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Smarter Chatbots, Strong Adoption: Analysing the Key Drivers of Adoption Intention in Indian Higher Education

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Abstract

Higher education is facing another new technology: artificial intelligence chatbots that will augment teaching and learning as well as supplement student services. Nonetheless, little evidence currently exists on the predictors of students' intention to utilise these technologies within an Indian higher education context. Examining the influence of performance expectancy, effort expectancy, social influence and perceived trust on students' intention to use an artificial intelligence-based chatbot. The present study utilised a quantitative research approach, and data were collected from students of Pondicherry University using a structured self-administered questionnaire. All eligible responses received were analysed (n = 477) using data analysis functions within IBM SPSS Statistics and SmartPLS. Findings showed performance expectancy as a significant contributor to students' adoption intention for chatbots, implying that if learning and academic benefits are explicitly evident, then students will adopt. Social influence, perceived trust and perceived intelligence had a significantly positive relationship on the adoption intention, while effort expectancy insignificantly affected students' behavioural intention, meaning that ease of use may not be prioritised for digitally literate learners. This study recommends that educational institutions focus on developing chatbot systems that are efficient, elegant, and academically apt, while promoting their use through institutional initiatives alongside peer influence. Combining the factors of the Technology Acceptance Model with artificial intelligence-specific features provides this study with a holistic view and practical advice to increase student acceptance and intent to engage.

Keywords: chatbots; students; trust; adoption intention

1. Introduction

Artificial intelligence (AI) is changing higher education at an astonishing speed, especially with the adoption of AI-driven chatbots. These systems are rapidly adopted by institutions to increase student engagement, provide instant academic support, and streamline administrative services [6]. By offering real-time, personalised interactions, chatbots represent a significant step toward digital transformation in education. But these depend heavily on students being willing to use them.

With internet penetration and smartphone usage also on the rise, digital technology adoption in Indian higher education has already accelerated. It encountered several significant structural challenges, including student enrolment, faculty shortages, and administrative inefficiencies [30]. AI-based solutions, such as chatbots, present a viable approach to address these issues by providing scalable, data-driven, and cost-effective support mechanisms [14]. Beyond conventional academic assistance, chatbots facilitate student counselling, career guidance, and administrative decision-making, offering 24/7 accessibility and instantaneous query resolutions [13]. This continuous availability fosters greater student engagement, satisfaction, and overall academic success [8]. Additionally, chatbots have demonstrated effectiveness in specialised domains such as science, technology, engineering, and mathematics (STEM) education and medical training, where they stimulate real-world problem-solving scenarios, fostering experiential learning [1].

Despite these benefits, the success of chatbot implementation is not assured, as user acceptance remains a critical challenge that varies based on several factors, including the chatbot's intelligence, reliability, and user experience [10]. Factors influencing students' adoption intention are performance expectancy (PE), effort expectancy (EE) and trust [38]. Certainly, concerns around privacy and risk could also lessen their trust, making them less inclined to use such technologies.

Numerous theoretical models have been used to explain user technology adoption behaviour, including the Technology Acceptance Model (TAM) [15] and Unified Theory of Acceptance and Use of Technology (UTAUT) [51]. However, chatbot technologies offer unique features, such as AI-driven personalisation and conversational interfaces, that require further exploration beyond traditional models. In particular, understanding how these factors collectively drive students' intention to adopt in the Indian context remains underexplored, as most existing studies have focused primarily on chatbots in Western institutions. Additionally, the role of trust and intelligence in chatbot adoption remains unexamined [24].

