesh et al., 2012; Naji et al., 2026). Since the theory describes technology use from both utilitarian and hedonistic viewpoints, it can be considered applicable to conversational services, where people might use a service due to its usefulness, easy interaction, enjoyment, value, or mere habit. Moreover, the original UTAUT2 study showed the importance of the described extensions for explaining behavioral intention and technology use.

However, even though the application of the theory of UTAUT2 is rather beneficial for understanding the usage of the innovation, it is still poorly applied in terms of AI chatbots for personalized digital marketing in language learning contexts. The existing literature on chatbots is predominantly based on analysis of system properties, quality of the interaction, adoption, and particular aspects of user experience (Bavaresco et al., 2020; Mariani et al., 2023). Therefore, less focus is paid to the interplay of technology acceptance factors, satisfaction, and engagement in explanation of continuous usage in the environment where learning and marketing happen simultaneously. It is important to distinguish that acceptance of a chatbot at a certain point of time does not guarantee that people will continuously interact with it. Continuous use may require that the interaction remains useful, satisfactory, engaging, and trustworthy throughout the process. In this case, trust plays a crucial role. Conversational agents are able to collect and process users' preferences, interactions, achievements, and behavioral patterns. As the level of personalization increases, worries related to privacy, data processing, transparency, and reliability of the results may emerge. Such issues may affect users' attitude toward using the system and their willingness to engage with it in the future. The human-like communication may have both positive and negative effects on the continuous use. On the one hand, conversational behaviors lead to better relational outcomes. However, on the other hand, people expect higher degree of transparency and accuracy from systems that communicate more naturally (Feine et al., 2020).

The advent of generative AI makes this problem all the more topical. LLM-powered applications are capable of providing more context-aware and adaptive answers than numerous preceding rule-based solutions. This brings about both new possibilities for personalization and concerns with regard to accuracy, transparency, privacy, and the extent of dependency on AI-powered answers. Hence, the increasing research agenda on AI-powered conversational agents suggests that one should look into not just adoption but also factors fostering long-term engagement with such applications (Mariani et al., 2023).

In light of the above discussion, this research analyzes the use of AI chatbots in the personalized digital marketing of digital language learning applications. Specifically, this paper is set to explore the relationships between the variables defined by UTAUT2 and user engagement, satisfaction, and intention to continue using. This research goes beyond merely analyzing chatbot acceptance and explores the experience of interacting with the AI-based application over time.

The research has four major aims. First, it will explore the use of AI chatbots in digital marketing and personalized engagement on language learning platforms. Secondly, it will investigate whether or not UTAUT2 variables predict users' continued use intention. Thirdly, it will investigate the role of satisfaction and engagement as mediators between perceptions of technology and continuance intention. Lastly, it will investigate the possible influence of trust, personalization, interaction, and transparency on continuance intention towards AI-based technology. This research contributes to the existing body of knowledge by extending the application of UTAUT2 theory to a new and emerging context where education, digital marketing and conversational AI technology overlap. And as against to the previous researches that continuance will depend on technology acceptance, this research suggests that the effect of perception of technology on continuance will go through the experience process of users. And the findings will generate great practical implications for language learning platforms, and others, digital, products, and services, that intend to launch an AI chatbot successfully and transparently to users.

2 Theoretical background

2.1 AI Chatbots in digital Marketing

The adoption of AI chatbots has been revolutionize approach to digital marketing with their intelligent responses and scalable interactions that surpass the capabilities of conventional rule-based processes. NLLP, ML, and AI chatbots can interpret user queries, predict intentions, and generate context-aware and adaptive responses that continuously improve over time (Gnewuch et al., 2017; Ikumoro & Jawad, 2019). These systems offer several strategic advantages for digital marketing, including scalability and 24/7 availability (able to cope with thousands of real-time transactions across different time zones without fatigue or latency); personalization, achieved through analyzing user behavior, purchase history, preferences, and engagement patterns to deliver tailored recommendations, content, and guidance (Chung et al., 2020; Wang et al., 2026).

Chatbots offer operational advantages by reducing costs, providing 24/7 customer service, and handling high volumes of questions efficiently (Grewal et al., 2020). They can also provide valuable data on customer behavior, enabling segmentation, prediction, and best practice improvement for companies (Chatterjee et al., 2021). In language e-learning contexts, chatbots allow for conversational practice, the tailoring of feedback, and learner tracking while supporting recommendations, subscriptions, and retention of learners (Jeon, 2024).

Nevertheless, there is still much to explore in regards to long-term engagement, cross-cultural usage, and marketing benefits aside from technical and linguistic means (Wiboolyasarin et al., 2025).

2. 2 AI Chatbots in shaping user satisfaction engagement and continuance intention

Customer engagement refers to the extent to which consumers are cognitively, emotionally, and behaviorally involved in their interactions with a brand or platform (Brodie et al., 2011; Hollebeek et al., 2024). In digital marketing and language learning, engagement is fostered through personalized, real-time, and interactive experiences. AI chatbots support learner engagement through three key affordances: timely feedback, personalized learning, and interactive communication, which facilitate participation, motivation, and sustained learning (Huang et al., 2022). Highlighting findings from research in digital marketing, it can also be taken to suggest that conversational interaction fostered by AI-enabled technologies can mean positive consumer engagement, perceived value and richer human AI relationships (Hollebeek et al., 2024). Bridging pedagogical capability with marketing aim, chatbots can this way be able to support learners' interaction and learning possibilities; and simultaneously build active brand relationships.

Real Time Interactivity: AI chatbots can respond to users at their own speed, reducing frustration, waiting, and other issues. These responses are called Real Time Interactivity (RTI). Learner-focused interactivity provides immediate, personalized feedback on exercises, pronunciation, comprehension, and grammar, supporting skill development and learner engagement (Gnewuch et al., 2017). In digital marketing, chatbot responsiveness improves customer satisfaction, reduces disengagement, and strengthens perceptions of reliability and personalized service, fostering more engaging user experiences.

Through using AI Chatbots, behavioral analytics, and understanding of second language, AI chatbots can offer highly customized products and recommendations. Chatbot can create and deliver customized learning, exercise, and marketing to individual user profiles by customizing content based on user's progresses preferences behavioral history, and preferences (Vorobyeva et al., 2025). Customized service interaction maximizes, perceived value of service, stimulating repeated usage and ultimately long term retention, subscription adoption, and conversion (Chung et al., 2020).

Using anthropomorphic signals (like humor, tone of voice, conversational language and play acting social behaviors) allows chatbots to interact in a human-like way, promoting trust, emotional bonds and branding attachment (Feine et al., 2019). In language learning contexts, learners are more motivated to persist with their learning, feel more supported, understood, and socially connected, and derive greater enjoyment from the experience by such anthropomorphism (Richet, 2025). That means, by appealing to social presence, chatbots convert transactional interactions into sociable and relational experiences.

Service providers create integrated experiences so consumers are engaged across various web sites, mobile applications, social media services and messaging platforms without experience an unpredictable discontinuity. They benefit from being able to engage with the company/brand across multiple devices and in multiple contexts; this helps to reinforce the company's branding efforts, it also improves accessibility for users (Grewal et al., 2021). For language learning

product or services this helps flexible learning schedules, enable continuous practice and marketers can deliver relevant promotion messages at just the right time.

AI chatbots in digital language learning could serve two functions learning and engagement. They provide interactive language practice and personalized help to users, and it is proven that they have a positive impact on EFL learners' behavioral, cognitive, and emotional engagement (Wang & Xue, 2024). Interestingly, in digital marketing the application of AI chatbots towards promoting products or services to consumers through online channels chatbots enabled conversational interaction could also lead to satisfaction and engagement, and have an effect on purchase intention and consumers' willingness to pay (Jiang et al., 2022). Presumably, the combination of a pedagogical and marketing function could help digital language-learning websites among other digital services maintain user engagement, besides generating retention and commercial value.

Even so, the constraints of AI chatbots' dependence on personalization pose serious ethical and privacy concerns. For instance, privacy fears and concerns can occur from over spread of data collection, over personalized communication, or lack of clarity around the utilization of a learner's information (Weber et al., 2020). So, transparent data practices, consent, and responsible management are imperative for user engagement, trust, and sustained use of AI powered educational marketing innovations.

