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Adoption Intention of AI-Powered Chatbot: An Empirical Study Among Higher Education Students in India

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ABSTRACT

This study examines the intention to adopt AI-powered chatbots among higher education students in India, focusing on the roles of performance expectancy and effort expectancy, and the mediating effect of perceived trust in linking social influence, perceived intelligence, and perceived risk with adoption intention. A quantitative survey of 575 students was analysed using Structural Equation Modelling in AMOS and the PROCESS macro, with reliability and validity confirmed through composite reliability (CR), average variance extracted (AVE), discriminant validity, and satisfactory model fit indices (CFI = 0.926; RMSEA = 0.04). The findings reveal that performance expectancy ($\beta = 0.4729$, $p < 0.001$) and effort expectancy ($\beta = 0.2283$, $p < 0.001$) significantly influence chatbot adoption intention, while perceived trust plays a central mediating role between social influence ($\beta = 0.0724$), perceived intelligence ($\beta = 0.0656$), perceived risk ($\beta = -0.0979$), and adoption intention. The study extends TAM and UTAUT by incorporating perceived intelligence, risk, and trust, offering deeper insights into AI adoption in higher education, and suggests that institutions should enhance chatbot usability, intelligence, transparency, and faculty and peer endorsement to strengthen trust and mitigate risk perceptions

Keywords: - AI-powered chatbots, adoption intention, perceived trust, TAM, UTAUT, higher education

INTRODUCTION:

In the Indian higher education system, the teaching-learning framework and administrative activities are under scrutiny and are expected to undergo rapid transformation (Menon et al., 2014). The workload is increasing, and many students are joining (Chatterjee & Bhattacharjee, 2020); in this context, there is an urge to incorporate AI applications to address these problems (Andrea et al., 2015; Croxford & Raffe, 2015).

AI can improve the educational learning experience and may create future needs (Moraes, 2021). If AI is adopted in education, it can be beneficial (Bilquise et al., 2023). For example, Jill Watson assists in tech teaching through AI-powered chatbots, which encourage teachers to spend more time in deep discussion with students (Bilquise et al., 2023). AI-based conversation agents are overcoming human limitations by effectively advising interactions with 24/7 availability to solve student queries (Bilquise & Shaalan, 2022) and by accurately updating technology (Chrisinger, 2019).

An AI-powered chatbot is an innovative tool powered by machine learning that understands and responds in a way that feels like a real human conversation. It works using natural language processing, which means it can communicate in the same everyday language we use-acting like a virtual personal assistant, capable of handling multiple tasks like answering questions, searching for information, and maintaining conversations to create a more personal experience (Sheehan et al., 2020) and "admission queries of students administration decision-making" (Chatterjee & Bhattacharjee, 2020). An AI-powered chatbot provides a personalised learning experience for students and significantly improves the emotional aspects of the interaction process (Moraes, 2021; Bilquise et al., 2022). An AI-powered chatbot provides human-like conversations (Kuhail et al., 2022) and supports students' queries in their preferred languages (Bilquise et al., 2022a).

This research aims to analyse how the key constructs in this study affect students' chatbot adoption intention in Indian higher education institutions. Key theoretical frameworks utilised in this research are Unified Theory of Acceptance and Use of Technology (UTAUT) and Technology Acceptance Model (TAM), which propose a comprehensive conceptual model that incorporates critical predictors of adoption, such as performance expectancy, effort expectancy, social influence, perceived intelligence, perceived risk, perceived trust, and AI-powered chatbot adoption intention. By empirically analysing the effect of AI-powered chatbot adoption on student performance, this study contributes to the growing literature on AI incorporation in higher education. It offers strategic perceptions for enhancing digital learning infrastructures within the Indian academic context.

2. REVIEW OF LITERATURE

In higher education, AI tools like chatbots are rapidly shifting the landscape by enhancing personalisation, responsiveness, and accessibility. The amalgamation of AI-powered chatbots into educational contexts has been explored across multiple dimensions, including academic advising, learning motivation, gender disparities, and TAM.