2. Literature Review

2.1. Chatbots Background

The greatest opportunities from Artificial Intelligence lie in its potential to enhance the learner experience, while potentially predicting future needs [32]. AI-powered chatbots are one of the main killer features behind this revolution. A chatbot, according to Lexico Dictionaries, is "A computer program designed to simulate conversation with human users, especially over the Internet"; "These versatile entities are also recognised by various terms, including smart bots, interactive agents, digital assistants, or artificial conversation entities" [3]. A machine learning system in the form of an AI-powered chatbot is a natural language processor created based on human conversations with humans. It is also a personal assistant that helps in completing several tasks, such as [45]. Chatbots can provide strong emotional support to learning processes, achieving a more individualised experience for students [32]. For example, Example is an AI-based chatbot supporting as an academic advisor [11], [26]. We employ an AI-based chatbot to help solve undecided decisions, as a bot can respond to the students' inquiry at all times (an indecisive student does not have a clear time zone); besides, it allows advisors to focus more on qualitative time being spent with their advisees [11], [9].

2.2. Theoretical Framework

UTAUT, a more recent technology acceptance model [51], is an extension of TAM incorporating functional variables or additional constructs (namely performance expectancy, effort expectancy, social influence and facilitating conditions) associated with technology acceptance. The model was further extended in the UTAUT2 by adding hedonic motivation [52]. Raffaghelli et al. (2022) used the UTAUT model to assess awareness, interest and evaluation of systems, conducted in an effort to ensure that students accept the AI-driven Early Warning Systems. Consequently, this review arrives at the conclusion based on extant literature that users now have different expectations about technology, and neither TAM nor UTAUT can capture them to explain behavioural intentions in an education setting.

To accommodate our educational context, we appropriated some variables from these theories to develop a conceptual model. This research has incorporated the technological, social cognitive and relational antecedents of students to adopt an AI-powered chatbot. Five main factors include: performance expectancy, effort expectancy, social influence, perceived trust and perceived intelligence. This study extended the UTAUT to include perceived trust and perceived intelligence. This study aims to explore the direct relationship of the identified variables of AI-powered chatbot adoption intention.

2.3. Hypotheses Development

- **Performance Expectancy**

Performance Expectancy is defined as “the degree to which individuals believe that using a particular top technology would enhance their job performance”. This refers to the “degree to which one believes that using a system will increase job performance or improve one's learning process, information performance” [51]. Performance expectancy resembles and is equivalent to perceived usefulness; similarly, outcome expectancy is equal to relative advantage [13]. PE has been a reliable forecaster of behavioural intention according to Strzelecki (2023), and chatbots are an example of useful technology that students would adopt. Raffaghelli et al. (2022) have identified an important predictor of behavioural intention. The direct positive influence of PE regarding the adoption of AI-powered chatbots is also suggested in areas like tourism [38] and customer services [18], [6], [9]. As a result, students will likely adopt chatbots if they find that they can be used in the advising process. We posit the hypothesis:

  - H1. Performance Expectancy positively influences the chatbot adoption intention

- **Effort expectancy**

“Effort Expectancy is defined as the degree of ease associated with using technology” [51]. Similar constructs, for instance, PEOU [47], ease of use and complexity are also included. This is a significant forecaster of technology acceptance, and it is directly related to the use of technologies, which leads to no issues when working on AI-Enabled Chatbots. This proves that although for higher education, it was relatively easy to use this technology, it did not have an impact on the behavioural intention [47]. According to Pillai & Sivathanu (2020), PEOU of AI-driven chatbots for travel and planning positively influenced their adoption in higher education institutions. Ragheb et al. (2022) in higher education institutions. Dwivedi et al. (2017) and Brachten et al. (2021): Ease of use improves users' intention to use the system. Chatbots are user-friendly, with smooth interactions that require no extra mental effort or time [5]. When students feel their task is complicated, they are more likely to complete it quickly and effectively and prefer these chatbots [9]. However, complicated interactions or difficult conversation processes may create frustration and lead users to stop using the chatbot [4], [21], [18]. We conjecture that easier and more effortless chatbots for students lead to higher adoption levels among students. Therefore, we posit the hypothesis:

