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AI CHATBOTS AS LEARNING COMPANIONS: A CONSUMER BEHAVIOUR PERSPECTIVE ON STUDENT ADOPTION IN HIGHER EDUCATION

Pavithra V[1], Dr. Kavitha Muthukumaran[2]

[1]Assistant Professor, Department of Management Studies, DMI College of Engineering, Chennai, Tamil Nadu, India
pavithra2550015@ssn.edu.in
[2]Associate Professor, Department of Management Studies,
Sri Sivasubramaniya Nadar College of Engineering, Chennai, Tamil Nadu, India

Correspondence: Kavitha Muthukumaran, mkavitha@ssn.edu.in

Abstract
This study examines student adoption of AI chatbots in higher education from a consumer behaviour perspective. As AI chatbots increasingly function as digital learning companions, students' intention to adopt them depends not only on technological features but also on psychological and contextual factors. Drawing on the Stimulus–Organism–Response (SOR) framework, this study investigates how perceived accuracy, perceived usefulness, perceived responsiveness, and perceived personalization influence adoption intention through trust and self-efficacy. The study also examines the moderating role of the learning environment in strengthening the relationship between psychological states and adoption intention. Data collected from 632 higher education students were analysed using Structural Equation Modelling. The findings show that perceived usefulness is the most consistent predictor of trust and self-efficacy, while trust and self-efficacy significantly influence adoption intention. Perceived responsiveness and personalization showed selective effects, whereas perceived accuracy did not significantly influence trust or self-efficacy in the direct model. The results further indicate that a supportive learning environment strengthens the relationship between psychological readiness and adoption intention. The results further indicate that a supportive learning environment strengthens the effect of psychological readiness on adoption intention. The study contributes to consumer behaviour and educational technology literature by showing that AI chatbot adoption is shaped by the interaction of system perceptions, psychological mechanisms, and contextual support.

Keywords: AI chatbots, consumer behaviour, student adoption, adoption intention, trust, self-efficacy, digital learning, SOR framework, higher education.

1. Introduction

Artificial Intelligence (AI) has transformed various sectors, with its inclusion in teaching technologies among the most remarkable. Recently, AI-integrated, teacher-assistant chatbots have been embedded in numerous digital learning environments (Ilieva et al. 2023; Labadze et al., 2023). These offer students real-time support for their learning activities, enable personalized learning, improve the inclusivity of learning opportunities, and allow students to engage with learning technologies in more diverse ways (Stöhr et al., 2024; Jo, 2024).

The adoption rate of AI-based chatbots is low among students, even with the clear potential of these technologies. Learning and performance outcomes are enhanced with technology, but acceptance is driven by psychological factors, including trust, and the perception that the technology is useful and belief in the individual's capability to use the tool (self-efficacy) (Biswas et al., 2025; Eşiyok et al., 2024). It is evident that technology adoption is driven by the psychological system and can't solely be attributed to design system (Shahzad et al. 2024; Stöhr et al. 2024).

In the context of digital learning, students can be viewed as consumers of AI-enabled learning services. Their decision to adopt AI chatbots is shaped by perceived value, usefulness, responsiveness, personalization, trust, and confidence in using the technology. Therefore, AI chatbot adoption is not merely a technological issue but also a consumer behaviour issue, as students evaluate, accept, resist, and continue using these tools based on their perceived benefits and psychological readiness.

In this regard, students' assessment of the accuracy, usefulness, responsiveness and ability of AI chatbots to provide personalized learning (Park & Lee, 2023; Jo, 2024) are the primary drivers of the perception of the trust and efficacy of the technology and their intent to adopt the use of chatbots for learning (Durak & Onan, 2024; Eşiyok et al., 2024).

This research uses the Stimulus–Organism–Response (SOR) model as an underpinning theory. This model concerns how an external stimulus impacts an organism's internal state and subsequently drives a behavioral response (Duong, 2024; Ye et al., 2022). In this research, the stimulus is AI Chatbots, the organism is trust and self-efficacy, and the response is the intention to adopt.

Shahzad and colleagues (2024) and Zhao and colleagues (2025) argue that trust and self-efficacy operate in the AI context such that trust helps to mitigate uncertainty when dealing with AI, and self-efficacy helps users feel confident to engage with the AI. Current research, however, does not articulate a complete model that accounts for technology, psychological mechanisms, and contextual factors in an articulated way (McGrath et al., 2024; Stöhr et al., 2024). Notably, the interaction between trust, self-efficacy and the intention to adopt AI Chatbots, with the consideration of the learning environment as a moderating variable, has received limited attention (Rahman et al., 2025; Saihi et al., 2024).

An articulated model is needed to demonstrate how AI Chatbots are perceived in different learning environments and the extent to which they influence the intention to adopt through psychological mechanisms.

Although prior studies have examined AI chatbot adoption using technology acceptance models, limited attention has been given to how students behave as digital learning consumers. In particular, there is a need to understand how students evaluate AI chatbot features, how these evaluations create trust and self-efficacy, and how these psychological states lead to adoption intention. This study addresses this gap by applying the SOR framework to explain student adoption of AI chatbots from a consumer behaviour perspective.

The primary aim of this study is to examine students' adoption behaviour toward AI chatbots in higher education from a consumer behaviour perspective by applying the SOR framework. Specifically, the study examines how perceived AI chatbot characteristics, namely accuracy, usefulness, responsiveness, and personalization, influence trust and self-efficacy. It further analyses how trust and self-efficacy affect students' adoption intention toward AI chatbots. In addition, the study investigates the mediating role of trust and self-efficacy in the relationship between perceived AI chatbot characteristics and adoption intention and assesses the moderating role of learning environment in the relationship between psychological factors and adoption intention.

2. Literature Review and Hypothesis Development

2.1 Theoretical Foundation

This study relies on the Stimulus–Organism–Response (SOR) framework which outlines the process by which external stimuli (S) affect internal cognitive and emotional states (O), and subsequently provoke behavioural responses (R) (Duong, 2024; Loureiro et al., 2020; Ye et al., 2022). Initially, the SOR framework was developed in the field of environmental psychology but has since proliferated to retail, information systems and educational technology research. In higher education, it has been used to investigate students' online learning behaviour and their engagement in MOOCs, as well as the adoption of VR-based learning (Loh et al., 2021; Ye et al., 2022). Scholars affirm that the SOR framework is appropriate to examine AI-related technology and how it impacts learners' internal assessment and their intention to adopt such technology (Duong, 2024; McGrath et al., 2024).

In the adoption of AI chatbots, stimuli are the system features, trust and self-efficacy are internal states, and the intended behaviour is adoption. This framework is favoured over TAM and UTAUT as it incorporates both cognitive and emotional components, and also permits consideration of culture and context (Cheng et al., 2021; Duong, 2024).

The SOR framework is also widely relevant to consumer behaviour research because it explains how external stimuli influence internal psychological states and behavioural responses. In this study, AI chatbot characteristics act as external stimuli that influence students' internal evaluations, namely trust and self-efficacy. These psychological states then shape adoption intention. This makes the SOR framework suitable for explaining student adoption of AI chatbots as a form of digital consumer behaviour in higher education.

AI Chatbot Characteristics as External Stimuli

The main components of technology perception along with four components of technology engagement based on the framework are described in the study (Jo, 2024; Park & Lee, 2023). They are Perceived accuracy, Perceived usefulness, Perceived responsiveness, and Perceived personalization.