Several studies demonstrate that AI-powered chatbots have become indispensable tools for supporting student needs around the clock. For instance, Bilquise and Shaalan (2022) emphasised that AI-driven “chatbots equipped with natural language processing” (NLP) can provide emotionally intelligent, anthropomorphic interactions that mimic human advising sessions, thereby improving inclusivity and timeliness in responding to student concerns. These systems also support predictive interventions for at-risk students, aligning with Lim et al.'s (2021) findings and highlighting the potential of AI-powered chatbots for early-stage academic support.

Complementing this, Kuhail et al. (2022) synthesised 36 empirical studies and concluded that the most effective AI-powered chatbot designs emulate peer or tutor roles and offer personalised and natural interactions. However, they also noted inconsistencies in design standards and called for better pedagogical alignment. Similarly, Chen et al. (2024) proposed a personalised, adaptive, AI-powered chatbot (PMTutor) that demonstrated measurable improvements in engagement and learning through real-time feedback.

From a behavioural standpoint, many studies have extended traditional models such as TAM and UTAUT to capture nuances in the adoption of AI-powered chatbots. Chatterjee and Bhattacharjee (2020) found that facilitating conditions and attitudes were more predictive of behavioural intention than performance expectancy, signalling a shift in the motivational drivers for AI use. In alignment with Strzelecki (2024), hedonic motivation, performance expectancy, and habits were key determinants of students' intention to use ChatGPT, whereas social influence had a limited impact.

Moreover, integrating learner personas into TAM has yielded important insights. For example, Amer Jid Almahri et al. (2024) used educational personas such as age and learning engagement level to show that perceived effort and habit significantly influenced acceptance, whereas facilitating conditions and social influence did not. Their work highlights the need to design AI-powered chatbot experiences that are sensitive to learners' individual differences.

Other studies emphasised contextual and ethical considerations. Nazri et al. (2023a) incorporated institutional readiness and ethical awareness into a TAM framework and found these factors significantly shaped student attitudes toward AI in Malaysian higher education. Likewise, Idroes et al. (2023) noted that students in Indonesia were generally optimistic about AI’s potential but remained concerned about fairness, privacy, and overreliance.

Gender disparities emerged as a critical theme in Mogelvang et al. (2024), who found that male students in Norway used generative AI (genAI)-enabled chatbots more frequently and for diverse tasks, linking their use to employability. In contrast, female students exhibited greater scepticism regarding trust and critical thinking issues. These insights underscore the need for inclusive AI-powered chatbot designs and gender-sensitive integration strategies in higher education.

Shah (2023) introduced an AI-driven learning chatbot with adaptive feedback and collaborative scaffolding regarding pedagogical innovation. His findings showed enhanced student motivation and understanding, although broader trials are still needed. In addition, Pillai et al. (2023) tested an AI-based teacher bot (T-bot). They found that anthropomorphism, personalisation, and perceived intelligence significantly influenced students’ attitudes, though many still preferred human teachers, indicating a transitional phase in acceptance.

Finally, regional and cultural factors significantly influence the adoption of AI-powered chatbots. Ayanwale and Molefi (2024), focusing on students in Lesotho, used innovation diffusion theory to identify trust, relative advantage, and trialability as key predictors. Their study adds a much-needed African perspective to the literature and underscores the critical role of cultural context in shaping student perceptions.

Despite emerging research on AI-powered chatbot adoption in higher education globally, there remains a significant gap in context-specific, empirically grounded studies that explore how Indian higher education students form their behavioural intentions toward AI-powered chatbots. Prior Indian studies have either focused broadly on AI (Chatterjee & Bhattacharjee, 2020; Sharma et al., 2023) or on teacher-bots (Pillai et al., 2023), but few have isolated AI-powered chatbot adoption as a distinct phenomenon.