  - H2. Effort Expectancy positively impacts the chatbot adoption intention

- **Social influence**

Which is defined “as the extent to which important others, such as family and friends, believe that an individual should use a particular technology” [51]. It has a “very low effect on the behavioural intention” to use chatbots; those who are early adopters, well educated, and technology students are more likely to adopt AI-enabled chatbot tools without being influenced by others; the study found that not yet widely used, and there is no strong social pressure for using the technology ChatGPT [47]. In earlier studies, social influence significantly affected behavioural intention in mobile learning [25] and e-learning [48]. According to Alotumi et al. (2022) and Kumar & Bervell (2019) on "Google Classroom acceptance", intended users try to adopt AI technologies due to strong social influence [22]. Ragheb et al. (2022) study, which showed that SI positively impacted students' behavioural intention towards learning and teaching. Some research does not support technology, and social influence may play an increasing role over time. Sawang et al. (2014) showed that group behaviour, family and peers influence users' intentions to behave a certain way. Thus, we posit the hypothesis:

- H3. Social Influence positively impacts the chatbot adoption intention

- **Perceived trust**

Perceived trust refers to "the extent to which an individual believes the technology is credible, reliable, and secure [9]. Trust is a crucial construct in a personalised automated system since a user's belief that the chatbot is efficient and dependable provides confidence, which signifies trust in the chatbot's capabilities" [53]. When users trust the technology, they feel more confident and positive about using it, which increases their acceptance of the system [18]. When they trust the chatbots, they used to share personal information to plan travel using them [38]. Aslam (2022) found that greater trust in service chatbots increases users' willingness to use them. Thus, the adoption intention of students to use chatbots is affected by the perceived trustworthiness of the chatbot, as they will reveal personal information regarding their academic performance [9]. Thus, we propose the hypothesis:

- H4: Perceived trust has a positive impact on chatbot adoption intention

- **Perceived intelligence**

Previous studies have explained that people often judge the intelligence of robots or chatbots based on their speech, voice, appearance, and interaction style [16], [31]. Perceived intelligence "refers to the chatbot's ability to provide useful, efficient, and accurate responses to users" [31], [54], [33]. It also includes how effectively the chatbot solves customer problems with limited interactions [7]. Research shows that intelligent robots are often viewed as more human-like and attractive to users [46]. Also, perceived intelligence has been recognised as an important determinant for the acceptance intention of hotel service robots and intelligent virtual assistants [50], [34]. Prior research related to the perception of intelligence indicated one dimension underlying the adoption of tourism chatbots and intelligent virtual assistants [38], [34]. Students who have faith in the chatbot being smart and effective are more likely to accept and use these tech devices. We propose the hypothesis:

- H5: Perceived Intelligence is positively associated with chatbot adoption intention.

2.4. Proposed Research Model

The proposed conceptual framework illustrating the key drivers influencing chatbot adoption intention in Indian higher education is presented in Figure 1.