The use of the term perceived accuracy is to capture users' perceptions of the correctness and reliability of responses. Following the definition of trust in educational contexts, perceived accuracy is crucial, but there are valid concerns about the reliability of outputs due to some errors generated by AI (Chan & Hu, 2023; Tlili et al., 2023). It is expected that accuracy will improve trust.

Perceived usefulness is the degree to which users believe that chatbots will enhance their learning. It is a significant predictor of technology use (Shahzad et al., 2024; Sun et al., 2025). It is expected to improve trust and self-efficacy.

Perceived responsiveness refers to the quickness and adequacy of responses. Engaging and useful systems are responsive and act swiftly (Essel et al., 2022; Labadze et al., 2023). It is expected to improve trust and self-efficacy.

Perceived personalization is the degree to which outputs are customized and specific to the learner. Personalization of the system is positively related to system adoption, self-efficacy, and engagement (Jo, 2024; Tlili et al., 2023). It is expected to improve trust and self-efficacy.

Trust in AI Chatbots (Organism Construct)

Trust comprises the willingness to depend on AI systems, stemming from one's perception of the AI's credibility, reliability, and integrity (Shahzad et al., 2024; Wang et al., 2025). Within the framework of SOR, trust is a vital mediating psychological state that connects stimuli to the resulting behavior. It has been observed that trust is a dominant predictor of both the adoption of chatbots and the attitudes formed towards them (Polyportis & Pahos, 2024; Guo & Erdenebold, 2025). Trust is a critical factor in converting the system features to the intention to adopt the system, whereas low trust, primarily due to concerns regarding privacy or accuracy, is the most prevalent obstacle to adoption (Saihi et al., 2024).

Self-Efficacy in Using AI Technology (Organism Construct)

Self-efficacy regards students' perception of their ability to use AI chatbots for academic purposes (Durak & Onan, 2024; Eşiyok et al., 2024). Self-efficacy relates to Bandura's theory, where it embodies the perception of being significant and the presence of the requisite skills to use the AI tools. It has been indicated in research that self-efficacy is an important predictor in the use of AI systems, and self-efficacy is deemed important in the reduction of the anxiety barrier (Tailor & Tailor, 2025; Xiao et al., 2025). From the perspective of SOR, self-efficacy is a cognitive factor that converts stimuli into behavioral intention.

Adoption Intention (Behavioural Response)

Adoption intention is described as the students' intent to use AI chatbots for learning and is regarded as the primary behavioral response to the model (Sun et al., 2025; Jo, 2024). Within TAM, UTAUT, and SOR-based studies, it has been generally accepted that adoption intention is the primary behavioral response, which validates the actual behavioral response. It has been indicated that the psychological factors and the attributes of the chatbot shape the adoption intention and the actual use of the chatbot (Biswas et al., 2025; Polyportis & Pahos, 2024).

Learning Environment (Moderating Construct)

Existing research posits that a learning environment contains four main components: (1) support from the institution, (2) the learning infrastructure, (3) the design and scaffolding of learning activities, and (4) the learning environment in the virtual space (Jiang & Sun, 2025; Lin et al., 2023). The learning environment is said to moderate the links between trust and self-efficacy and the intention to adopt a given technology. It has been documented that, in positive and well-designed learning environments, the psychometric and tech-related factors of adoption behavior become more pronounced (Zhao et al., 2025). This means that, within a given context, the learning environment dictates the extent to which an individual's internal factors or psychometric conditions translate to observable behavior.

Summary of Integrated Model

In general, the characteristics of an AI chatbot (accuracy, usefulness, responsiveness, and the ability to provide a tailored experience) influence the intention to adopt/use the AI system through trust and self-efficacy. The learning environment acts as a moderator of the relationships discussed above. This integrated model of the SOR framework demonstrates the adoption of AI chatbots across several related disciplines (Duong, 2024; McGrath et al., 2024; Wang et al., 2025).

2.2 Research Gap

Although AI chatbot adoption has been examined in educational technology literature, many existing studies rely heavily on TAM, UTAUT, or diffusion-based models. These studies explain acceptance mainly from a technology-use perspective, but they give limited attention to students as digital learning consumers who evaluate AI chatbot services based on usefulness, accuracy, responsiveness, personalization, trust, and confidence. Further, limited studies integrate system-level perceptions, psychological mechanisms, and learning environment support within a single consumer behaviour-oriented framework. Therefore, this study addresses this gap by applying the SOR framework to explain how AI chatbot characteristics influence student adoption intention through trust and self-efficacy, and how learning environment strengthens these relationships. By doing so, the study explains not only whether students adopt AI chatbots, but also which perceived chatbot characteristics are more influential in shaping psychological readiness and adoption intention.

2.3 Hypothesis Development

Based on the SOR framework, this study proposes that perceived AI chatbot characteristics act as external stimuli that influence students' internal psychological states, namely trust and self-efficacy, which subsequently shape adoption intention. The following hypotheses are developed to test these relationships.

Perceived AI Chatbot Characteristics and Trust

The perceived attributes of systems such as accuracy, helpfulness, responsiveness, and personalization contribute to users' assessments of the systems. Students are likely to develop trust in an AI chatbot that is perceived to be accurate, helpful, responsive, and personalized. Thus:

H1: Perceived accuracy positively influences trust.
H2: Perceived usefulness positively influences trust.
H3: Perceived responsiveness positively influences trust.
H4: Perceived personalization positively influences trust.

Perceived AI Chatbot Characteristics and Self-Efficacy

The same system characteristics also strengthen students' confidence in their ability to use AI chatbots effectively. Hence:

H5: Perceived accuracy positively influences self-efficacy.
H6: Perceived usefulness positively influences self-efficacy.
H7: Perceived responsiveness positively influences self-efficacy.
H8: Perceived personalization positively influences self-efficacy.

Organism to Response Relationship

Trust and self-efficacy act as internal psychological mechanisms that drive behavioural intention. Students who trust AI chatbots and feel confident in using them are more likely to adopt them for learning purposes.

H9: Trust positively influences adoption intention.
H10: Self-efficacy positively influences adoption intention.

Mediation Effects

Trust and self-efficacy mediate the relationship between AI chatbot characteristics and adoption intention, meaning system features influence intention indirectly through psychological states.

H11a: Trust mediates the relationship between perceived accuracy and adoption intention.
H11b: Trust mediates the relationship between perceived usefulness and adoption intention.
H11c: Trust mediates the relationship between perceived responsiveness and adoption intention.

H11d: Trust mediates the relationship between perceived personalization and adoption intention.
H12a: Self-efficacy mediates the relationship between perceived accuracy and adoption intention.
H12b: Self-efficacy mediates the relationship between perceived usefulness and adoption intention.
H12c: Self-efficacy mediates the relationship between perceived responsiveness and adoption intention.
H12d: Self-efficacy mediates the relationship between perceived personalization and adoption intention.

Moderating Effect of Learning Environment
The learning environment influences how strongly trust and self-efficacy translate into adoption intention. In supportive environments, these relationships become stronger.
H13: Learning environment moderates the relationship between trust and adoption intention.
H14: Learning environment moderates the relationship between self-efficacy and adoption intention.