Additionally, emerging variables such as trust, perceived risk, and perceived intelligence, which are increasingly relevant to human-AI interaction, are often understudied within a single integrated framework, particularly in the Indian context (Pillai et al., 2023; Bilquise et al., 2024; Shuhaiber et al., 2024).

Overall, the literature establishes that while AI-powered chatbots are becoming essential in higher education, successful adoption depends on thoughtful integration into pedagogical structures, attention to learner diversity, ethical design, and contextual adaptability. Thus, this research focuses on filling a significant gap by developing and validating an integrated AI-powered chatbot adoption model that incorporates classical and emerging behavioural predictors among higher education students in India.

2.1. Theoretical Framework and Hypothesis Development

Davis developed the Technology Acceptance Model (TAM) in 1989, which is one of the most widely used models for understanding users’ behavioural intention to adopt technology. The original TAM comprises two key antecedents: Perceived Ease of Use (PEOU) and Perceived Usefulness (PU). Gradually, TAM has gone through multiple refinements. TAM2 (Venkatesh & Davis, 2000) introduced Subjective Norms and Cognitive Instrumental Processes, while TAM3 (Venkatesh & Bala, 2008) further extended the study by integrating Perceived Trust and Perceived Risk, recognising that trust and security concerns are crucial in technology adoption decisions.

"The Unified Theory of Acceptance and Use of Technology (UTAUT) was developed by Venkatesh et al. (2003)" from the roots of TAM. It introduced four key variables related to the intention and use of technology: Performance Expectancy (PE) (functionally equivalent to PU), Effort Expectancy (EE) (identical to PEOU), Social Influence (SI), and Facilitating Conditions (FC) (Venkatesh et al., 2012).

Recent studies in AI-powered chatbot adoption contexts have extended these foundational models by integrating additional constructs relevant to human-AI interaction, such as Perceived Trust, Perceived Risk (Pillai et al., 2023; Bilquise et al., 2024; Shuhaiber et al., 2024). These additions reflect the evolving nature of intelligent systems and the increasing need for emotional, ethical, and social alignment between users and AI tools.

Figure 1: Proposed Research Model

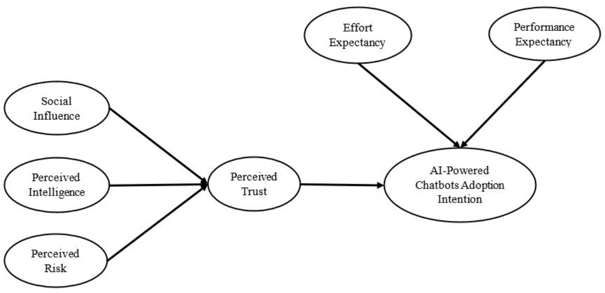

Fig. 1 presents the conceptual framework of this study, grounded in established technology adoption theories and adapted to the higher education context. It seeks to investigate the influence of a combination of functional, cognitive, and relational constructs on students' behavioural intention to adopt an AI-powered chatbot. This model incorporates key antecedents: Performance expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Perceived Trust (PT), Perceived Risk (PR), Perceived Intelligence (PI), and AI-powered Chatbot Adoption Intention (CAI). These constructs have been chosen based on their theoretical relevance and empirical significance in prior literature. They aim to capture students' expectations regarding the usefulness, usability, credibility, and social validation of AI-powered chatbot technology within academic environments.

Performance expectancy (PE)

Performance expectancy is the degree to which students believe that using an AI-powered chatbot can help them perform better in their studies (Davis, 1989). Performance expectancy significantly and positively impacts attitude (Chatterjee & Bhattacharjee, 2020). Students are more likely to adopt AI in higher education (Sharma et al., 2023). Research indicates that PE significantly predicts students' adoption of AI-powered chatbots (Almahri et al., 2020). According to Davis (1989), users are eager to adopt new technology when they believe it enhances their skills. AI-powered chatbot adoption intention is influenced by performance expectancy (Sugumar & Chandra, 2021). A recent study also highlights that PE is a key determinant of the intention to adopt an AI-powered chatbot in the educational context. Furthermore, PE contributes to users' continued engagement with technology (Huang et al., 2021).