2. 3 Adoption of the technology and the UTAUT2 construct.

To understand how AI chatbots have been implemented, an ample knowledge of theories, which justify adoption or continuance intention toward technology is needed. The Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) offers a model, which aims at pinpointing seven factors that influence technology acceptance, i. e. performance expectancy, effort expectancy, social influence, helping conditions, hedonic motivation, habit, and price value (Venkatesh et al., 2012). Several studies have revealed the effect that these factors have on can be perceived perception and the likelihood to adopt AI chatbots. One of these factors is effort expectancy, that is the perceived ease of use of the system. A system that is easy to access, controlled by users, and takes less cognitive effort is more tolerated while users generally expect to interact with it for a long time. It is known that, for the case of language learning, AI chatbots that are useful and fit the particular learning context offering step-by-step guidance based on explicit prompts or making students less frustrated by applying a clear interface for language learning processes are said to increase learners' engagement and users' perceptions of ease-of-use that lead to long-term usage (Wiboolyasarin et al. 2024; Wiboolyasarin et al., 2025). During social exchanges, if a learner finds that the AI chatbot does not present a challenge and is intuitive to use, they are expected to sustain an engaging, positive experience.

In the field of marketing where the adoption of AI chatbots also has been found to increase as the user-friendliness and the low cognitive load, such systems coexist with more positive consumers' responses. As reported, if consumers feel that the chatbot is easy to use, this can only improve their degrees of trust, identify the utility of a platform and provide the best customer experience (Chiu et al., 2023). As a case illustrated, easier-to-use retail and e-commerce AI chatbots is more probable to improve customer service, consumer loyalty and provide better products recommendations (Zhang, et al, 2024). The lower way that an application is tested to be simple and accessible it is more likely to be adopted also for marketing and shopping activities. Also, effort expectancy is associated to other effects of adoption

including usage-related effects of helping conditions and social influence. Enabling conditions, like stable internet or adequate technical support, help users interact with chatbot without any interference from the outside world; and social influence, coming from friends or/or best reviews or other third-party endorsement, has the power of encouraging users to try-and-adopt chatbot and keep on chatting if they experience until some extent that other might have had good chatting with it (Cataldo, et al., 2023). For the both pedagogic and marketing chatbots, social endorsement might acquire more interactions when users tend to believe it is both convenient-to-use and generally acceptable-by-others.

In addition, hedonic motivation, which refers to the enjoyment or pleasure from using a technology also may motivate sustained engagement with AI chatbots (Venkatesh et al., 2012). For example, more engaging activities like gamification, interactive stories, or even humor will make the user experience more fun and positive (Temel & Cesur, 2024). This is in particular relevant in language learning, since users like learning platforms that are rewarding and pleasurable, which leads to more positive and consistent habits (Guan, & Yang. 2026). Lastly, price value of the cost benefit tradeoff will affect the adoption of AI chatbots. Consumers compare perceived value of the chatbot interaction relative to the time and money they devote to the platform. Because of this, in digital marketing and language learning contexts, bots that deliver measurable value such as more rapid learning and more value-driven marketing can greatly improve user conversion and value (Du, & Daniel, 2024). If users can clearly see the added values of the chatbot either via the translated academic results or the personal customer service, it is more likely for them to consider the adoption to be worthwhile. Really, recent research indicated that UTAUT2 could be extended to the AI chatbot context to include trust, perceived personalization, privacy, and transparency. Trust have directly impact on the users' willingness to provide privacy information, to follow the recommendation and take cues from automated feedback (Huang et al., 2022). Perceived personalization, that the system upholds the users' needs or preferences, would also boost the engagement and satisfaction (Alsadoun & Alnasser, 2025), while in digital language learning, the learners would also disclose sensitive information including their learning issues, progress, and personal info (Weber et al., 2020).

2. 4 AI Chatbot implementation challenges

Notwithstanding their potential to support e-language learning and digital marketing, AI chatbots face technical, and operational challenges. Conversational limitations, including misunderstandings, incorrect contextual responses, and difficulty handling ambiguity, can reduce user confidence and engagement (Gnewuch et al., 2017).

Also, ethical challenges related to privacy and data security should be also addressed given that chatbots depend on a large amount of training data, including learners' private data like entire learning histories and identification of behavioral patterns (Weber et al., 2020). Another important issue is transparency, as users need to know that they make interactions with Chabots, not human beings (Luo et al., 2019). Finally, challenges related to algorithmic bias and fairness should also be considered, since the chatbots could inherit biases if these are present in the training data, that’s why fueling cultural biases, discrimination, and offensive responses in multi-lingual computer mediated learning contexts (Binns et al., 2017). So, it is also important that iterations of the training process involve pre-empting strategies aimed to identify, rectify, or lessen potential learned biases from the training data. Same here, ethical marketing featuring chatbot functionality is also a key to be followed, should personalization of responses become

manipulative, mainly if it is over-focused on profit-making priorities than learner's learning needs (Crawford & Paglen, 2021).

Both of these issues are mostly critical in a digital language learning environment, as the learners' sensitive data and learner benefits are directly affected. A transparent design, ethically governed data management and responsible personalization practices will be critical in ensuring learners' trust and continuance intention.

The literature on AI chatbots in both digital marketing and language learning has led me to a multidimensional structure that relates the adoption of this technology, engagement, and the achievement of marketing/language learning goals. The proposed view highlights the relationship among adoption determinants, engagement processes, management contexts and deployment strategies to optimize benefits.

Adoption drivers include UTAUT2 performance expectancy, effort expectancy, social influence, enabling condition, hedonic motivation, habit, and price value (Venkatesh et al., 2012). Recent work shows the importance of extending these constructs to include trust, privacy, transparency, and perceived personalization in contexts involving sensitive information, as in digital language learning or e-commerce (Huang et al., 2022). User trust is paramount in enabling a willingness to disclose information over time; transparency benefits users when it alleviates perceptions of manipulation or bias, and perceived personalization leads to higher user satisfaction when learning, recommendations, and content is tailored to their preferences.

Engagement Mechanisms: information processing can be increased by the perceived responsiveness, anthropomorphism, and personalized content and recommendations of new AI chatbots (Feine et al., 2019). Responsiveness brings rapid, relevant, and consistent feedback that promotes users conscious and unconscious cognitive and emotional attachment, whereas anthropomorphic features of conversational tone, humor, and empathy intensify social presence to build attachments and promote trust. On top of that, personalization increases behavioral engagement with personalized content, feedback, and recommendations that promote repeated engagement, purchases/subscriptions, or browsing/progression. Such mechanisms enable value-based interactions that boost learning deliverables to marketing deliverables.

Marketing and Learning Results: Engagement works as a mediator between chatbot usage and results related to loyalty satisfaction retention and continuance usage intention (Chung et al (Chung et al., 2020; Mariani et al., 2020). In language learning sites, engagement with AI chatbot can enable language learning outcome and continuance (Wang et al., 2025). In commercial sites, chatbot service quality can help in strengthening trust, e-brand loyalty, e-WOM (Shahzad et al., 2024). AI chatbots have the capacity to generate value both educational and commercial.

Contextual Moderators Adoption and participation depends on cross-cutting influences like culture, ethics, and regulations. Also, cultural norms and standards influence expectation of conversational formats, tone, and degree of formality, which in turn, predict satisfaction and perceived value (Kbaier et al. 2025). Ethics including fairness, counteracting bias and respectful personalization also influence trust and willingness to participate.

Strategic Integration: The proper implementation on various channels and touchpoints can majorly boost the value of AI chatbots. For instance, omni channel arrangement on mobile app

browser social media and messaging device could enable messages, reviews, and guides to effectively attain user through a scalable, integrated, and persist systems (Grewal et al., 2021). By adopting such integration, the sales, branding, and accessibilities would be benefited; meanwhile, transition of knowledge can be sustained in educational context.

The findings from these literature review can also be summarized and further illustrated by the conceptual system shown in Figure 1. The figure illustrates how the critical factors influencing AI chatbot adoption, like UTAUT2 variables trust perceived personalization and privacy concerns, are connected to user acceptance, satisfaction, and continuous usage intentions, with satisfaction and engagement mediating the influence of adoption factors on long-term behavioral outcomes in digital language learning experiences.