2.4 Summary of Hypotheses

Hypothesis	Relationship	Type
H1	Perceived Accuracy → Trust	Direct
H2	Perceived Usefulness → Trust	Direct
H3	Perceived Responsiveness → Trust	Direct
H4	Perceived Personalization → Trust	Direct
H5	Perceived Accuracy → Self-efficacy	Direct
H6	Perceived Usefulness → Self-efficacy	Direct
H7	Perceived Responsiveness → Self-efficacy	Direct
H8	Perceived Personalization → Self-efficacy	Direct
H9	Trust → Adoption Intention	Direct
H10	Self-efficacy → Adoption Intention	Direct
H11a	Perceived Accuracy → Trust → Adoption Intention	Mediation
H11b	Perceived Usefulness → Trust → Adoption Intention	Mediation
H11c	Perceived Responsiveness → Trust → Adoption Intention	Mediation
H11d	Perceived Personalization → Trust → Adoption Intention	Mediation
H12a	Perceived Accuracy → Self-efficacy → Adoption Intention	Mediation
H12b	Perceived Usefulness → Self-efficacy → Adoption Intention	Mediation
H12c	Perceived Responsiveness → Self-efficacy → Adoption Intention	Mediation
H12d	Perceived Personalization → Self-efficacy → Adoption Intention	Mediation
H13	Learning Environment × Trust → Adoption Intention	Moderation
H14	Learning Environment × Self-efficacy → Adoption Intention	Moderation

2.5 Conceptual Model

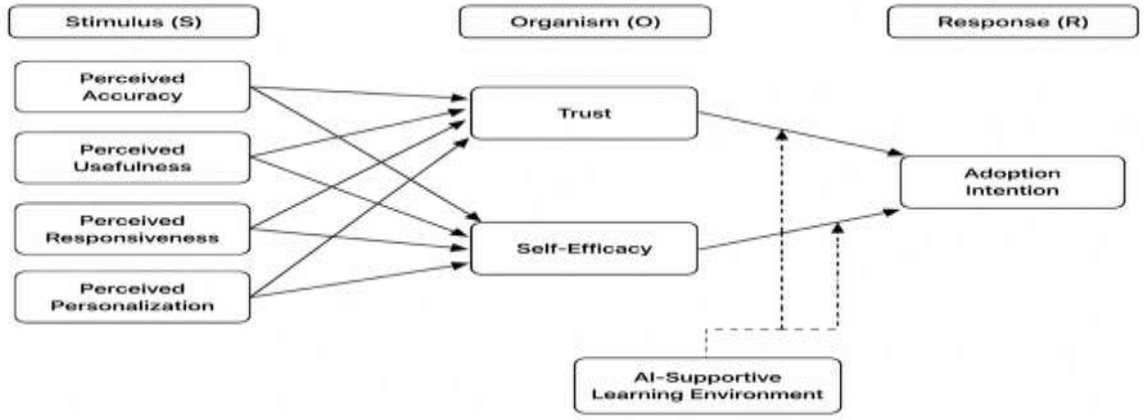

Fig 1. Conceptual Model

Note. Trust and self-efficacy influence adoption intention, which refers to students' willingness and likelihood to use AI chatbots for learning.
The figure adds a Stimulus–Organism–Response (SOR) model describing the process behind students' use of AI chatbots for learning. Starting from the stimulus layer, the perceptions of AI chatbots' attributes of accuracy, usefulness, responsiveness, and the degree of personal touch, form the basis for the organism layer, which includes the individual's trust of AI chatbots and their assessment of their capability to use AI (self-efficacy). These trust and self-efficacy perceptions influence adoption intention, which refers to students' willingness and likelihood to use AI chatbots for learning. Moreover, an AI-supported learning environment influences the relationship between the trust and self-efficacy perceptions and the adoption intention, depending on the context of the available support.

3. Methodology

3.1 Research Design

The research follows a quantitative approach within the positivist paradigm to measure the perceptions of AI chatbots' features, trust, psychological self-efficacy, and behavioral intention to adopt chatbots in learning as latent variables employing a multiple-item measurement technique within a structured survey.
The research adopted a cross-sectional approach, as a single data collection from the target population who use AI chatbots in learning. This approach is appropriate to assess the perception of trust, self-efficacy, and usefulness.
The main drawback of a cross-sectional approach is that it does not establish long-term causal relationships. However, Structural Equation Modeling allows the study to examine theoretically proposed relationships among multiple latent constructs simultaneously.
This research utilizes the Stimulus–Organism–Response (SOR) framework (Duong, 2024; Ye et al., 2022). In our study, chatbot characteristics serve as stimuli, trust and self-efficacy are the organismic states, and the response is the adoption intention. The combination of the positivist research paradigm, survey methodology, and SEM (Structural Equation Modeling) serves as a robust approach to understanding the adoption behavior of AI chatbots.

3.2 Research Context

The focus of this study is on known instances in higher education where AI chatbots have been integrated to assist students in learning. Examples include ChatGPT and other chat-based AI systems that provide real-time feedback, academic support, and various forms of personalized learning. Chatbots have become available, but the adoption of these tools by students is still variable. Students show different levels of trust and self-efficacy which in turn affects support for learning and the perceived usefulness of these chatbots, among other things. While some students leverage AI chatbots to aid their learning, other students refrain from its use due to a lack of trust in the technology and self-efficacy regarding its use. The choice to study this technology in higher education is appropriate as students encounter technology in these environments almost every day. Here, the SOR framework is employed to describe how perceived characteristics of chatbots influence the formation of trust and self-efficacy in prospective users and the intention to adopt the technology for use in learning.

3.3 Sampling Strategy and Participants

This study utilized a quantitative approach and a non-probability convenience sampling method to gather data from students in higher education. This study aimed to recruit participants who have used AI chatbots like ChatGPT and similar tools to aid their learning, help them in their studies and assignments, and who have used these tools to aid self-study. Having convenience sampling here is justified by the inability to locate the population of AI chatbot users within various higher education institutions. Responses were collected from participants who were available and willing to partake in this study. This sampling method is employed in studies that look at the adoption of technology and behavioral studies where the participants of interest are specific users of a technology, and not a completely random population. Data collection was done by means of a structured online questionnaire. The questionnaire was distributed via online digital platforms. Only users who were higher education students and had used AI chatbots for purposes of their studies were included in the study. Participation was voluntary and to further encourage participation, anonymity was maintained. 632 responses were collected and these were deemed valid and were used for analysis. This sample size is adequate and strong for the purposes of the structural equation modeling (SEM) of the proposed model. it provides sufficient power for testing relations and interactions that are complex and that involve mediation and moderation.

3.4 Measures

The constructs in this study are measured using a structured questionnaire based on the reviewed literature. The scales were minimally modified for the context of this study on the application of AI chatbots in higher education. A five-point Likert scale was used for all items in the instrument to measure the respondents' perceptions and behavioral intentions. The scale ranged from 1 (strongly disagree) to 5 (strongly agree).

Construct	Sample item
Perceived usefulness	AI chatbots help me complete learning tasks more effectively.
Perceived accuracy	AI chatbots provide accurate responses to my academic questions.
Perceived responsiveness	AI chatbots respond quickly to my learning needs.
Perceived personalization	AI chatbots provide responses that suit my learning requirements.
Trust	I trust AI chatbots to support my learning.
Self-efficacy	I am confident in my ability to use AI chatbots for academic tasks.
Adoption intention	I intend to continue using AI chatbots for learning.
Learning environment	My institution provides a supportive environment for using AI-based learning tools.