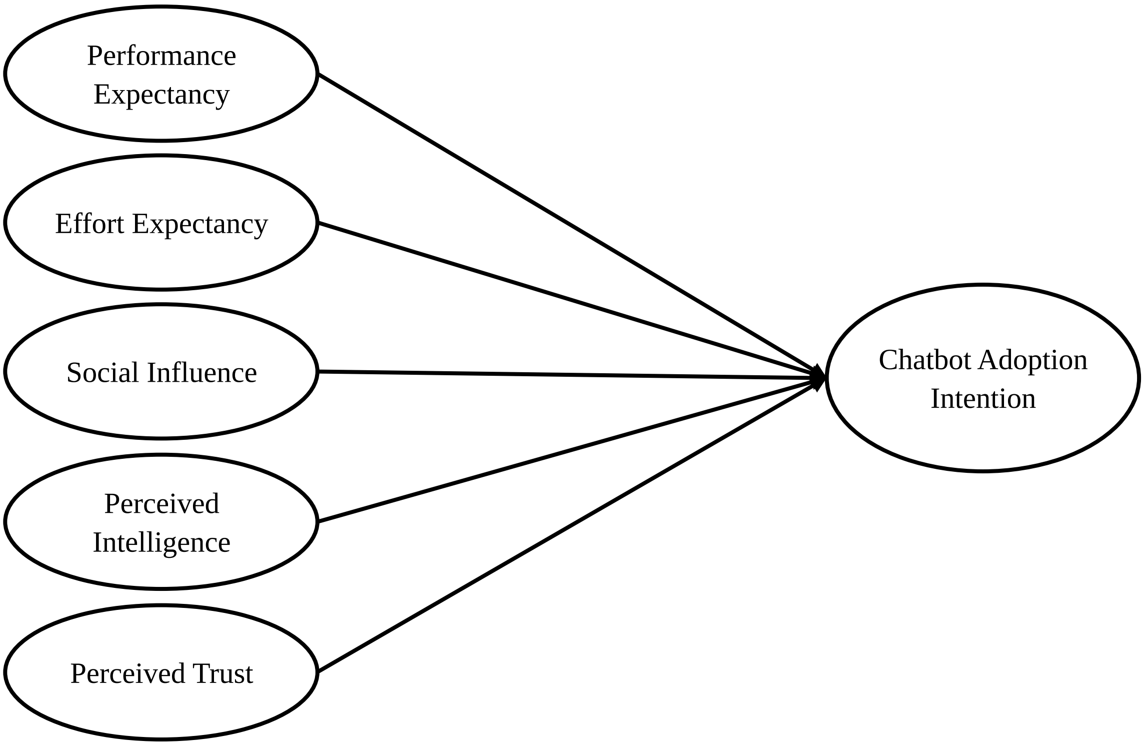

Fig. 1. Proposed Research Model.

3. Methodology

This study is aimed at using a quantitative technique that analyses the intent to adopt chatbots in Indian higher education institutes. To collect data and validate the proposed conceptual framework, a structured survey questionnaire was adopted using scales adapted from secondary sources that aligned with UTAUT [51].

The questionnaire comprises demographic information and construct measurement. The demographic section consists of respondents' age, gender, academic discipline, and prior experience with chatbots. The construct measurement section captured information on the factors utilised in this study, namely performance expectancy, effort expectancy, social influence, perceived intelligence, perceived trust and chatbot adoption intention. The constructs we used are measured by a five-point Likert scale [28], where 1 denotes the strongest disagreement, and 5 denotes the strongest agreement. A pilot study that included 30 students was executed for the content clarity and validity prior to conducting the main survey.

A convenient sampling technique was employed to target students familiar with AI-driven technologies in educational settings. Data were collected from students across 57 departments of Pondicherry University. As a central university with students representing diverse socio-cultural and geographical backgrounds from various parts of India, the sample also enhances the broader generalizability of the study findings. Out of 521 responses, 477 were obtained for analysis after data cleaning.

Data were collected and subjected to analysis using IBM SPSS Statistics 21.0 and SmartPLS 4 through a two-phased analysis: First, exploratory factor analysis (EFA) was performed to identify the underlying dimensions and test reliability. This was followed by confirmatory factor analysis (CFA) and structural equation modelling

(SEM) to test the hypotheses. Composite reliability (CR), average variance extracted (AVE), HTMT ratio, and variance inflation factors (VIFs) were applied to analyse the reliability and validity.

4. Results

IBM-SPSS & SmartPLS were used in analysing the data which was collected, in order to confirm the hypothesised relationships among variables and to determine the proposed research framework. The first part, is that the demographic characteristics of the respondents are reported to show a sample profile. Next, the construct reliability, convergent validity and discriminant validity were estimated to check the reliability and validity of the measurement model. Finally, the structural model was evaluated through PLS–SEM for significance and strength of hypothesised relationships.

Table 1. Demographic Information.