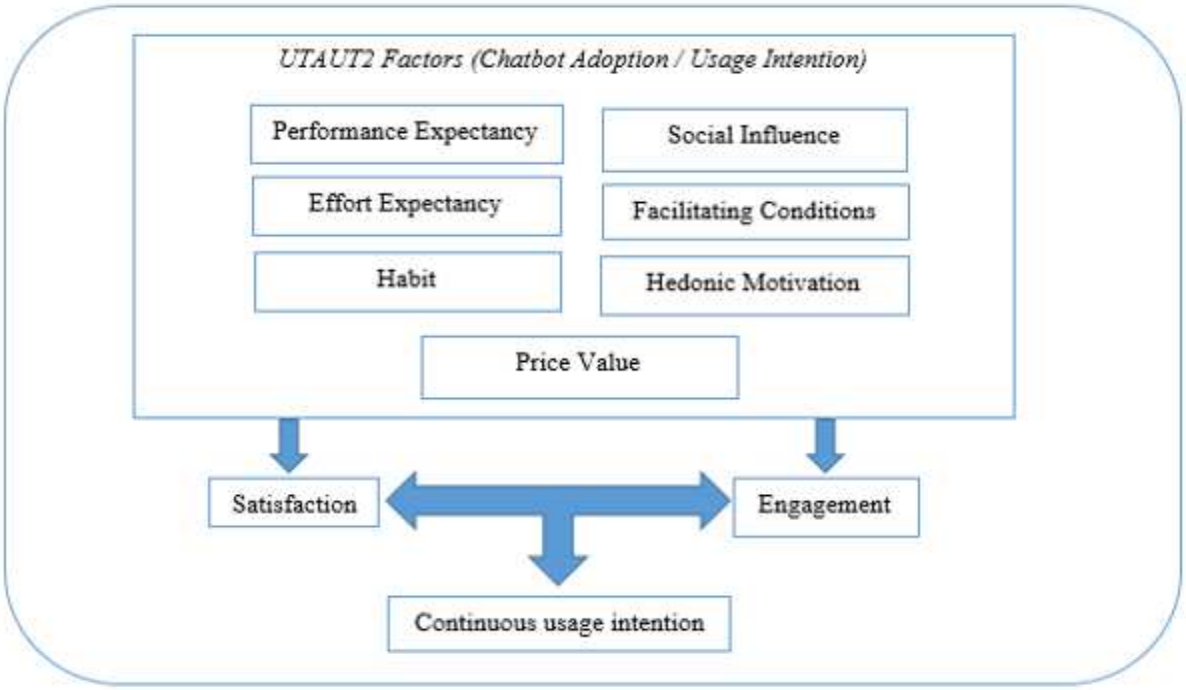


Fig. 1 The model UTAUT2 of the chatbot adoption in language learning platforms

The framework highlights the role of AI chatbots in personalized marketing and language learning, where adoption drivers, engagement, and contextual factors influence satisfaction and continuance intention. Ethics, privacy, and transparency are also essential for sustaining user trust and long-term chatbot use. Accordingly, the following hypotheses are proposed:

H1a: Performance expectancy positively influences user satisfaction.
H1b: Performance expectancy positively influences continuous usage intention.
H2a: Effort expectancy positively influences user satisfaction.
H2b: Effort expectancy positively influences continuous usage intention.
H3a: User satisfaction mediates the relationship between performance expectancy and continuous usage intention.
H3b: User satisfaction mediates the relationship between effort expectancy and continuous usage intention.
H4a: Facilitating conditions positively influence user engagement.
H4b: User engagement positively influences continuous usage intention.

H4c: User engagement mediates the relationship between facilitating conditions and continuous usage intention.
H5a: Hedonic motivation positively influences user engagement.
H5b: User engagement positively influences continuous usage intention.
H5c: Engagement mediates the relationship between hedonic motivation and continuous usage intention.
H6a: Habit positively influences user engagement.
H6b: User engagement positively influences continuous usage intention.
H6c: User engagement mediates the relationship between habit and continuous usage intention.
H7a: Price value positively influences user engagement.
H7b: User engagement positively influences continuous usage intention.
H7c: User engagement mediates the relationship between price value and continuous usage intention.
H8a: Social influence positively influences user engagement.
H8b: User engagement positively influences continuous usage intention.
H8c: User engagement mediates the relationship between social influence and continuous usage intention.

3 Methodology

The researcher applies a mixed-methods research design to investigate approach of AI chatbot adoption, user engagement and satisfaction, and marketing resulting in digital context, mainly in the language learning industry. Use of both quantitative and qualitative method not only allows for a comprehensive investigation of users' perceptions, behavioral intentions, and industry professionals' strategic considerations but also improves validity as the quantitative data can test theoretical relationships statistically and the qualitative data can provide contextual information from experienced professionals.

3.1 Research Design

Mixed-methods will be used in this research to investigate the clients' AI chatbot adoption, users' use, satisfaction, and marketing outputs in personalized language learning. The quantitative part will be conducted through a web-based questionnaire based on UTAUT2 model, and data will be analyzed using descriptive statistics, reliability, and validity tests, as well as by employing Partial Least Squares-Structural Equation Modeling (PLS-SEM). The qualitative part will be conducted through semi-structured interviews with digital marketing experts and educational technologists on the chatbot implementations, users' uses, customer journey process, data security and privacy, and ethical issues. Results from the two approaches will be integrated to give a thick description of the clients' AI chatbot adoption and outputs (Creswell et al., 2018).

3.2 Sample and Participants

The quantitative research conducted included a survey of 642 consumers with both chatbot practitioner and user perspectives. The sampling included participants from e-learning services with a stratified random sampling technique whereby predetermined group categories were identified and a sample was representatively taken from each group to ensuring counteracting bias, maximizing presentation of diverse perspectives and increasing reliability, validity, and generalizability of the findings to the context of educational chatbot adoption and interaction.

Also a total of 20 practitioners and system usage data, which were analyzed thematically and used to provide additional insight into the observed relationships.

3.3 Measurement

This study employed validated measurement scales adapted from prior research to ensure high reliability and construct validity. UTAUT2 constructs performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, and price value were measured using items from Venkatesh et al. (2012). Marketing and learning outcomes, including engagement, satisfaction, and continuous usage intention, were assessed using established scales from Brodie et al. (2011). The items were apprehended using seven-point Likert scales (1 = strongly disagree, 7 = strongly agree) adapted from Huang et al. (2022) and Rahim et al. (2022).

A pilot test involving 30 participants from the target population was conducted to assess the clarity, relevance, and comprehensibility of the survey items. Participants were selected based on their eligibility and experience with AI-powered language-learning chatbots. Their feedback was used to refine the questionnaire before the main data collection. All constructs exceeded the recommended threshold for internal consistency, with Cronbach's alpha values above 0.70.