H1: Performance expectancy (PE) significantly affects AI-powered Chatbot Adoption Intention (CAI).

Effort Expectancy (EE)

Effort Expectancy is the degree to which students perceive that using and interacting with an AI-powered chatbot is easy (Davis, 1989; Venkatesh et al., 2003). EE is an important and effective predictor of attitude toward technology acceptance (Lu et al., 2005). If it is easy to use, the more individuals are willing to adopt a technology (Almahri et al., 2020). A user-friendly system increases the likelihood of adoption and long-term usage (Almahri et al., 2020; Ayanwale & Molefi, 2024). Ease of use directly increases the intention to use technology (Dwivedi et al., 2019; Brachten et al., 2021). In higher education, EE significantly influences students' behavioural intention to adopt AI-powered chatbot technology (Ragheb et al., 2022). Students who understand how to use AI-powered chatbots are more likely to adopt the system and effectively complete their tasks (Bilquise et al., 2023).

H2: Effort Expectancy (EE) significantly affects AI-powered Chatbot Adoption Intention (CAI).

Social Influence (SI)

Social Influence is about how much students' decisions to use AI-powered chatbots are affected by what their friends, teachers, family, or school suggest or require (Venkatesh et al., 2003). Studies have found "that peer influence has a more substantial impact than managerial influence" on organisational AI-powered chatbot adoption (Brachten et al., 2021). Strong social influence drives change, encouraging students to embrace AI technology and making it more practical and valuable (Gursoy et al., 2019). Additionally, research highlights the significant role of SI in students' adoption of AI-powered chatbots for teaching and learning (Regheb et al., 2022). SI positively impacts behavioural intention, particularly in the case of an advisory AI-powered chatbot (Bilquise et al., 2023). SI influences technology adoption by shaping user behaviour (Shuhaiber et al., 2024). In the context of an AI-powered chatbot, SI determines which users are most eager to adopt it for knowledge-sharing (Kim et al., 2021).

H3: Perceived Trust (PT) mediates the relationship between Social Influence (SI) and AI-powered Chatbot Adoption Intention (CAI).

Perceived Intelligence (PI)

Perceived Intelligence is the extent to which students see AI-powered chatbots as innovative tools that can understand questions, provide personalised answers, and adapt to each user's needs (Wirtz et al., 2018). AI-powered chatbots have been widely studied in the tourism sector, where they have been identified as key predictors of adoption (Pillai & Sivathanu, 2020). Teaching bots assist students seamlessly, eliminating hesitation and addressing queries effectively. PI has positively influenced the adoption of teaching bots (Pillai et al., 2023).

H4: Perceived Trust (PT) mediates the relationship between Perceived Intelligence (PI) and AI-powered Chatbot Adoption Intention (CAI).

Perceived Risk (PR)

Perceived Risk is the extent to which people worry that something might go wrong or that they could face problems when using an AI-powered chatbot, such as receiving incorrect information or privacy concerns (Alagarsamy & Mehrolia, 2023). Users may perceive financial risks, data privacy concerns, or security threats when using AI technology. PR assesses potential uncertainties or negative consequences of using a particular system (Chatterjee & Bhattacharjee, 2020). Many AI applications, such as robots and autonomous vehicles, face adoption challenges due to perceived risks, including financial losses, data breaches, privacy concerns, operational failures, usability complexity, and limited trial opportunities (Huang et al., 2021). Including PR in this study helps assess the risks users perceive when adopting AI-powered chatbots and how these risks affect student engagement in higher education. While PR harms user attitudes (Teo & Liu, 2007), a positive relationship exists between risk perception and behavioural intention. Concerns regarding AI's reliability and security are crucial to determining adoption rates, and addressing them can positively influence users' behavioural intention to adopt AI in higher education (Sharma et al., 2023).