	N=477	%		N=477	%
Age			**Awareness of AI-powered chatbots**		
18 - 25 years	380	79.7	High awareness	103	21.6
26 - 35 years	97	60.6	Moderate awareness	327	68.6
Gender			Low awareness	46	9.6
Male	188	39.4	No awareness	1	0.2
Female	289	60.6			
Current level of study			**How long have you been using chatbots**		
Bachelor's (Undergraduate)	16	3.4	Less than 1 year	132	27.7
Master's (Postgraduate)	342	71.7	1 to 2 years	251	52.6
Ph.D. (Research Scholar)	118	24.7	2 to 3 years	72	15.1
Others			More than 3 years	22	4.6
Occupation			**Frequency of using chatbots in services**		
Student	355	74.4	Daily	209	43.8
Research Scholar	120	25.2	Weekly	173	36.3
Employed	2	0.4	Monthly	33	6.9
			Rarely	62	13.0
Comfort level with technology			**Preferred interaction style**		
Very comfortable	218	45.7	Text-based	439	92.0
Somewhat comfortable	183	38.4	Voice-based	22	4.6
Neutral	72	15.1	Both	16	3.4
Uncomfortable	4	0.8			

Table 1 represents the demographic information and chatbot usage features of the respondents. The majority of the participants belong to the 18-25 years age group (79.7%), implying that the study predominantly represents young digital-native students who are more exposed to emerging technologies like chatbots [39]. Female respondents consist of 60.6% of the sample, which aligns with the prior studies [10] that highlight a growing trend of female participation in AI-powered education technology adoption.

The educational qualification of the distribution shows that most of the participants were postgraduate students (71.7%), followed by research scholars (24.7%). Although the study primarily focused on students, two employed respondents were included because they were pursuing higher education programs while simultaneously working, making them relevant to the study.

With respect to technological familiarity, 45.7% of respondents reported being very comfortable with technology, indicating the growing digital exposure and technological adaptability in academic settings [38]. However, only 21.6% demonstrated high awareness of AI-powered chatbots, while the majority showed moderate awareness (68.6%). This implies that even though students are technologically confident, their in-depth understanding of AI chatbot capabilities is still evolving. Furthermore, most respondents had been using chatbots for 1 to 2 years (52.6%) and preferred text-based interactions (92%), highlighting the increasing acceptance of conversational AI platforms in academic environments.

Table 2 shows the construct validity and reliability assessment results of the measurement model. All items had factor loadings greater than 0.70 [19], with PT4 (0.698) being the only item below the acceptable parameter, suggesting good scale reliability and sufficient correlation between each observed variable and its underlying construct. Although EE4 recorded a comparatively lower loading (0.534), it is considered practically significant [23], and it is retained to preserve construct content validity.

Table 2. Construct Validity and Reliability.

Variables	Item Codes	Factor Loading	CR	AVE	Cronbach's Alpha (α)
Performance Expectancy	PE1	0.788	**0.862**	**0.610**	**0.787**
	PE2	0.790			
	PE3	0.810			
	PE4	0.736			
Effort Expectancy	EE1	0.785	**0.823**	**0.543**	**0.722**
	EE2	0.806			
	EE3	0.786			
	EE4	0.537			
Social Influence	SI1	0.719	**0.833**	**0.556**	**0.734**
	SI2	0.763			
	SI3	0.715			
	SI4	0.784			
Perceived Intelligence	PI1	0.748	**0.852**	**0.591**	**0.769**
	PI2	0.766			
	PI3	0.784			
	PI4	0.776			
Perceived Trust	PT1	0.779	**0.876**	**0.640**	**0.811**
	PT2	0.861			
	PT3	0.850			
	PT4	0.698			
Chatbot Adoption Intention	CAI1	0.794	**0.898**	**0.689**	**0.849**
	CAI2	0.850			
	CAI3	0.853			
	CAI4	0.821			

The values of composite reliability (CR) ranged from 0.823 to 0.898. well above the 0.70 recommended cut-off [33], thus providing support for the strong internal consistency of the constructs. Second, Cronbach's alpha ranged from 0.722 to 0.849, indicating acceptable reliability of the measurement scales.

AVE for all constructs had values between 0.543 and 0.689, indicating that they also exceeded the minimum threshold of≥ 0.50 (Table 2) and therefore supported convergent validity. The results concluded that the model measurement is well and valid for further continue analyze to structural model.