Table 1 Measurement Items and Reliability for Educational Chatbots

Construct	Item Code	Measurement Item
Performance Expectancy (PE)	PE1	I find the educational chatbot useful in my learning activities.
	PE2	Using the educational chatbot increases my chances of understanding important concepts.
	PE3	Using the educational chatbot helps me complete study tasks more quickly.
	PE4	I can save time when I use the educational chatbot for learning or research.
Effort expectancy (EE)	EE1	Learning how to use the educational chatbot is easy for me.
	EE2	Interacting with the educational chatbot is clear and understandable.
	EE3	Using the educational chatbot is easy for me.
	EE4	It is easy for me to become skillful at using the educational chatbot.
Social Influence (SI)	SI1	People who are important to me think that I should use educational chatbots.
	SI2	People who influence my behavior think that I should use educational chatbots.
	SI3	People whose opinions I value prefer that I use educational chatbots.
Facilitating Conditions (FC)	FC1	I have the necessary resources to use the educational chatbot.
	FC2	I have the necessary knowledge to use the educational chatbot effectively.
	FC3	Support is available if I experience difficulties while using the educational chatbot.
	FC4	Using the educational chatbot fits well with the way I like to study or learn.
Hedonic Motivation (HM)	HM1	Using the educational chatbot is enjoyable.
	HM2	I have fun interacting with the educational chatbot.
	HM3	I find using the educational chatbot engaging.
	HM4	Interacting with the educational chatbot makes learning more enjoyable.
Price Value (PV)	PV1	Using the educational chatbot is worth the time and effort.
	PV2	Using the educational chatbot helps me achieve better learning outcomes at low cost.
	PV3	Overall, the benefits of using the educational chatbot outweigh any effort or time spent.
	PV4	I consider using the educational chatbot a good value for the time I invest.
Habit (HT)	HT1	Using the educational chatbot has become a habit for me.
	HT2	I use the educational chatbot automatically without much thinking.
	HT3	I feel naturally inclined to use the educational chatbot when learning.
	HT4	Using the educational chatbot is part of my regular learning routine.
Continuos usage intention (CUI)	CUI1	I intend to continue using the educational chatbot in the future.
	CUI2	I will frequently use the educational chatbot for learning or study purposes.
	CUI3	I plan to use the educational chatbot whenever I need academic information or help.
	CUI4	I am likely to recommend the educational chatbot to others.
Engagement (EN)	EN1	I spend a significant amount of time interacting with the educational chatbot.
	EN2	I actively participate in learning activities using the educational chatbot.
	EN3	I feel focused and absorbed when using the educational chatbot.
	EN4	I regularly explore different features of the educational chatbot to enhance my learning.
Satisfaction (SAT)	SAT1	I am satisfied with my overall experience using the educational chatbot
	SAT2	The educational chatbot meets my expectations for learning support.
	SAT3	I am pleased with the quality of responses and feedback from the educational chatbot.
	SAT4	Using the educational chatbot contributes positively to my learning experience.

In addition, the measurement model integrated UTAUT2 with personalization, and privacy concerns to provide a comprehensive explanation of chatbot adoption in learning and service environments. UTAUT2 predictors supported by personalization are expected to enhance adoption intentions, whereas privacy concerns are anticipated to weaken them. Adoption is proposed to activate engagement, which subsequently drives satisfaction and continuous usage intention. Thus, engagement serves as a central mediating mechanism linking technology adoption to behavioral outcomes. The measurement items used in this study align closely with the extended UTAUT2 framework (Venkatesh et al., 2012). Performance expectancy reflects perceived usefulness; effort expectancy captures perceived ease of use; social influence measures normative pressure; and facilitating conditions assess the availability of technological and organizational support. Hedonic motivation captures intrinsic enjoyment, price value represents the perceived trade-off between benefits and costs, and habit reflects the automaticity of repeated use. Behavioral intention serves as the key adoption metric.

To evaluate user experience and post-adoption behavior, the study incorporated engagement, satisfaction, and loyalty. Engagement items reflected active, focused interaction with the chatbot, drawing from established e-learning engagement frameworks (Fredricks et al., 2004; Dixson, 2015). Satisfaction was measured using well-validated technology satisfaction scales (Bhattacherjee, 2001; Sun et al., 2008). Continuous usage intention, recommendation, and long-term commitment, based on e-learning literature (Chiu et al., 2006; Kim et al., 2009). Together, these constructs provide a robust and theoretically grounded foundation for analyzing chatbot acceptance and user experience. Table 1 below presents the measurement items used in the study.

To ensure the reliability and validity of the measurement items for the educational chatbot constructs, we assessed internal consistency, composite reliability, and convergent validity. Cronbach's Alpha (α) was employed to evaluate the internal consistency of each construct, with values above 0.7 considered acceptable, indicating that the items consistently measure the same underlying concept (Nunnally & Bernstein, 1994). Composite Reliability (CR) was used as a complementary measure of internal consistency, with values exceeding 0.7 demonstrating satisfactory construct reliability (Hai et al., 2019). Average Variance Extracted (AVE) was calculated to assess convergent validity, with values above 0.5, indicating that the items capture the underlying latent construct adequately (Fornell & Larcker, 1981). The example values presented in Table 1 are consistent with prior research applying UTAUT2 in educational and technological contexts, including studies on educational chatbots and AI-based learning tools (Grassini et al., 2024).

3.4 Data Collection and Analysis

The study employed a mixed-methods approach to provide a comprehensive understanding of educational AI chatbot adoption. For the quantitative component, data were analyzed using PLS SEM to examine relationships among UTAUT2 constructs e-learning outcomes. Mediation and moderation analyses were also conducted to investigate indirect effects and the influence of contextual factors such as prior experience or cultural differences. The measurement model was rigorously evaluated for reliability, convergent and discriminant validity to ensure robustness (Hair et al., 2022). For the qualitative component, interviews were transcribed and analyzed using thematic analysis, identifying key themes related to adoption strategies, operational challenges, ethical considerations, and success factors. These qualitative findings were triangulated with quantitative results to enrich the understanding of chatbot effectiveness and user adoption.

4 Discussion and Interpretation of Results

As shown in Table 1, the measurement items were carefully adapted from established theories in information systems and educational technology to assess the main determinants of educational chatbot adoption and continued usage. The study incorporates key constructs that are largely derived from the UTAUT2 and supported by continuance intention and user experience models. The selected theoretical foundations have been widely applied and validated in previous research on digital learning technologies and user behavior (Venkatesh et al., 2012; Bhattacherjee, 2001).

The assessment of the measurement model was conducted using PLS-SEM, with indicator loadings reported in table 2 to evaluate reliability and convergent validity. The findings indicate that the majority of item loadings exceed the recommended threshold of 0.70, thereby confirming strong indicator reliability and satisfactory convergent validity. For example, constructs such as performance expectancy (0.722–0.884), effort expectancy (0.716–0.903), facilitating conditions (0.901–0.936), price value (0.832–0.922), satisfaction (0.698–0.893), and social influence (0.784–0.925) demonstrated consistently robust loadings. These results suggest that respondents exhibited a clear and consistent understanding of these constructs when evaluating educational chatbots. According to Hair et al. (2022), loadings above 0.70 indicate that constructs explain a substantial proportion of variance in their indicators, thus ensuring measurement reliability. With respect to continuous usage intention, most indicators display strong loadings (CUI1 = 0.942; CUI4 = 0.944), reflecting a high level of user commitment to sustained chatbot usage. Although CUI2 (0.684) fell slightly below the recommended threshold, it remained within the acceptable range for exploratory research and does not compromise the overall construct validity. This is consistent with methodological guidelines suggesting that indicators with loadings between 0.60 and 0.70 may be retained when supported by adequate composite reliability (Hair et al., 2022).

The engagement and hedonic motivation constructs exhibited acceptable but relatively heterogeneous loadings. Engagement ranged from 0.724 to 0.871, while hedonic motivation ranged from 0.680 to 0.884. The slightly lower loading of HM2 (0.680) and some engagement items (ENG1–ENG3) can be attributed to the inherently subjective and experiential nature of these constructs. User engagement and enjoyment are influenced by individual differences such as motivation, digital literacy, and prior interaction with AI-based tools. This variability is well-documented in the literature, where affective constructs tend to show greater dispersion, compared to cognitive constructs like usefulness and ease of use (Venkatesh et al., 2012; Liu et al., 2022).

The Habit construct presented an acceptable reliability. While HT1 (0.976) and HT4 (0.974) demonstrated excellent reliability, HT2 (0.670) and HT3 (0.773) showed moderate loadings. Within the UTAUT2 framework, habit reflects automatic behavior developed through repeated usage. The observed variation suggests that chatbot usage among respondents is still evolving toward habitual behavior but has not yet reached full automaticity. This transitional state is theoretically meaningful, particularly in the context of emerging educational technologies, where repeated exposure over time is necessary for habit formation. Therefore, while the construct remains acceptable, future research may refine these items to better capture behavioral automaticity.

A notable limitation is observed in the Price Value construct, where PV4 (0.582) fell below the recommended threshold, whereas PV1–PV3 exhibited strong loadings. This indicates that the

perception of "value for time invested" is less salient for respondents. A plausible explanation lies in the nature of educational chatbots, which are often freely accessible or institutionally provided. Consequently, users may evaluate value primarily in terms of learning effectiveness and performance outcomes rather than time or economic cost. This interpretation aligns with prior studies emphasizing that perceived value in educational technologies is driven more by utility than by cost considerations (Venkatesh et al., 2012; Al-Emran et al., 2020).