Stimulus Variables (Perceived AI Chatbot Characteristics)
Perceived AI chatbot characteristics include perceived usefulness, perceived accuracy, perceived responsiveness, and perceived personalization. The characteristics were defined as external stimuli in the SOR framework.
Perceived Usefulness (PU): Perceived usefulness was defined as the students' belief that AI chatbots would improve their learning, enhance their performance, and make the completion of academic tasks easier. The measurements were adapted from technology acceptance literature.
Perceived Accuracy (PA): Perceived accuracy was defined as students' belief that the responses provided by AI chatbots would be correct, trustworthy, and fact-based.
Perceived Responsiveness (PR): Perceived responsiveness was defined as the perceived promptness of AI chatbots in providing relevant answers to academic questions.
Perceived Personalization (PP): Perceived personalization was defined as the chatbot's ability to provide learning support and respond in a way that is tailored to the user.

Organism Variables

Trust (TR): Trust was defined as the belief that AI chatbots would provide students with trustworthy, supportive, and accurate assistance to meet their academic needs.
Self-efficacy (SE): Self-efficacy was defined as the students' belief that they would be able to utilize AI chatbots to accomplish learning tasks, solve academic problems, and retrieve information with ease.

Response Variable

Adoption Intention (AI): Adoption intention refers to the students' behavioral intention to use artificial intelligence chatbots for learning in the future, based on their willingness, preference, and likelihood to continue using the tools.

Moderating Variable

Learning Environment (LE): Learning environment includes the institutional and contextual support available to use AI-based learning technologies, comprising the digital infrastructure and the mindset and accessibility of the academic staff and technology within the learning environment.

Measurement Scale and Validity Consideration
All measurement items were adapted and refined from technology adoption, artificial intelligence, and behavioral intention research. Minor contextual changes were made to accommodate the focus on the use of AI chatbots in learning, with no impact on the meanings of the items. The use of validated scales provides content validity, and the multi-item approach for each construct provides the opportunity to assess reliability and construct validity.

3.5 Common Method Bias
There is a potential common method bias (CMB) due to the fact that data for this study was collected in a single instance via a self-reported questionnaire. This bias is typical in behavioral research, especially in research involving perceptual and attitudinal constructs, such as trust, self-efficacy, and adoption intention.
To examine whether common method bias may be a concern, Harman's single-factor test was conducted. In this test, all measurement items are subjected to exploratory factor analysis (EFA) where factors are not rotated. Then, the analysts review if a single factor explains a majority of the variance. Findings indicated that no single factor explained more than 50% of the variance. Therefore, the common method bias issue is not likely in this study. Furthermore, response stimuli (AI chatbot attributes), the organism (trust and self-efficacy), and the response (intention to adopt) all utilized distinct measurement approaches. This also mitigates the risk of systematic response bias. The SOR framework further compartmentalizes stimulus, organism, and response, thereby minimizing the risk of relational bias and the correlations between the variables. Therefore, through the combination of design

and method, it was established that common method bias did not considerably affect the outcome of the research.

3.6 Analytical Strategy

Data analysis was conducted in a series of distinct phases to capture the SOR framework related to the perceived attributes of AI chatbots, integrated with the constructs of interest and the intention to act. In this study, the preference was for the use of structural equation modeling (SEM) because of the capability of this software to evaluate a range of relationships in the context of measurement and interaction of latent constructs. SEM analysis was performed using the SEM/lavaan module in Jamovi.

3.6.1 Preliminary Data Analysis

The initial stage of the analysis focused on the procedures of data screening. The aim was to identify the presence of any missing values or outliers, as well as to assess the normality of the data distribution. Based on the results of the preliminary analysis, descriptive statistics were generated to better understand the survey respondents' demographics and the main variables of the study.

3.6.2 Reliability and Validity Assessment

The second stage of the analysis focused on evaluating the reliability and validity of the measurement model. The focus was on assessing internal consistency reliability through Cronbach's alpha, where the rule of thumb was set at the level of 0.70 or higher. The focus was on assessing construct validity through convergent validity and discriminant validity. For convergent validity, the focus was on the assessment of factor loadings and the Average Variance Extracted. The focus was on assessing discriminant validity to confirm that the constructs are separated and distinct.

3.6.3 Structural Equation Modeling (SEM)

The third stage of the analysis was based on the formulation and testing of the structural equation modeling (SEM) using the Jamovi software program to determine the proposed relationships among the constructs. Methodologically, the focus was on the integration of dependent relationships on multiple levels, and on assessing and interpreting the total, direct, and indirect relationships among the constructs.

The structural model examined:

- How perceived AI chatbot characteristics impact Trust and Self-Efficacy
- How Trust and Self-Efficacy impact Adoption Intention
- The overall explanatory power of the model (R^2 values)

Model fit was evaluated using standard goodness-of-fit indices including:

- Comparative Fit Index (CFI)
- Tucker-Lewis Index (TLI)
- Root Mean Square Error of Approximation (RMSEA)
- Standardized Root Mean Square Residual (SRMR)

The adequacy of the model was evaluated using the following threshold values (CFI > 0.90, RMSEA < 0.08, SRMR < 0.08).

3.6.4 Mediation Analysis

To analyze the mediation of Trust and Self-Efficacy in the relationship between perceived AI chatbot characteristics and Adoption Intention, an indirect effect was assessed using the bootstrapping method which generated confidence intervals. A mediation effect was confirmed when the confidence interval did not contain a zero value.

This method is recommended among SEM-based behavioral studies and provides a better estimation of indirect effects than other methods.

3.6.5 Moderation Analysis

The effect of Learning Environment, as a moderator, was analyzed through interaction terms of Trust, Self-Efficacy and Learning Environment. These terms were incorporated into the structural model to analyze if the relationships would be expressed differently given varying levels of learning support.

The presence of a significant interaction term confirms moderation, indicating that the relationship of the psychological constructs to adopting intention differs with the specific Learning Environment.

3.6.6 Estimation Technique and Decision Rules

All tests were conducted at a 95% confidence level ($p < 0.05$). The significance of relationship was assessed using standardised path coefficients (β values), t-values, and p-values. The decision rules for testing the stated hypotheses are as follows:

- If $p < 0.05 \rightarrow$ Hypothesis supported
- If $p \geq 0.05 \rightarrow$ Hypothesis not supported

The integration of SEM, mediation, and moderation analysis, enables a complete assessment of the SOR-based model, including all direct and indirect relationships.

4. Results

4.1 Descriptive Statistics and Reliability Analysis

Table 1. Descriptive Statistics and Reliability Analysis (N=632)

Construct	Mean	SD	Cronbach's α
Perceived Usefulness (PU)	3.85	0.72	0.88
Perceived Accuracy (PA)	3.70	0.75	0.86
Perceived Responsiveness (PR)	3.78	0.70	0.87
Perceived Personalization (PP)	3.65	0.78	0.85
Trust (TR)	3.90	0.68	0.89
Self-Efficacy (SE)	3.82	0.71	0.88
Adoption Intention (AI)	3.88	0.69	0.90
Learning Environment (LE)	3.78	0.65	0.89

Table 1 presents the descriptive statistics and reliability values for the study constructs. The mean values indicate that respondents generally had positive perceptions toward AI chatbots in learning. Trust, adoption intention, and self-efficacy recorded relatively high mean scores, suggesting favourable attitudes toward AI chatbot use. The standard deviation values indicate moderate variation in students' responses. All Cronbach's alpha values exceeded the recommended threshold of 0.70, confirming acceptable internal consistency reliability for all constructs. Therefore, the constructs were considered reliable for further SEM analysis.