Table 3. Discriminant Validity (HTMT Ratio).

	PE	EE	SI	PI	PT	CAI
PE						
EE	0.805					
SI	0.493	0.506				
PI	0.616	0.569	0.651			
PT	0.310	0.263	0.454	0.676		
CAI	0.687	0.574	0.624	0.667	0.470	

The discriminant validity calculation built on the Heterotrait-Monotrait (HTMT) ratio criterion is represented in Table 3. HTMT results were all below the recommended cut-off value of 0.85, showing adequate discriminant validity among constructs. Values ranged from 0·263 to 0·825. suggesting that any such construct is conceptually separable and represents a unique dimension in the model. Thus, these results confirm that the model of measurement presents good discriminant validity and the adequacy of constructs to structural model analysis.

Figure 2, Table 4 shows that Structural Model Analysis and Hypotheses Testing using PLS-SEM possesses the advantage of predictive modelling and variance explanation [23] . Chatbot Adoption Intention (CAI) is also explained by 46.4% of variance (R^2 = 0.464), showing a moderate explanatory power of the proposed framework with respect to students' intention to adopt AI-based chatbots in a higher education setting.

Outcomes indicate that performance expectancy (β = 0.311, p = 0.000) positively influences chatbot adoption intention and therefore supports H1. This implies that students develop a favourable attitude towards chatbots when they are perceived as useful academic entities. If we look through the prior studies, academic productivity improvements have been stated to be another significant reason for using chatbots [51], [43].

H3 was supported since social influence (β = 0.215, p = 0.000) also had a momentous positive effect, as peer and institutional influence have an important role in technology adoption behaviour. Previous studies indicate that social influence is especially important for areas such as higher education, where technology adoption has been guided mainly by students and peers [52], [1].

Table 4. Hypotheses Testing Results.

Hypothesis		Coefficient	P values	Result
H1	**PE -> CAI**	0.311	0	Supported
H2	**EE -> CAI**	0.087	0.087	Not Supported
H3	**SI -> CAI**	0.215	0	Supported
H4	**PI -> CAI**	0.179	0.002	Supported
H5	**PT -> CAI**	0.125	0.011	Supported

H4: Perceived intelligence (β = 0.179, p = 0.002) was used as a significant factor influencing chatbot adoption intention (see Table 4). This highlights the need for smart dialogue to improve student acceptability of chatbots. Pillai et al. (2023) confirm the role of chatbot intellect in predicting adoption intention. Such is the context of AI-driven learning tools, which we will discuss later in 2023. This is in line with the results of Ghazali et al. (2018), who showed that enhancing AI chatbots with humanlike attributes improves user engagement and satisfaction.