H5: Perceived Trust (PT) negatively mediates the relationship between Perceived Risk (PR) and AI-powered Chatbot Adoption Intention (CAI).

Perceived Trust (PT)

Perceived Trust is the extent to which people feel they can rely on the AI-powered chatbot to provide accurate and helpful answers and to act in their best interests (McKnight et al., 2002). Trust is crucial for technology adoption and continued use (Aslam et al., 2022; Pillai et al., 2023). A higher level of trust leads to greater adoption of AI-powered chatbots among users (Bilquise et al., 2024). Similarly, in the travel and tourism sector, trust influences users' willingness to utilise AI-powered chatbots for travel planning and sharing personal information (Pillai & Sivathanu, 2020). This study identifies trust as a significant factor in mediating user satisfaction (Lee & Choi, 2017).

Objectives:

To analyse the impact of independent constructs (perceived and effort expectancy) on the adoption intention of AI-powered chatbots.

To evaluate the mediating effect of perceived trust in the relationship between independent constructs (social influence, perceived intelligence, and perceived risk) and AI-powered chatbot adoption intention.

3. RESEARCH METHODOLOGY

Measurement and scale:

The research employs a quantitative approach to analyse the constructs that impact students' intention to adopt AI-powered chatbots in Indian higher education institutions. A systematic survey questionnaire was designed as the primary data collection mechanism to ensure a systematic and empirically grounded examination of the proposed conceptual framework. The measurement constructs were adapted from well-established theoretical models, notably the TAM (Davis, 1989), and UTAUT (Venkatesh et al., 2003), which are widely recognised for assessing technology adoption behaviour.

The questionnaire was designed based on validated scales from prior literature, with minor contextual modifications to reflect the use of an AI-powered chatbot in academic settings. It comprised two main sections:

Demographic Information: Captured data related to age, gender, academic discipline, and prior experience with an AI-powered chatbot.

Construct Measurement: Assessed key variables such as performance expectancy, effort expectancy, social influence, perceived intelligence, perceived risk, perceived trust, and AI-powered chatbot adoption intention using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree).

To ensure content validity, a pilot study was organised with a preliminary sample of 40 higher education students (n = 40). Minor revisions were made to enhance the clarity and comprehensibility of the questionnaire items based on the feedback (Hair et al., 2016).

The study adopted a convenience sampling technique, a non-probability sampling method, targeting students at Indian higher education institutions. This approach was selected to ensure the inclusion of participants with relevant exposure to AI technologies, particularly AI-powered chatbots used for academic purposes. The target population comprised students from diverse academic disciplines in India.

DATA COLLECTION:

To ensure maximum participation and accessibility, the study utilised a self-administered survey approach. Before participants began the questionnaire, they were provided with a brief introduction to AI-powered chatbot technology and visual examples of AI-powered chatbot interactions to minimise potential biases and ensure a common understanding. Out of the 600 surveys distributed, 575 valid responses were collected, aligning with Hair's (2009) recommendation of having 5 to 10 observations per parameter for robust statistical analysis.

Statistical Tool/Technique: To analyse the collected data, this study adopted a structured, two-phase approach to ensure the accuracy and reliability of its findings. The first phase involved conducting an Exploratory Factor

Analysis (EFA) using AMOS SEM. This step helped uncover the dataset's underlying dimensions and evaluate the reliability of the measurement constructs. EFA was useful for identifying how well individual survey items grouped to form meaningful factors.

In the second phase, a Confirmatory Factor Analysis (CFA) was performed using AMOS, allowing the researcher to test the measurement model's validity. CFA verified convergent validity, ensuring that items meant to measure the same concept were related, and discriminant validity, confirming that different constructs were clearly distinct.