Table 2 Measurement Items Loadings

	Continuous usage intention	Effort expectancy	Engagement	Facilitating Conditions	Hedonic Motivation	Habit	Performance Expectancy	Price Value	Satisfaction	Social Influence
CUI1	0.942									
CUI2	0.684									
CUI3	0.778									
CUI4	0.944									
EE1		0.839								
EE2		0.716								
EE3		0.903								
EE4		0.892								
ENG1			0.729							
ENG2			0.725							
ENG3			0.724							
ENG4			0.871							
FC1				0.932						
FC2				0.901						
FC3				0.931						
FC4				0.936						
HM1					0.828					
HM2					0.680					
HM3					0.883					
HM4					0.884					
HT1						0.976				
HT2						0.670				
HT3						0.773				
HT4						0.974				
PE1							0.796			
PE2							0.722			
PE3							0.829			
PE4							0.884			
PV1								0.897		
PV2								0.922		
PV3								0.832		
PV4								0.582		
SAT1									0.893	
SAT2									0.698	
SAT3									0.745	
SAT4									0.876	
SI1										0.784
SI2										0.794
SI3										0.925

Overall, the results from Table 1, Table 2, and Figure 2 confirm that the measurement model demonstrates strong reliability and convergent validity across most constructs. Core determinants such as perceived usefulness, ease of use, facilitating conditions, and satisfaction were robustly captured and consistent with established theoretical models.

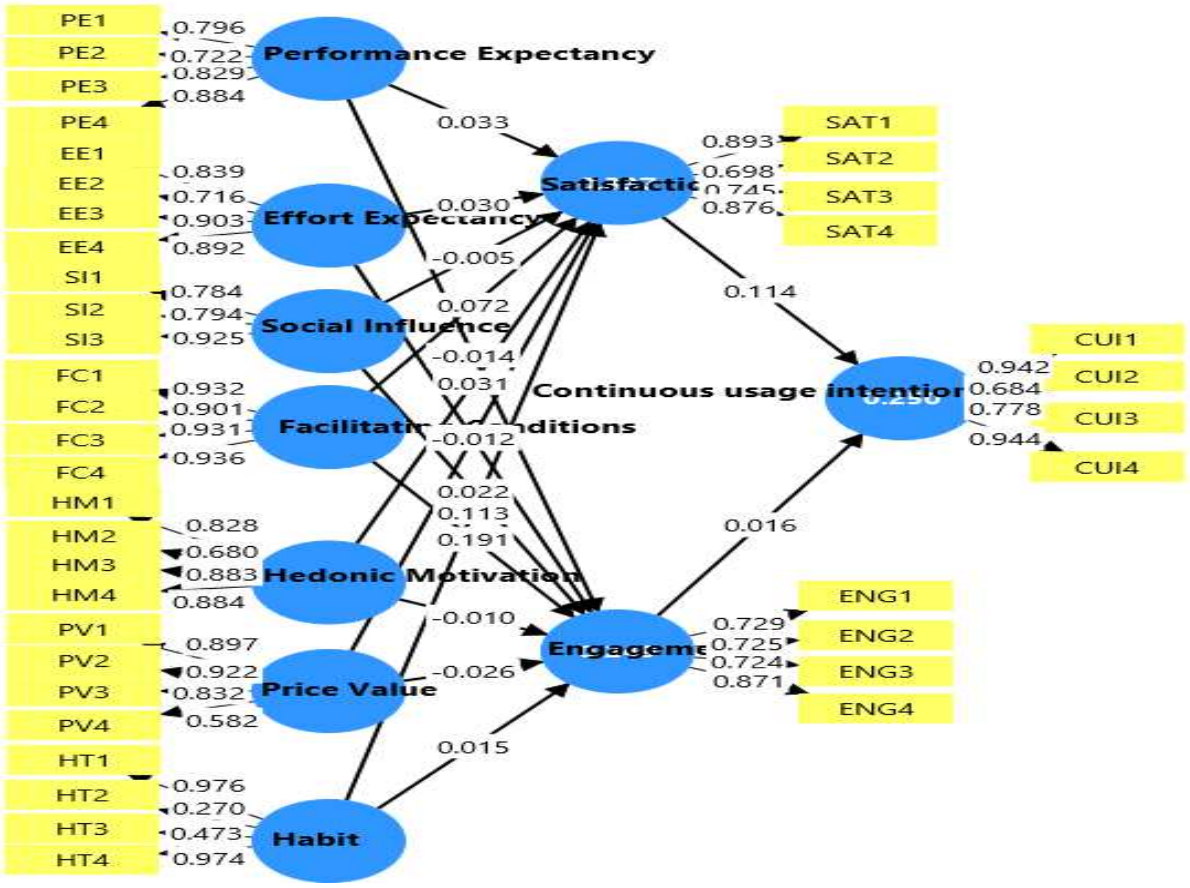


Fig. 2 Covariances

The results described in Table 3 below indicate that all constructs exhibited robust psychometric quality within the PLS-SEM framework. Reliability was assessed using Cronbach's alpha and composite reliability indices (rho_a and rho_c), while convergent validity was evaluated through the Average Variance Extracted (AVE), in accordance with the criteria recommended by Hair et al. (2022). The findings show that all measurement indicators met the accepted threshold values, confirming adequate internal consistency and convergent validity. Consequently, the measurement model can be considered reliable and appropriate for subsequent structural model assessment.

Table 3 Construct Reliability and Validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Continuous usage intention	0.860	0.881	0.907	0.713
Effort expectancy	0.866	0.905	0.905	0.707
Engagement	0.764	0.801	0.848	0.585
Facilitating Conditions	0.944	0.944	0.960	0.856
Habit	0.736	0.977	0.801	0.549
Hedonic Motivation	0.842	0.853	0.893	0.677
Performance Expectancy	0.836	0.878	0.884	0.656
Price Value	0.855	0.869	0.888	0.671
Satisfaction	0.820	0.847	0.881	0.652
Social Influence	0.789	0.892	0.875	0.701

In terms of internal consistency reliability, all Cronbach's alpha values exceeded the acceptable threshold of 0.70, ranging from 0.736 for Habit to 0.944 for Facilitating Conditions. This

indicates that all constructs consistently measured their intended theoretical dimensions. Composite reliability values further supported this result, with rho_c values ranging from 0.801 (Engagement) to 0.960 (Facilitating Conditions), confirming strong internal consistency across all latent variables. However, the very high value for Facilitating Conditions (0.960) suggests potential redundancy among indicators, as values above 0.95 may indicate overlapping measurement items.

Regarding convergent validity, all AVE values exceeded the recommended minimum of 0.50, ranging from 0.549 (Habit) to 0.856 (Facilitating Conditions). This confirms that each construct explains a sufficient proportion of variance in its indicators. Strong convergent validity is particularly evident in Continuous Usage Intention (0.713), Effort expectancy (0.707), and Social Influence (0.701), indicating well-aligned measurement items. At the construct level, Facilitating Conditions demonstrated the strongest psychometric performance ($\alpha = 0.944$; CR = 0.960; AVE = 0.856), reflecting a highly stable and well-defined construct. In contrast, Habit showed the weakest performance ($\alpha = 0.736$; AVE = 0.549), although it remained within acceptable limits. This suggests that habitual behavior toward educational chatbot use is still developing and not yet fully established among respondents. Similarly, Engagement (AVE = 0.585) showed moderate convergent validity, reflecting the affective and experiential nature of user engagement in digital learning environments. This aligns with prior research indicating that emotional and behavioral constructs tend to be more variable compared to cognitive constructs such as performance expectancy and effort expectancy (Venkatesh et al., 2012). Other constructs, including Hedonic Motivation, Price Value, Satisfaction, and Social Influence, also demonstrated satisfactory validity and reliability, confirming that the measurement items appropriately capture their theoretical dimensions.

Overall, the results in Table 3 confirm that the measurement model is robust, reliable, and valid. While minor concerns exist regarding potential redundancy in Facilitating Conditions and relatively lower performance in Habit and Engagement, these do not compromise the overall quality of the model. Instead, they highlight areas for future refinement, particularly in emerging contexts such as educational chatbot adoption, where user behavior is still evolving.