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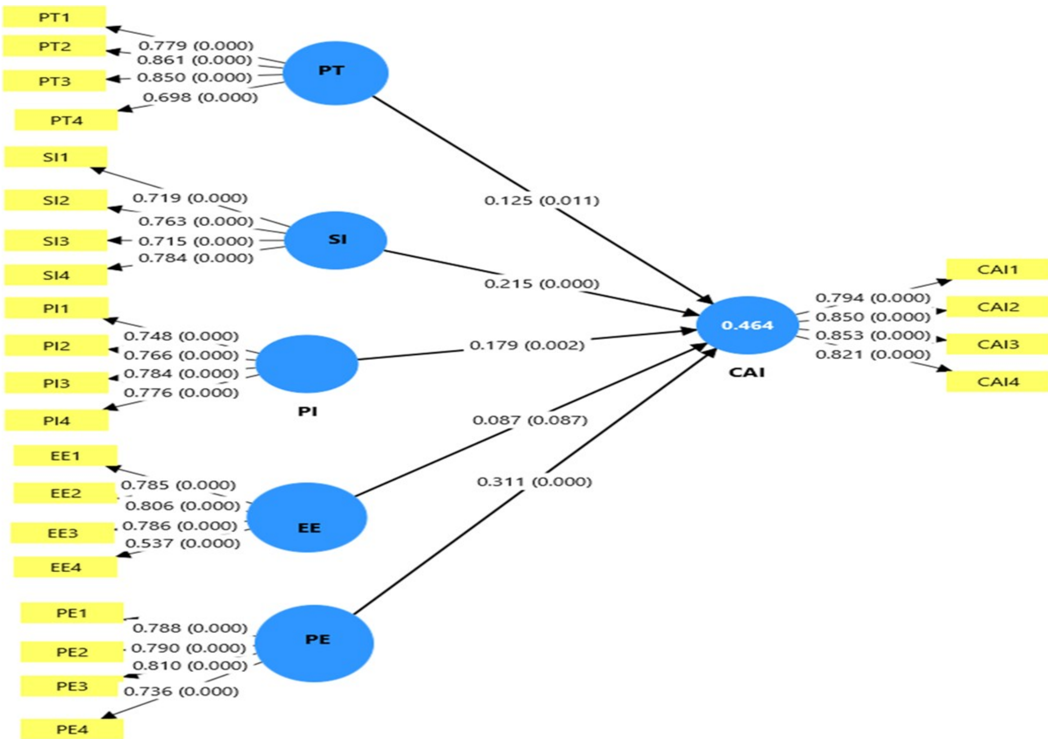

Fig. 2. Structural Model Results

H5 is also supported by the significant impact of perceived trust (β = 0.125, p = 0.011) on chatbot adoption intention. This will demonstrate the importance of validity in increasing student approval of chatbots. This is backed up by McKnight et al. (2002) explains that trust is an important precursor to technology adoption.

Surprisingly, Effort Expectancy (β = 0.087, p = 0.087) was not significant, leading to the rejection of H2 regarding adoption intention. This could suggest that, as digitally literate users, students do not regard ease of use as a major construct in the adoption of chatbot technologies. This result is consistent with Teo (2011), who found that high school students care more about a tool's usefulness than its ease of use.

5. Discussion

Mainly, the study focuses on analysing how students will adopt AI-powered chatbots in higher education. The outcomes verified that the measurement model demonstrated acceptable reliability and validity, which means that we were able to utilise these constructs for the subsequent analyses. Among the factors, effort expectancy did not significantly affect chatbot adoption intention. This shows students are digitally literate, which in turn greatly facilitates chatbot usage. The student is not very worried about the ease of use of an AI-based chatbot [36].

Performance expectancy was identified as the strongest positive factor to intention to adopt chatbot among all factors. This means that when students believe that the technology can help with their academic tasks, simplify learning tasks and provide help quickly, they are more likely to use AI-enabled chatbots. This result is in accordance with previous studies that recognised performance expectancy as an important driver of technology acceptance [38].

The social influence had a positive and strong impact on chatbot adoption intention. This implies that, while adopting chatbot technologies, students are influenced by their instructors, peers, institutions and family members, as pointed out by Almahri et al. (2024). Just as classmates and schools encouraged students to use resources like librarians when they could not find answers in books, so too should officials encourage the use of AI-powered chatbots: Students will be more inclined to leverage advice and assistance if they have it at their disposal.

PT has a significant effect on AI chatbot adoption intention, which can be interpreted as students are enthusiastic to adopt chatbots when they trust that chatbots are trustworthy, reliable, and secure. Building trust is another important factor that increases the adoption of AI technologies [10], [38].

Another element associated with intelligence demonstrated a significant positive effect on the willingness to use the chatbot. The students feel that the chatbots are capable of answering user queries, they react like a human being and also understand queries correctly. These developments support [39,38] — intelligent chatbots should improve interactions by enhancing students' experience and increasing their willingness to use AI-powered tools.