To understand how the various constructs in the model were related, the study used Structural Equation Modelling (SEM) via AMOS. SEM helped examine the strength of the connections between variables and the model's fit to the observed data.

To explore mediation effects more deeply, the study also used the PROCESS macro. This advanced statistical technique is widely used for testing complex models, especially those involving multiple direct and indirect relationships. This tool allowed for a closer look at how and why certain variables, such as trust, influenced students' adoption of AI chatbots, particularly as a bridge between other predictors, such as social influence, perceived intelligence, and perceived risk.

The reliability and validity of the model were validated through several measures, including Composite Reliability (CR) for internal consistency (threshold >0.70), Average Variance Extracted (AVE) for convergent validity (threshold >0.50), and both the Fornell-Larcker Criterion and the Heterotrait-Monotrait Ratio (HTMT) for discriminant validity (Hair et al., 2016). These steps ensured a robust and reliable analysis of students’ adoption of AI-powered chatbot technology in academic settings.

4. RESULTS AND FINDINGS

Table 1: Demographic Information of the Respondents

	N=575	%
Gender		
Male	225	39.1
Female	350	60.9
Age		
18-25	456	79.3
26-35	117	20.3
36-45	2	0.4
Education Qualification		
Bachelor's Degree	24	4.2
Master's Degree	413	71.8
Ph.D.	137	23.8
Other	1	.2
Occupation		
Student	431	75.0
Research Scholar	142	24.7
Employed	2	.3
Comfort level with Technology		
Very Comfortable	257	44.7
Somewhat Comfortable	224	39.0
Neutral	89	15.5
Uncomfortable	5	.9
Awareness of AI-powered chatbot		
High awareness	123	21.4
Moderate awareness	396	68.9
Low Awareness	53	9.2
No awareness	3	.5
How long have you been using an AI-powered chatbot?		
Less than 1 year	166	28.9
1 to 2 years	294	51.1
2 to 3 years	86	15.0
More than 3 years	29	5.0
Frequency of using AI-powered chatbots in services		
Daily	257	44.7
Weekly	201	35.0
Monthly	44	7.7

Rarely	73	12.7
Preferred Interaction Style		
Text-Based	533	92.7
Voice-Based	24	4.2
Both	18	3.1

Demographic information for the 575 samples (N=575) is presented in Table 1. Most respondents were female (60.9%), reflecting growing inclusivity in AI-based learning technologies. Most participants (79.3%) were aged 18–25, indicating that younger learners are more engaged with digital tools. Regarding qualification, 71.8% were master's students, 23.8% PhD scholars, and 4.2% bachelor's students, highlighting postgraduate learners' inclination toward technology-enhanced support.

The majority were students (75.0%) and research scholars (24.7%), with minimal employed participants (0.3%), reflecting the academic focus of chatbot use. Technological readiness was high, with 44.7% very comfortable and 39.0% somewhat comfortable using technology (Pillai & Sivathanu, 2020). Awareness of AI-powered chatbots was moderate (68.9%), while usage experience showed most had used them for 1–2 years (51.1%), suggesting adoption is recent but growing.

Regarding usage frequency, 44.7% reported daily and 35.0% weekly, indicating regular integration into academic routines. Text-based interaction was strongly preferred (92.7%), while only a small proportion favoured voice (4.2%) or both (3.1%), supporting the dominance of text-based chatbot design in education.