The results reported in Table 4 and Figure 3 below evaluate the discriminant validity of the study constructs through inter-construct correlation analysis. Discriminant validity is generally considered satisfactory when the correlations among constructs remain below established threshold values, typically 0.70 for moderate associations and 0.85 under more stringent criteria, as recommended in structural equation modeling research (Hair et al., 2022).

Table 4 Discriminant validity

	1	2	3	4	5	6	7	8	9
1. Continuous usage intention									
2. Effort expectancy	0.200								
3. Engagement	0.138	0.221							
4. Facilitating Conditions	0.111	0.048	0.485						
5. Habit	0.931	0.343	0.212	0.132					
6. Hedonic Motivation	0.199	1.137	0.212	0.053	0.347				
7. Performance Expectancy	0.177	1.062	0.206	0.044	0.303	1.102			
8. Price Value	0.227	0.340	0.170	0.161	0.894	0.352	0.329		
9. Satisfaction	0.583	0.188	0.290	0.194	0.510	0.197	0.202	0.158	
10. Social Influence	0.303	0.316	0.193	0.239	0.582	0.334	0.293	0.524	0.101

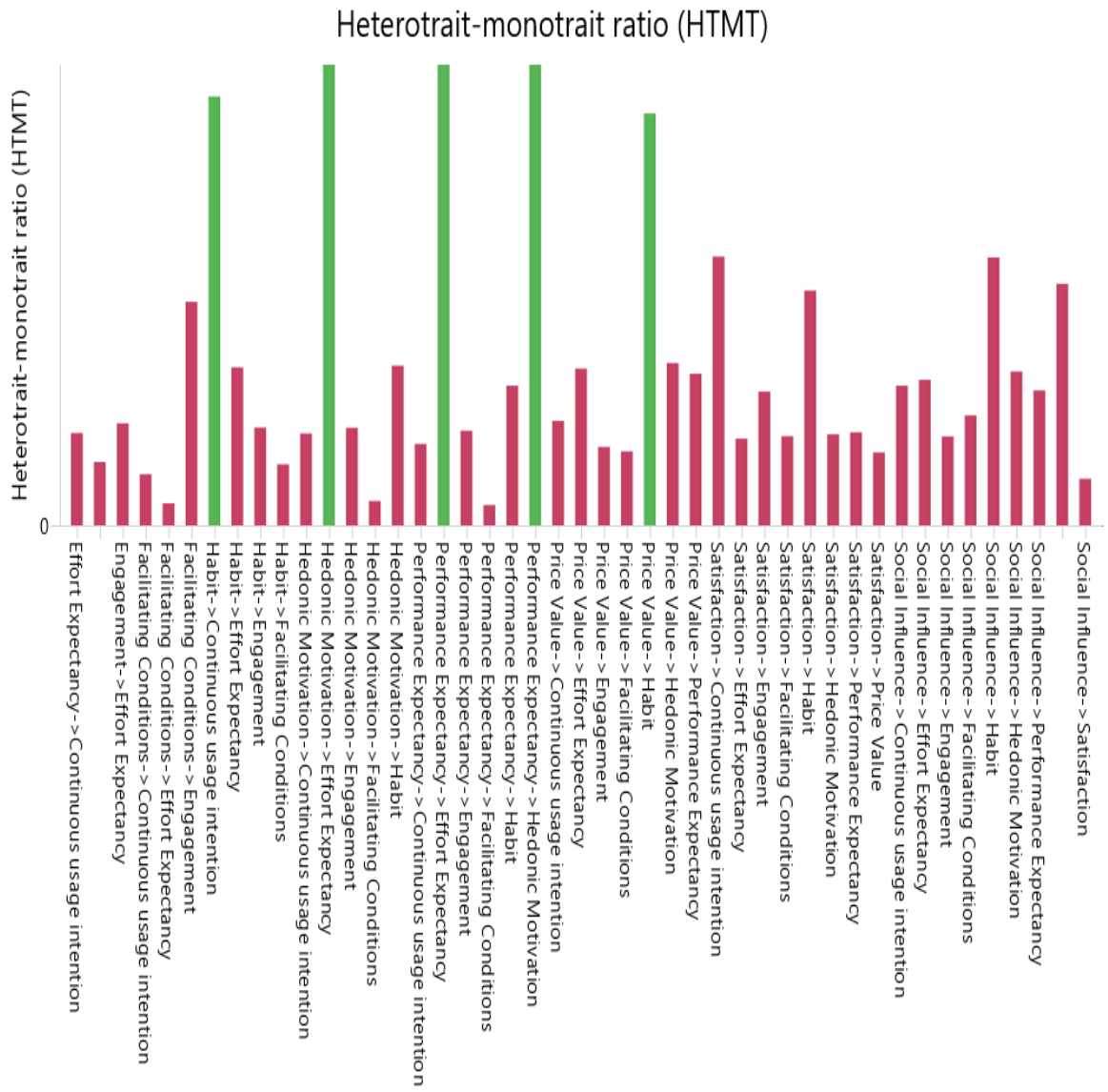


Fig. 3 Discriminant Validity Chart

Overall, most constructs demonstrate acceptable discriminant validity as the majority of correlation coefficients are relatively low (e.g., Continuous Usage Intention with Effort expectancy = 0.200; Engagement = 0.138; Facilitating Conditions = 0.111). These results indicate that the constructs are conceptually distinct and measure different underlying theoretical dimensions. However, some concerns emerge regarding potential multicollinearity or overlap between certain constructs. Notably, Habit showed a very strong correlation with Continuous Usage Intention (0.931), suggesting a substantial conceptual overlap between habitual behavior and continued usage behavior. Similarly, high correlations were observed between Hedonic Motivation and Effort expectancy (1.137), and Performance Expectancy (1.102), which exceed the acceptable range and may indicate issues such as common method bias, measurement redundancy, or data scaling problems. Additionally, Price Value also showed a relatively high correlation with Habit (0.894), further suggesting overlap between behavioral and value-based constructs. Moderate correlations were observed between Satisfaction and Habit (0.510), Satisfaction and Social Influence (0.101–0.583 range), and

Social Influence with Habit (0.582), which remain within acceptable limits but still indicate meaningful relationships among user experience-related constructs.

Taken together, while the general pattern supports discriminant validity for most constructs, the presence of several unusually high correlations suggests the need for further diagnostic testing. In particular, the values exceeding 1.0 (e.g., 1.137; 1.102) are statistically problematic and may indicate errors in output (e.g., non-standardized estimates, HTMT matrix misreporting, or multi-collinearity issues). Therefore, it is strongly recommended to re-examine the results using more robust discriminant validity criteria such as the Heterotrait–Monotrait Ratio (HTMT) as proposed by Henseler et al. (2015), which is considered more reliable than simple cross-loadings or correlation inspection.

In conclusion, most constructs demonstrate adequate discriminant validity. Table 5 reports the goodness-of-fit indices for both the saturated and estimated models within the structural equation modeling framework. Model adequacy was evaluated using several widely accepted PLS-SEM fit indicators, including the Standardized Root Mean Square Residual (SRMR), squared Euclidean distance (d_ULS), geodesic distance (d_G), and Chi-square statistics. These measures provide a comprehensive assessment of the extent to which the proposed model adequately represents the observed data.

Table 5 Model fit

Fit Index	Saturated Model	Estimated Model	Acceptable Values (Guidelines)
SRMR	0.146	0.166	≤ 0.08 (acceptable ≤ 0.10)
d_ULS	16.633	21.478	Lower than bootstrap HI95
d_G	10.584	11.651	Lower than bootstrap HI95
Chi-square	19,486.556	20,784.377	No fixed threshold (sample-size sensitive)

The Standardized Root Mean Square Residual (SRMR) values for both the saturated model (0.146) and the estimated model (0.166) exceeded the commonly recommended threshold of 0.08, indicating a moderate level of model misfit. Similarly, the d_ULS (16.633; 21.478) and d_G (10.584; 11.651) values indicate notable differences between the empirical and model-implied matrices, further supporting the presence of some degree of model misfit. These indices do not have fixed universal cut-off values but are typically interpreted through bootstrap-based comparisons; however, the relatively high values here suggest that the model could benefit from refinement. Moreover, the Chi-square values for both models (19,486.556 for the saturated model and 20,784.377 for the estimated model) are high (Figure 7), which is common in large sample sizes and complex models.