5.1. Theoretical Implications

By integrating factors such as perceived intelligence and perceived trust along with UTAUT variables such as performance expectancy, effort expectancy, and social influence, this study contributes to the emergent literature on AI technologies in higher education [20], [24]. The outcomes support the importance of performance expectancy and social influence in shaping intention to adopt a chatbot, while also providing some evidence for the emergence of relatively new constructs related to AI expectations as part of the elements of educational technology acceptance. The insignificant effect of effort expectancy further indicates that students perceive themselves as more comfortable and ready to adapt to new digital tools [49]. In addition, this study adds to the literature on chatbot adoption studies in the Indian higher education setting, which is a relatively under-researched domain.

5.2. Practical Implications

These results deliver useful information for institutions, policymakers, and chatbot developers seeking to enhance chatbot adoption among students. Since performance expectancy emerged as the strongest predictor, institutions should focus on developing chatbots that provide precise, efficient, and academically pertinent support services. The importance of perceived trust and perceived intelligence indicates the importance of designing reliable, responsive, and human-like chatbot interactions to improve user confidence and engagement [39]. Additionally, the influence of social factors suggests that universities can encourage adoption through peer recommendations, awareness programs, and institutional promotion. These approaches would assist in the successful implementation of AI-based chatbots alongside higher education institutions.

6. Conclusion

The study extends prior literature on AI adoption in higher education and explores the main factors influencing chatbot adoption intention among students in India. The results show that performance expectancy, social influence, perceived intelligence, and perceived trust significantly affect students' learning engagement when integrating chatbots. On the other hand, effort expectancy does not make a significant contribution, implying greater importance of functionality over usability in students' acceptance of AI-driven learning tools.

We help educators, policymakers, and AI developers in the context of practical implications. And then, in the case of higher education institutions, focus on what chatbots can offer academics, leverage peer or faculty influence for adoption and uptake, and deploy intelligent, trustworthy, and ethical chatbots. Improving students' trust-related concerns regarding data security, accuracy, and transparency will continue to ensure students engage with chatbot technologies over the long term.

6.1. Limitations and Future Research Directions

The limitations of this study need to be addressed. First, the study uses only data from self-reported surveys, which could introduce response bias [40]. Second, the research focuses on Indian higher education institutions, limiting the generalisability of the outcomes to other cultural and academic settings. An upcoming study could conduct cross-cultural comparative studies to explore chatbot adoption patterns across diverse educational environments [52]. Additionally, while this study examines direct relationships between constructs, forthcoming research could explore moderating or mediating effects of constructs such as technology readiness and digital literacy [37].

This study provides numerous directions for future research on the intention to adopt AI-powered chatbots in higher education. An upcoming study may incorporate extra constructs such as user satisfaction, perceived risk, user engagement, self-efficacy, and technology anxiety to provide a more holistic view of chatbot adoption behaviour. Comparative studies across different educational levels and disciplines may help determine whether cultural, demographic, and institutional differences influence chatbot adoption intention. A forthcoming study is required to better understand the longer-term effects of adopting chatbots on learning outcomes, using longitudinal data to assess changes in student engagement over time. Addressing these gaps will enhance our understanding of AI-driven educational technologies and support more robust theoretical models for chatbot adoption in higher education.

Conflict of Interest

Author Disclosure Statement: The authors declare no conflict of interest.

Data Availability Statement

Availability of Data and Materials: The data that support the findings of this study are available from the corresponding author upon reasonable request. The data are not publicly available as they contain both non-public information of the research subjects that could lead to a breach of confidentiality of their personal data.

AI Usage Disclosure

The authors used ChatGPT (GPT-5. 5, OpenAI) to help refine grammar, edit writing, and improve clarity of the manuscript. The authors take full responsibility for the final manuscript, with all scientific content, including analyses, interpretations and conclusions developed, reviewed and verified by them.

Author Contributions

Conceptualization, K. Srilekha and Dr. J. Rama Krishna Naik; methodology, K. Srilekha; analysis, D. Vamsi; writing-original draft, K. Srilekha; writing-review and editing, all authors. All authors have read and agreed to the published version of the manuscript.

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