Table 2: Factor Loadings with Reference

Construct Source	Item code	Items	Factor Loading
Performance expectancy (CR=0.891, AVE=0.672, CA=0.899)			
(Pillai et al., 2023;	PE1	Using an AI-powered chatbot has increased my academic productivity and saved me time.	0.803
Bilquise et al., 2023;	PE2	I feel that AI-powered chatbots are valuable resources for getting personalised academic support.	0.849
Chatterjee & Bhattacharje e 2020;	PE3	I have learned many unknown things with the help of an AI-powered chatbot.	0.827
Almahri et al., 2024)	PE4	When I do not understand what the professor is teaching, I use the AI-powered chatbot's help.	0.801
Effort Expectancy (CR= 0.902, AVE= 0.698, CA=0.912)			
(Pillai et al., 2023;	EE1	I feel that AI-powered chatbots can easily solve academic problems.	0.821
Almahri et al., 2024;	EE2	Using an AI-powered chatbot for my academic work would require little effort.	0.834
Chatterjee & Bhattacharje e (2020).	EE3	I find the AI-powered chatbot's interface intuitive and user-friendly.	0.822
	EE4	I feel that sometimes the AI-powered chatbot does not understand my questions.	0.865
Social Influence (CR= 0.895, AVE= 0.682, CA=0.897)			
(Bilquise et al., 2023;	SI1	My peers encouraged me to utilise an AI-powered chatbot for academic purposes.	0.843
Almahri et al., 2024)	SI2	I have adopted an AI-powered chatbot based on positive feedback from other students.	0.854
	SI3	Faculty members often recommend using an AI-powered chatbot for academic support.	0.798

	SI4	My classmates' widespread adoption of AI-powered chatbots influenced my decision.	0.808
Perceived Intelligence (CR= 0.872, AVE= 0.630, CA=869)			
(Pillai et al., 2023;	PI1	I feel that an AI-powered chatbot provides human-like responses that feel intelligent.	0.786
Pillai & Sivathanu (2020).)	PI2	I believe the AI-powered chatbot can be competent for students.	0.758
	PI3	AI-powered chatbots suggest the best services based on my needs and demands.	0.789
	PI4	An AI-powered chatbot will provide the information that I need effectively and efficiently.	0.842
Perceived Trust (CR= 0.865, AVE= 0.618, CA= 0.855)			
(Pillai et al., 2023;	PT1	I trust that the AI-powered chatbot is safe to interact with.	0.823
Bilquise et al., 2023)	PT2	I feel that an AI-powered chatbot would provide ethical and transparent information.	0.813
	PT3	Given the information, I feel the AI-powered chatbot is honest and trustworthy.	0.807
	PT4	I feel that the AI-powered chatbot would provide us with unbiased information.	0.695
Perceived Risk (CR= 0.852, AVE= 0.592, CA=867)			
(Chatterjee & Bhattacharjee 2020;		Using the AI-powered chatbot may lead to the misuse of my personal data.	0.719
Shuhaiber et al. 2024)		I am concerned that the AI-powered chatbot might not always give accurate answers.	0.828
		I feel there is a privacy risk that AI-powered chatbot responses may mislead students in their studies.	0.729
		I feel hesitant when the AI-powered chatbot does not perform well, which creates problems.	0.798
AI-powered chatbot Adoption Intention (CR= 0.845, AVE= 0.578, CA=0.858)			
(Pillai et al., 2023;	CAI 1	I intend to use an AI-powered chatbot for academic assistance in the future.	0.784
Bilquise et al., 2023;	CAI 2	I believe an AI-powered chatbot will be essential to my educational experience.	0.764
Chattarjee & Bhattacharjee (2020).	CAI 3	I am likely to recommend an AI-powered chatbot to other students or faculty.	0.767
	CAI 4	I am willing to integrate an AI-powered chatbot into my daily learning process.	0.723