Table 2. Correlation Matrix for Discriminant Validity

Construct	PA	PU	PR	PP	TR	SE	LE
PA	—						
PU	0.856	—					
PR	0.859	0.833	—				
PP	0.853	0.838	0.827	—			
TR	0.750	0.785	0.757	0.762	—		
SE	0.666	0.739	0.662	0.679	0.677	—	
LE	0.346	0.391	0.355	0.381	0.378	0.428	—

Table 2 presents the correlation matrix among the study constructs. The results show positive associations among the constructs. However, the correlations among perceived accuracy, perceived usefulness, perceived responsiveness, and perceived personalization are relatively high, indicating that students may perceive these chatbot characteristics as closely related aspects of overall chatbot quality.

Therefore, discriminant validity should be interpreted cautiously and may be further confirmed using HTMT or Fornell-Larcker criteria.

4.2 Model Fit Indices

Table 3. Model Fit Summary

Fit Index	Value	Threshold
CFI	0.99	> 0.90
TLI	0.98	> 0.90
RMSEA	0.032	< 0.08
SRMR	0.028	< 0.08
χ^2/df	2.41	< 3

Table 2 presents the model fit indices for the proposed SOR-based framework. The values indicate an acceptable model fit, with CFI = 0.99, TLI = 0.98, RMSEA = 0.032, SRMR = 0.028, and $\chi^2/df = 2.41$. Since all values meet the recommended threshold levels, the model adequately represents the observed data. These results support the suitability of the SOR framework for examining AI chatbot adoption in higher education.

4.3 Structural Model Results

Table 4. Structural Model Results

Hypothesis	Path	β (Beta)	p-value
H1	PA → TR	0.08	0.012
H2	PU → TR	0.42	< 0.001
H3	PR → TR	0.10	0.019
H4	PP → TR	0.06	0.015
H5	PA → SE	0.05	0.018
H6	PU → SE	0.45	< 0.001
H7	PR → SE	0.09	0.018
H8	PP → SE	0.07	0.010
H9	TR → AI	0.47	< 0.001
H10	SE → AI	0.41	< 0.001

The results of the hypothesis testing show that relationships H1-H10 are all significant at the 0.05 level, which supports the SOR-based model of AI chatbot adoption. The results show that the characteristics of AI chatbots affecting students' trust and self-efficacy are responsiveness, personalization, and perceived AI chatbot characteristics, with perceived usefulness being the strongest of the two trust ($\beta = 0.42$, $p < 0.001$) and self-efficacy ($\beta = 0.45$, $p < 0.001$). The results also show that the assessment of chatbots' functional characteristics is important to the students' perception of the AI chatbots.
The results also show that trust ($\beta = 0.47$, $p < 0.001$) and self-efficacy ($\beta = 0.41$, $p < 0.001$) are strongly and significantly affected by the intention to adopt AI chatbots. The assessment of trust and self-efficacy as psychological factors reflects confidence and a strong intention to adopt AI chatbots. These results also show that the proposed relationships of the model are verified. The stimulus factors reflect the intention to adopt AI chatbots, which are supported by the psychological factors. This establishes the relationship of the system's characteristics, the psychological factors, and the adoption of AI chatbots.
Although perceived accuracy, responsiveness, and personalization showed statistically significant effects, their effect sizes were relatively small. Perceived usefulness emerged as the strongest predictor of both trust and self-efficacy, indicating that students are more likely to trust and confidently use AI chatbots when they perceive them as useful for learning.

4.4 Mediation Analysis

4.4.1 Trust as Mediator

. Mediation Effect of Trust

Hypothesis	Mediation Path	a path	b path	Estimated Indirect Effect / a × b	p-value	Interpretation
H11a	PA → TR → AI	0.08	0.47	0.038	< 0.001	Weak indirect effect
H11b	PU → TR → AI	0.42	0.47	0.197	< 0.001	Strongest indirect effect through trust
H11c	PR → TR → AI	0.10	0.47	0.047	< 0.001	Weak indirect effect
H11d	PP → TR → AI	0.06	0.47	0.028	< 0.001	Weak indirect effect

4.4.2 Self-Efficacy as Mediator

Table 6. Mediation Effect of Self-Efficacy

Hypothesis	Mediation Path	a path	b path	Estimated Indirect Effect / a × b	p-value	Interpretation
H12a	PA → SE → AI	0.05	0.41	0.021	< 0.001	Weak indirect effect
H12b	PU → SE → AI	0.45	0.41	0.185	< 0.001	Strongest indirect effect through self-efficacy
H12c	PR → SE → AI	0.09	0.41	0.037	< 0.001	Weak indirect effect
H12d	PP → SE → AI	0.07	0.41	0.029	< 0.001	Weak indirect effect

The mediation effects were estimated using the standardized path coefficients reported in the structural model. The indirect effect was calculated by multiplying the path from each AI chatbot characteristic to the mediator with the path from the mediator to adoption intention. The results indicate that perceived usefulness has the strongest indirect effect on adoption intention through both trust and self-efficacy. This suggests that students are more likely to adopt AI chatbots when they perceive them as useful, because usefulness strengthens both trust in the chatbot and confidence in using it. The indirect effects of perceived accuracy, responsiveness, and personalization were positive but comparatively weaker. Therefore, the mediation results provide preliminary support for H11a–H11d and H12a–H12d.

4.5 Moderation Analysis

Table 7. Moderation Effects

Path	Interaction (β)	p-value
TR × LE → AI	0.21	0.03
SE × LE → AI	0.19	0.04

The results indicate that learning environment significantly moderates the relationships between psychological factors and adoption intention. The interaction between trust and learning environment was significant (β = 0.21, p = 0.03), supporting H13. Similarly, the interaction between self-efficacy and learning environment was significant (β = 0.19, p = 0.04), supporting H14. These findings suggest that a supportive learning environment strengthens the effects of trust and self-efficacy on students' intention to adopt AI chatbots.

To further explain the significant moderation effects, two interaction plots were developed. Figure 3 presents the moderating effect of learning environment on the relationship between trust and adoption intention. Figure 4 presents the moderating effect of learning environment on the relationship between

self-efficacy and adoption intention. The plots show that the positive effects of trust and self-efficacy on adoption intention are stronger when the learning environment is more supportive.