4.1 Interpretation of Direct Effects

The direct effects results reported in Tables 6 and 7 and Figure 5, within the PLS-SEM framework, provide evidence of the immediate relationships between the study constructs and the endogenous variables, particularly Continuous Usage Intention, Engagement, and Satisfaction. Overall, the findings reveal that the structural model is primarily driven by Satisfaction and Habit, while other constructs exert comparatively weaker direct influences.

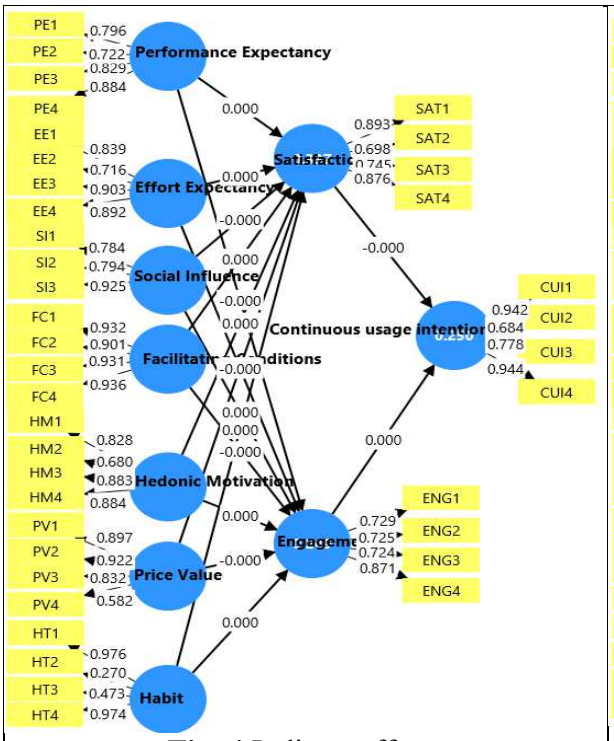


Fig. 4 Indirect effects

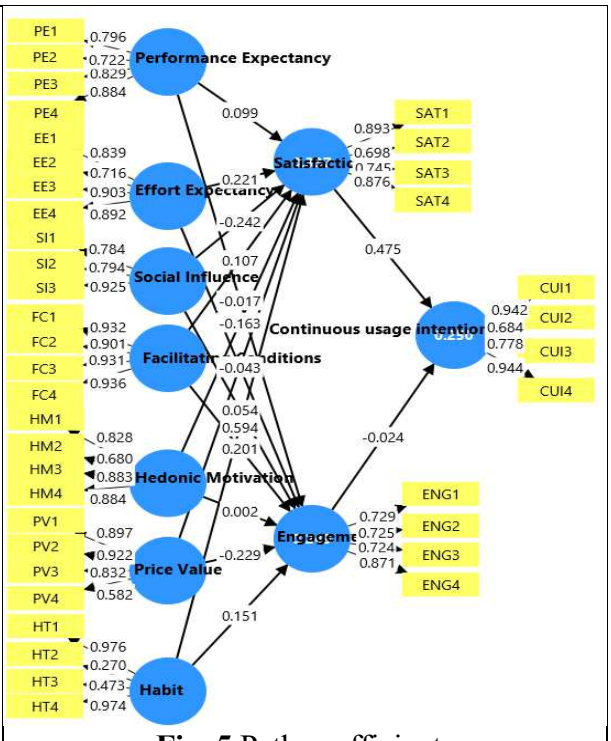


Fig. 5 Path coefficients

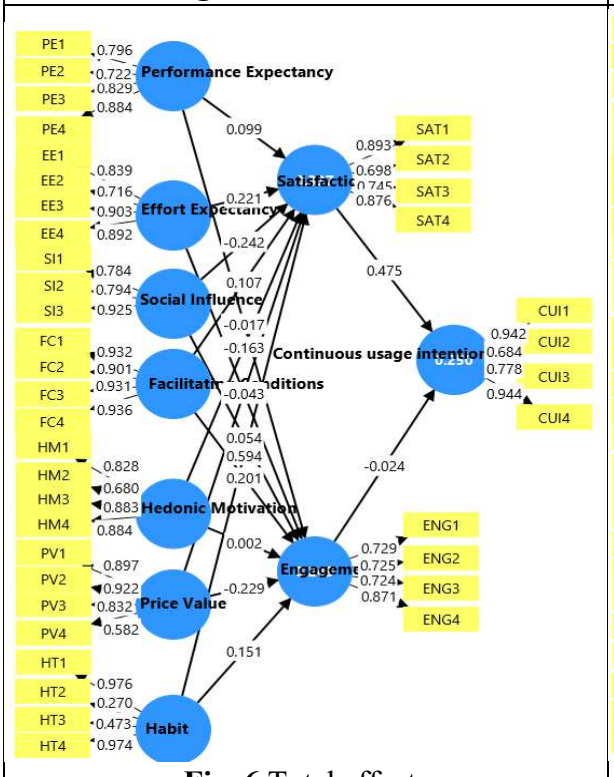


Fig. 6 Total effects

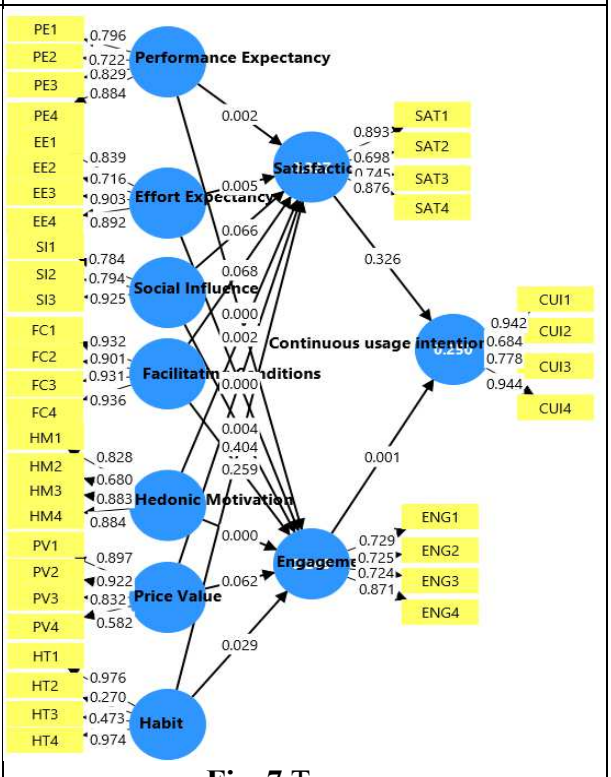


Fig. 7 T-square

Overall, the model shows an acceptable global fit, and the measurement and structural relationships are theoretically sound. However, further refinement such as re-specifying constructs, removing redundant indicators, and reassessing latent relationships could improve parsimony and explanatory power (Figure 6).