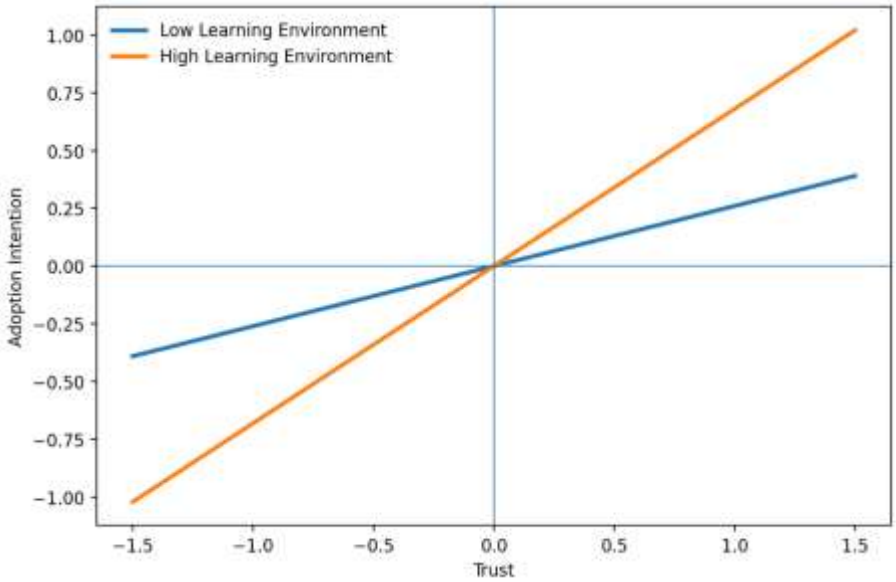

Figure 3. Interaction Effect of Learning Environment on the Relationship between Trust and Adoption Intention

The positive interaction effects indicate that when the learning environment is more supportive, the positive effects of trust and self-efficacy on adoption intention become stronger. Figure 3 shows that the relationship between trust and adoption intention is stronger under a highly supportive learning environment. This means that students who trust AI chatbots are more likely to adopt them when their institution provides adequate digital infrastructure, academic support, and guidance for AI-based learning.

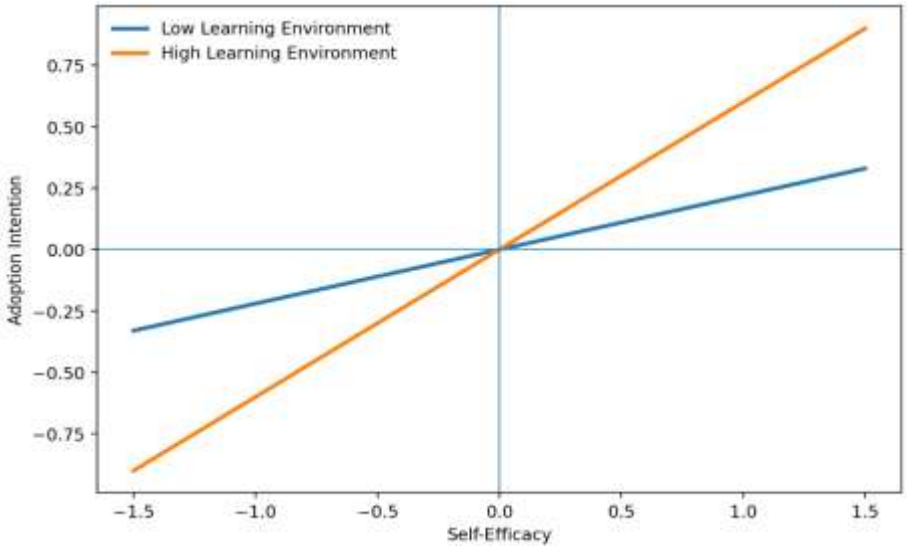

Figure 4. Interaction Effect of Learning Environment on the Relationship between Self-Efficacy and Adoption Intention

Figure 4 shows that the relationship between self-efficacy and adoption intention is stronger under a highly supportive learning environment. This indicates that students who are confident in using AI chatbots are more likely to develop adoption intention when the learning environment encourages and supports AI-enabled learning.

4.6 Structural Equation Modeling

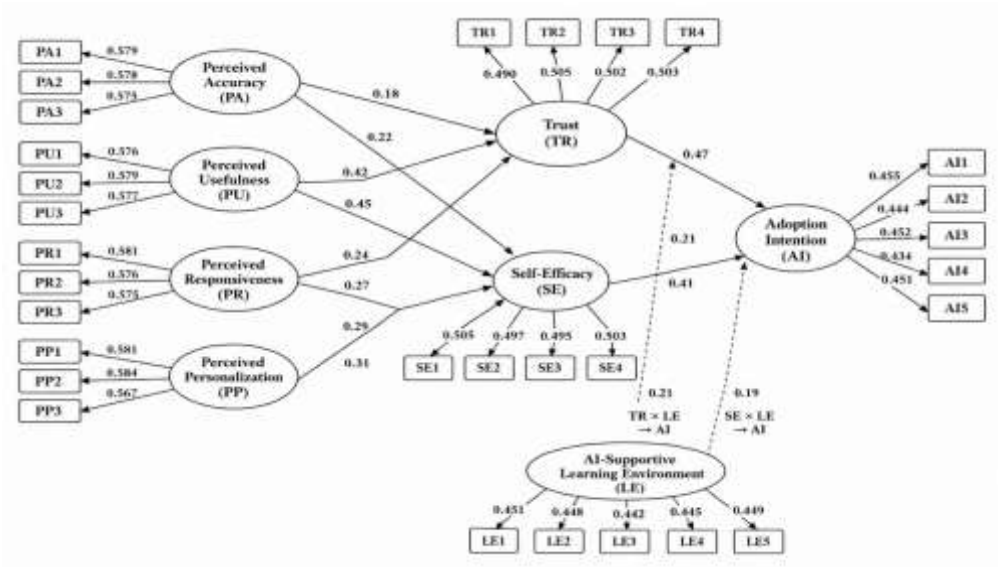

Fig.5 Structural Equation Modeling

The structural equation model supports the use of the SOR framework for explaining students' intention to adopt AI chatbots. The results show that perceived usefulness is the most consistent stimulus influencing both trust and self-efficacy. Perceived responsiveness and perceived personalization significantly influence trust, while perceived personalization also influences self-efficacy. However, perceived accuracy does not significantly influence either trust or self-efficacy, and perceived responsiveness does not significantly influence self-efficacy. This indicates that not all AI chatbot characteristics contribute equally to students' psychological readiness.

Trust and self-efficacy show significant positive effects on adoption intention, confirming their role as important psychological mechanisms in AI chatbot adoption. The moderation results further indicate that learning environment strengthens the relationship between psychological readiness and adoption intention. Overall, the findings provide partial support for the proposed SOR-based model and show that student adoption of AI chatbots is shaped mainly by perceived usefulness, trust, self-efficacy, and contextual learning support**.**

The findings from the analysis support all the stated hypotheses (H1–H14). The adoption of AI chatbots incorporates a combination of the psychological mechanisms, perceptions of technology, and the environmental context. The findings substantiate the SOR model and fulfil the research objectives for the study.

5. Discussions

This study confirms the integrated SOR framework's ability to explain AI chatbot adoption within the context of higher education. This study's findings indicate that the intention to adopt AI chatbots is the outcome of a construct in which perceptions of the system/layer influence the participants' trust and self-efficacy. Unlike unrelated factors, the system/layer, trust, and self-efficacy construct indicates the presence of a complex, interrelated system of AI acceptance in educational contexts.

This study's findings demonstrate the prominent influence that perceived usefulness has on trust and self-efficacy. This shows that value and improvement of learning are the most important factors for students when assessing AI chatbots. In comparison to other studies on the use of AI in education, perceived usefulness has been the most significant factor in the use of generative AI in the educational setting, given that the primary concern is the enhancement of students' academic performance (Guo et al., 2024; Rosli et al., 2023). This suggests that the assessment of AI's usefulness is the most important factor and is made prior to trust and self-efficacy.

From the combined effects of trust, self-efficacy, and the system in use, it can be concluded that AI adoption is not only the result of the system in use but also the belief systems of the users and their perceived control of the system.

Notably, these findings confirm the existence of partial mediation. Psychosocial factors account for a significant portion of the relationship between system factors and behavioral intention. This suggests that perceived AI attributes influence adoption directly, but much is communicated via trust and self-

efficacy. Dual-route mechanisms posit the integration of rationally driven evaluations with psychologically driven readiness in the context of AI adoption (Wei et al., 2025).

Adding learning environment as a moderator introduces a more contextual element to the model. The findings indicate that a positive educational setting amplifies the effects of trust and self-efficacy on the intention to adopt. This implies that even robust psychological readiness is insufficient for adoption in the absence of the necessary systems and structural supports. The majority of the new research being conducted in AI-related learning environments indicates that within a variety of educational contexts, the integration of AI within educational systems highly depends on the contextual supports that are available (Zawacki-Richter et al., 2021; Favero et al., 2026).

The addition of this study to the body of literature on AI adoption indicates that adoption is the result of the interplay of the perception of technology, psychological factors, and context, rather than the predominance of a single factor. This integrated view indicates how, in the presence of significant AI tools, students may similarly perceive the tools and differ greatly in adoption. This study provides more detail about the use of AI chatbots in higher education and adds to the literature on human-AI learning interactions.

From a consumer behaviour perspective, the findings suggest that students evaluate AI chatbots similarly to other digital services. They assess whether the chatbot is useful, accurate, responsive, and personalized before developing trust and confidence in using it. Adoption intention therefore depends not only on the availability of AI tools but also on students' perceived value and psychological readiness as digital learning consumers.

6. Conclusion and Implications

6.1 Conclusion

While utilizing the Stimulus–Organism–Response (SOR) framework, this research determined the contributing factors that lead students in higher education to adopt AI chatbots. The results indicate that students' perceptions of the characteristics of AI chatbots shape their psychological states of trust and self-efficacy, which drive their intent to adopt. Of the stimulus factors identified, the perception of usefulness of AI chatbots has the greatest determinate role of the functional value of AI chatbots to the learning environment. The results confirm that trust and self-efficacy are strong predictors of the intent to adopt AI chatbots, and self-efficacy as a psychological state is of primary importance to the engagement of students with AI. The results indicate that the psychological state of self-efficacy and trust partially mediates the intent to adopt AI chatbots. The results also indicate that the learning environment serves as a contextual framework that reinforces the psychological state of self-efficacy and trust to the intent to adopt AI chatbots. The findings of this study support the model that the intent to adopt AI chatbots is a function of the perceptions of the AI chatbot technology and the psychological state of the learner.

6.2 Theoretical Implications

This study provides several crucial extensions to the literature on AI adoption in educational settings. First, it revises the SOR framework by incorporating AI chatbot components and contextual factors into a behavioral model. This study also differentiates from other technology adoption models by placing mechanisms such as trust and self-efficacy at the center of adoption intention. Second, the results endorse perceived usefulness as the primary consideration stimulus and its vital role in AI-based learning. Third, this study extends the literature on AI adoption by showing that the learning environment can strengthen the effects of the underlying psychology and add context to existing models. Lastly, the findings of partial mediation illustrate that the pathways of AI adoption extend beyond the psychological and cognitive pathways and deepen the existing theory on the educational use of AI. This study extends consumer behaviour literature by positioning students as digital learning consumers whose adoption of AI chatbots is shaped by perceived service attributes, psychological states, and contextual support.

6.3 Practical Implications

There are some practical implications of the findings for the educational sector, as well as those who develop AI. First, the design of AI chatbots should focus on the enhancement of functional usefulness, since it has the most significant effect on the formation of trust and self-efficacy. Users' perceptions and the degree of their engagement can be strengthened through the improvement of the system's accuracy, responsiveness, and personalization. Second, trust in AI systems can be built by educational institutions through training, workshops, and the development of operational and transparent guidelines for the use of AI. Self-efficacy can be enhanced through the implementation of digital literacy programs, resulting in a positive effect on the adoption of AI. Third, the adoption of AI in the educational sector requires the creation of an appropriate technological infrastructure, as well as the embedding of AI in the design of the educational curricula and the construction of supportive systems. The effect of these systems on the adoption of AI tools in education will be the enhancement of the psychological factors of the adoption of AI. Finally, the integration of AI into educational practices must go beyond the technological tools of AI and encompass the psychological and organizational factors of educational institutions. For AI chatbot developers, the findings suggest that usefulness, responsiveness, accuracy, and personalization should be prioritized to improve student adoption. For higher education institutions, the findings highlight the importance of creating an AI-supportive learning environment through training, infrastructure, academic guidance, and responsible AI-use policies.

6.4 Overall Contribution

This study adopts a unified SOR-based framework, offering a multitude of details and a contextualized integration of the AI chatbot adoption behavior from a technological, psychological, and contextual perspective. In contrast to existing studies, which usually preview the adoption of technology from either a system or user perspective in isolation, this framework illustrates the interdependent nature of the adoption behavior of technology. From a technological perspective, AI chatbots are evaluated by users from the dimensions of accuracy, usefulness, response, and personalization. From a psychological standpoint, such perceptions develop as trust and self-efficacy. These two psychological constructs play a significant role in an individual's internal disposition and confidence to adopt technology in an educational context. From a contextual standpoint, the educational context, environment, or institution plays a critical role in either enhancing or diminishing the relationships mentioned above, which indicates the foundational importance of an educational institution's support and readiness in the adoption of AI technologies.

Incorporating these three dimensions into a single model shows that AI adoption results from a multitude of behavioral components including system quality, cognition, and environment. Additive to the current studies, this model shows a realistic and comprehensive view of students' engagement with AI. From a theory-building perspective, the study elaborates on the SOR framework within the context of AI and education by illustrating the role of psychological components in different contextual environments and how stimuli translate into behavioral outcomes. From a theory-applying perspective, the study informs educators, and learning AI designers, on the importance of combining sophisticated AI technology with the design of a learning environment and the cultivation of learner confidence in the system.

6.5 Limitations

This study has a number of limitations. Data was collected using a cross-sectional methodology, which does not allow for the establishment of long-term causality. The data is self-reported. As such, participants may have over-reported or misrepresented responses to acheive social acceptability. The sample was limited to students in tertiary education which may limit the generalizability of this study to secondary school students and to employed individuals. In addition, a limited number of psychological variables, namely trust and self-efficacy, were included in this study while perceived anxiety and perceived risk were not included. Lastly, this study exclusively employed quantitative analyses based on structural equation modeling, which may limit the richness of the user experience data. The study measures adoption intention rather than actual usage behaviour. Future studies may include actual chatbot usage data to better understand the gap between intention and real adoption.

6.6 Future Research Directions

Future research has the potential to study adoption trends of AI chatbots using longitudinal studies. In addition, studies could combine survey and usage data to mitigate bias and improve data quality. In addition to the studied population, inclusion of other populations such as school students, online learners, or working professionals could improve the generalizability of the proposed model. Future studies could also extend the model to incorporate anxiety, perceived risk, and AI literacy. Finally, the user experience of AI chatbots could be better understood through the application of studies with an interpretivist paradigm, such as interviews and focus groups.