Table 6 Post-hoc power analysis

	Path coefficients	Alpha 1%	Alpha 5%
Effort expectancy -> Engagement	-0.043	0.106	0.286
Effort expectancy -> Satisfaction	0.221	0.999	1.000
Engagement -> Continuous usage intention	-0.024	0.043	0.151
Facilitating Conditions -> Engagement	0.201	0.997	1.000
Facilitating Conditions -> Satisfaction	0.107	0.654	0.859
Habit -> Engagement	0.151	0.933	0.985
Habit -> Satisfaction	0.594	1.000	1.000
Hedonic Motivation -> Engagement	0.002	0.011	0.056
Hedonic Motivation -> Satisfaction	-0.163	0.963	0.993
Performance Expectancy -> Engagement	-0.017	0.028	0.111
Performance Expectancy -> Satisfaction	0.099	0.571	0.805
Price Value -> Engagement	-0.229	1.000	1.000
Price Value -> Satisfaction	0.014	0.025	0.099
Satisfaction -> Continuous usage intention	0.475	1.000	1.000
Social Influence -> Engagement	0.054	0.169	0.391
Social Influence -> Satisfaction	-0.242	1.000	1.000

Table 7 Total effets

	Continuous usage intention	Engagement	Satisfaction
Continuos usage intention			
Effort expectancy	0.106	-0.043	0.221
Engagement	-0.024		
Facilitating Conditions	0.046	0.201	0.107
Habit	0.278	0.151	0.594
Hedonic Motivation	-0.077	0.002	-0.163
Performance Expectancy	0.047	-0.017	0.099
Price Value	0.012	-0.229	0.014
Satisfaction	0.475		
Social Influence	-0.116	0.054	-0.242

The most influential direct predictor of continuous usage intention is satisfaction ($\beta = 0.475$)**,** confirming its central role in post-adoption behavior. This finding strongly supports the expectation confirmation model (Bhattacherjee, 2001), which posits that users' continuance decisions are primarily shaped by their satisfaction following actual system use. Similarly, Habit ($\beta = 0.278$) demonstrated a strong positive direct effect, indicating that repeated and automatic use significantly reinforces continued usage behavior. This is consistent with IS continuance literature, which emphasizes that habit formation gradually replaces conscious decision-making in long-term technology use (Limayem et al., 2007).

Cognitive-based concepts as effort expectancy, performance expectancy, and facilitating conditions exhibited weak direct effects ($\beta \approx 0.046–0.106$) on Continuous Usage Intention. This intends that ease of use, usefulness, and support infrastructure are more relevant at the implementation stage rather than at the continuance stage, where users rely more on experience-based evaluations such as satisfaction.

Affective and social constructs showed limited or even negative direct effects. Hedonic motivation (-0.077) and Social influence (-0.116) did not contribute positively to continuance intention. This reveals that enjoyment and social influences are not enough for long term use and may actually decrease the level of autonomy or intrinsic satisfaction in some instances.

Among antecedents of satisfaction**,** habit showed the strongest effect ($\beta = 0.594$)**,** highlighting that repeated use leads to stronger positive evaluation of the system. In contrast, Engagement received relatively weak and inconsistent direct effects from most predictors, suggesting it is not a stable or dominant outcome variable in this model.

Overall, the direct effects highlight satisfaction and habit as key drivers of continuous usage intention, while cognitive, emotional, and social factors play a secondary role. This finding is consistent with expectation–confirmation theory and the information systems continuance Model, which emphasize the importance of post-adoption satisfaction and habitual use in sustaining technology continuance (Bhattacherjee, 2001; Limayem et al., 2007).

4.2 Interpretation of Indirect Effects

The indirect effects presented in Tables 8 and 9 and Figure 4 below provide insight into the mediating mechanisms through which exogenous variables influence Continuous Usage Intention. The results highlight that Satisfaction is the dominant mediating pathway, whereas Engagement plays a negligible role.

Table 8 Total Indirect Effects

	Continuous usage intention
Continuous usage intention	
Effort expectancy	0.106
Engagement	
Facilitating Conditions	0.046
Habit	0.278
Hedonic Motivation	-0.077
Performance Expectancy	0.047
Price Value	0.012
Satisfaction	
Social Influence	-0.116

Table 9 Specific Indirect Effects

	Specific indirect effects
Facilitating Conditions -> Engagement -> Continuous usage intention	-0.005
Social Influence -> Satisfaction -> Continuous usage intention	-0.115
Habit -> Engagement -> Continuous usage intention	-0.004
Hedonic Motivation -> Engagement -> Continuous usage intention	-0.000
Performance Expectancy -> Engagement -> Continuous usage intention	0.000
Price Value -> Engagement -> Continuous usage intention	0.006
Social Influence -> Engagement -> Continuous usage intention	-0.001
Effort expectancy -> Satisfaction -> Continuous usage intention	0.105
Facilitating Conditions -> Satisfaction -> Continuous usage intention	0.051
Habit -> Satisfaction -> Continuous usage intention	0.282
Hedonic Motivation -> Satisfaction -> Continuous usage intention	-0.077
Performance Expectancy -> Satisfaction -> Continuous us age intention	0.047
Effort expectancy -> Engagement -> Continuous usage intention	0.001
Price Value -> Satisfaction -> Continuous usage intention	0.007

Satisfaction emerged as the central mediator linking key antecedents to continuous usage intention. The strongest indirect effect was observed for habit, satisfaction, continuous usage intention ($\beta = 0.282$), indicating that habitual use is associated with greater satisfaction and, consequently, stronger continuance intention. This finding is consistent with the expectation confirmation model, which identifies satisfaction as an important mechanism underlying continued technology use (Bhattacherjee, 2001). Additional indirect effects were observed for effort expectancy ($\beta = 0.105$), facilitating conditions ($\beta = 0.051$), and performance expectancy ($\beta = 0.047$), suggesting that these factors contribute to continuance partly through satisfaction.

In contrast, engagement showed negligible mediation effects, including the pathway from hedonic motivation through engagement to continuous usage intention ($\beta \approx 0.000$). Social influence also exhibited a negative indirect effect through satisfaction ($\beta = -0.116$), indicating an inverse association with continuance through this pathway. Overall, the findings highlight satisfaction as a key mechanism underlying continuous usage intention, with habit showing the

strongest indirect effect, while engagement appears to play a limited mediating role in the proposed model. This indicates that social pressure may reduce satisfaction or create psychological resistance, thereby weakening continuance intention. Such findings are consistent with self-determination theory (Deci & Ryan, 1985), which suggests that external pressure can undermine intrinsic motivation.

Overall, the indirect effects indicate that continuous usage intention is primarily associated with satisfaction and habit formation, while engagement and social influence show weaker or inconsistent mediating effects.

5 Conclusion

The findings highlight satisfaction and habit as key post-adoption factors associated with continuous usage intention in educational AI Chatbots. Satisfaction reflects users' evaluations of previous experiences, while habit reflects repeated usage patterns, supporting continuance-oriented perspectives within the expectation confirmation model and utaut2 (Bhattacherjee, 2001; Venkatesh et al., 2012). In contrast, engagement showed a limited mediating role, while social influence exhibited an inverse indirect relationship through satisfaction, suggesting that these factors may operate differently in educational Chatbot contexts.

From a managerial perspective, the findings emphasize user-centered Chatbot design, reliable performance, accurate responses, personalized learning support, and ease of interaction. Consistent integration into learners' routines may facilitate continued use. Privacy, transparency, fairness, and data security should also remain central to responsible ai implementation. Human–ai collaboration can further complement instructors by combining automated, personalized assistance with human expertise.

Future research should examine the development of satisfaction and habit over time using longitudinal and cross-cultural designs. Greater attention is also needed to generative AI and large language model-based Chatbots, particularly their effects on trust, perceived competence, social presence, satisfaction, and continued engagement (Bavaresco et al., 2020; Mariani et al., 2023). Conversational characteristics also warrant further investigation. Pescatore et al. (2026) show that semantic congruence between emojis and accompanying text can influence perceived Chatbot competence and satisfaction, highlighting the relevance of conversational style and design.

Overall, the findings indicate that satisfaction and habit are important mechanisms associated with continued Chatbot use, whereas engagement has a more limited mediating role. The results highlight the importance of consistent user value, user-centered design, responsible ai practices, and effective Human–AI collaboration. In conclusion, educational Chatbot effectiveness depends not only on technological capabilities but also on user experience, satisfaction, and repeated usage patterns. Integrating reliable Chatbot interactions into learners' regular activities, supported by ethical governance and Human–AI collaboration, can promote sustainable use of conversational AI in personalized language e-learning.

Declarations

Data Availability Statement

The datasets generated and/or analyses during the current study are not publicly available due to privacy and confidentiality considerations concerning the study participants but are available from the corresponding author on reasonable request."

Ethics Approval Statement

This study was approved by the Marketing Department Research Committee at Northern Border University, Saudi Arabia, and was conducted in accordance with the ethical guidelines and regulations of the committee and the principles of the Declaration of Helsinki, where applicable.

Consent to Participate Statement

Informed consent was obtained from all participants involved in the study prior to their participation. Participation was voluntary, and participants were informed about the purpose of the research and the confidentiality of their responses.

Consent for Publication
Not applicable.

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