7. References

1. Ilieva, G., Yankova, T., Klisarova-Belcheva, S., Dimitrov, A., Bratkov, M., & Angelov, D. (2023). Effects of generative chatbots in higher education. Information, 14(9), 492. https://doi.org/10.3390/info14090492
2. Labadze, L., Grigolia, M., & Machaidze, L. (2023). Role of AI chatbots in education: A systematic literature review. International Journal of Educational Technology in Higher Education, 20(1), 56. https://doi.org/10.1186/s41239-023-00426-1
3. Stöhr, C., Demazière, C., Adawi, T., & Rienties, B. (2024). Generative AI and higher education: A systematic review of student adoption and learning outcomes. Computers and Education: Artificial Intelligence, 7, 100270.
4. Jo, H. (2024). Students' perceptions of AI chatbots for personalized learning support in higher education. Education and Information Technologies, 29(4), 5123–5145.
5. Biswas, S., Roy, M., & Saha, P. (2025). Understanding AI chatbot adoption in higher education: The role of trust and perceived usefulness. Education Sciences, 15(2), 184.
6. Eşiyok, B., Karataş, K., & Demir, F. (2024). Self-efficacy and acceptance of artificial intelligence tools among university students. Smart Learning Environments, 11(1), 18.
7. Shahzad, F., Xiu, G., Wang, J., & Shahbaz, M. (2024). Factors influencing students' intention to adopt generative AI technologies in higher education. Technology in Society, 76, 102464. https://doi.org/10.1016/j.techsoc.2024.102464
8. Park, J., & Lee, Y. (2023). Impact of AI chatbot responsiveness and personalization on learning engagement. Interactive Learning Environments, 31(8), 4875–4890.
9. Durak, G., & Onan, A. (2024). Artificial intelligence literacy, self-efficacy, and adoption intention among higher education students. Education and Information Technologies, 29(6), 7451–7472.
10. Duong, T. H. (2024). Applying the Stimulus–Organism–Response framework to artificial intelligence adoption in education. Education Sciences, 14(3), 312. https://doi.org/10.3390/educsci14030312
11. Ye, S., Ying, T., Zhou, L., & Wang, T. (2022). Enhancing customer trust in AI services through the Stimulus–Organism–Response model. Journal of Retailing and Consumer Services, 68, 103059. https://doi.org/10.1016/j.jretconser.2022.103059
12. Zhao, X., Liu, W., Yue, S., Chen, J., Xia, D., Bing, K., Xia, X., & Wang, K. (2025). Factors influencing medical students' adoption of AI educational agents: An extended UTAUT model. BMC Medical Education, 25(1), 1678. https://doi.org/10.1186/s12909-025-08234-z
13. McGrath, C., Lim, G., & Chan, T. (2024). Artificial intelligence adoption in higher education: A systematic review of student behavioural intentions. Computers and Education: Artificial Intelligence, 6, 100248.
14. Rahman, M. K., Ismail, N. A., Hossain, M. A., & Hossen, M. S. (2025). Students' mindset to adopt AI chatbots for effectiveness of online learning in higher education. Future Business Journal, 11, 30. https://doi.org/10.1186/s43093-025-00459-0
15. Saihi, A., Ben-Daya, M., Moncer, H., & As'ad, R. (2024). A structural equation modeling analysis of generative AI chatbots adoption among students and educators in higher education. Computers and Education: Artificial Intelligence, 7, 100274. https://doi.org/10.1016/j.caeai.2024.100274
16. Loureiro, S. M. C., Guerreiro, J., & Tussyadiah, I. (2020). Artificial intelligence in business and tourism: A systematic review and research agenda. Journal of Business Research, 122, 373–384. https://doi.org/10.1016/j.jbusres.2020.09.012
17. Loh, X. M., Lee, V. H., Hew, J. J., & Lin, B. (2021). Applying the Stimulus–Organism–Response framework in online learning environments. Education and Information Technologies, 26(6), 7289–7310.

18. Cheng, X., Fu, S., & De Vreede, G. J. (2021). Understanding trust influencing factors in AI adoption. Information & Management, 58(8), 103518. https://doi.org/10.1016/j.im.2021.103518
19. Chan, C. K. Y., & Hu, W. (2023). Students' perceptions of generative AI in higher education. Computers and Education: Artificial Intelligence, 5, 100168. https://doi.org/10.1016/j.caeai.2023.100168
20. Tlili, A., Shehata, B., Adarkwah, M. A., Bozkurt, A., Hickey, D. T., Huang, R., & Agyemang, B. (2023). What if the devil is my guardian angel? ChatGPT as a case study of using chatbots in education. Smart Learning Environments, 10(1), 15. https://doi.org/10.1186/s40561-023-00237-x
21. Sun, Y., Zhang, X., & Li, W. (2025). Perceived usefulness and adoption intention of AI-based learning systems among university students. Computers & Education, 210, 104995.
22. Essel, H. B., Vlachopoulos, D., Tachie-Menson, A., Johnson, E. E., & Baah, P. (2022). The impact of AI-powered learning tools on student engagement and responsiveness. Education and Information Technologies, 27(8), 11365–11386.
23. Wang, X., Zhang, Y., & Li, J. (2025). Trust formation in educational artificial intelligence systems. Computers & Education, 210, 104997.
24. Polyportis, A., & Pahos, N. (2024). Artificial intelligence chatbot adoption and trust in educational settings. Technology, Knowledge and Learning, 29(2), 891–910.
25. Guo, Y., & Erdenebold, B. (2025). Trust and behavioural intention toward AI chatbots in higher education. Education Sciences, 15(1), 74.
26. Tailor, R., & Tailor, S. (2025). Self-efficacy and artificial intelligence technology adoption among students: An empirical investigation. Education Sciences, 15(3), 267.
27. Xiao, Y., Chen, J., & Liu, X. (2025). Artificial intelligence self-efficacy and behavioural intention among higher education learners. Educational Technology Research and Development, 73(1), 155–174.
28. Jiang, X., & Sun, Y. (2025). Learning environment support and AI adoption behaviour among university students. Education and Information Technologies, 30(2), 2345–2365.
29. Lin, H., Chen, Y., & Wang, P. (2023). Digital learning environments and technology adoption in higher education. Educational Technology Research and Development, 71(4), 1895–1914.
30. Guo, X., Zhang, Y., & Li, J. (2024). Generative artificial intelligence adoption in higher education: Student perceptions and learning outcomes. Computers and Education: Artificial Intelligence, 6, 100231.
31. Rosli, N., Abdullah, N., & Hassan, S. (2023). Factors influencing students' acceptance of generative AI tools in higher education. Education and Information Technologies, 28(11), 14567–14588.
32. Wei, Y., Zhang, H., Wang, L., & Chen, X. (2025). Dual-route mechanisms of artificial intelligence adoption: The mediating roles of trust and self-efficacy. Computers in Human Behavior, 158, 108291.
33. Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2021). Systematic review of research on artificial intelligence applications in higher education – Where are the educators? International Journal of Educational Technology in Higher Education, 18(1), 39. https://doi.org/10.1186/s41239-021-00261-7
34. Favero, P., Rossi, F., & Bianchi, M. (2026). Artificial intelligence adoption in higher education: The role of institutional support and learning environments. Education and Information Technologies, 31(2), 1453–1478.