The Table 2 measurement model showed strong reliability and validity of all constructs. Performance expectancy (CR = 0.891, AVE = 0.672, α = 0.899) confirmed students' belief in chatbots' usefulness for productivity, learning efficiency, and personalisation, while Effort Expectancy (CR = 0.902, AVE = 0.698, α = 0.912) highlighted ease of use as a key driver of adoption. Social Influence (CR = 0.895, AVE = 0.682, α = 0.897) showed the role of peer and faculty encouragement. In contrast, Perceived Intelligence (CR = 0.872, AVE = 0.630, α = 0.869) reflected students' trust in chatbots' capability to provide accurate, context-aware responses. Perceived Trust (CR = 0.865, AVE = 0.618, α = 0.855) indicated confidence in the ethical and unbiased nature of chatbot outputs, while Perceived Risk (CR = 0.852, AVE = 0.592, α = 0.867) captured concerns about data privacy and system reliability. Finally, Chatbot Adoption Intention (CR = 0.845, AVE = 0.578, α = 0.858) showed students' willingness to integrate chatbots into academic routines. All constructs exceeded the thresholds for CR, AVE, and factor loadings (Hair et al., 2016), confirming the robustness of the model and its appropriateness for further structural analysis.

Discriminant Validity Test:

Table 3: Estimation of Cronbach's α and AVE (Discriminant Validity Test)

	PE	EE	SI	PI	PT	PR	CAI	AVE	Cronbach's Alpha
PE	0.820							0.672	0.889
EE	0.6	0.835						0.698	0.912
SI	0.358	0.273	0.826					0.682	0.897
PI	0.547	0.401	0.479	0.794				0.63	0.869
PT	0.288	0.178	0.371	0.676	0.786			0.618	0.855
PR	0.031	0.079	-0.01	-0.094	-0.32	0.7694		0.592	0.867
CAI	0.636	0.371	0.474	0.629	0.411	0.056	0.760	0.578	0.858

The study applied the Fornell-Larcker criterion to analyse discriminant validity, requiring each factor's square root of the Average Variance Extracted (√AVE) to be greater than its correlations with any other construct. This ensures that each latent variable captures its intended concept more strongly than it overlaps with other latent variables in the model. Based on this criterion, all constructs in the current study demonstrate satisfactory discriminant validity.

Performance expectancy (PE) had an √AVE of 0.820, notably higher than its correlations with other constructs (e.g., 0.593 with Effort Expectancy, 0.367 with Social Influence, and 0.645 with Adoption Intention). This confirms that students' perceptions of chatbots improving academic productivity are uniquely captured, without being confounded by factors such as effort or social pressure.

Effort Expectancy (EE) had an √AVE of 0.835, exceeding its correlations with all other constructs. This supports the conclusion that students recognise ease of use as a distinct and independent factor influencing adoption.

Social Influence (SI) demonstrated an √AVE of 0.826, surpassing its highest inter-construct correlation (0.478 with CAI). This shows that the influence of peers and faculty is conceptually distinct from perceptions of trust, usefulness, or intelligence.

Perceived Intelligence (PI) reported an √AVE of 0.794, greater than its correlations with PE (0.560), SI (0.490), and CAI (0.632). This indicates students clearly distinguish chatbot intelligence (e.g., human-like, context-aware responses) from general usefulness or ease of use.

Perceived Trust (PT) had an √AVE of 0.786, comfortably higher than its correlations with other constructs such as PI (0.683), PE (0.304), and CAI (0.417). Despite strong theoretical links between trust and other predictors, the discriminant validity confirms that trust operates as an independent psychological factor in the adoption process.

Perceived Risk (PR) showed an √AVE of 0.769, which exceeded all its correlations (all near zero or negative, with the highest being −0.175 with PT). This reinforces that students' concerns about data privacy and chatbot reliability are uniquely captured and not conflated with perceptions of trust or performance.

AI-powered Chatbot Adoption Intention (CAI) had an √AVE of 0.760, higher than its strongest correlation (0.645 with PE). This confirms that behavioural intention is statistically distinct from all independent and mediating constructs in the model.

The outcomes from the Fornell-Larcker test confirm that each construct in the model possesses strong discriminant validity. This reinforces the theoretical integrity of the model, indicating that students differentiate between performance expectancy, effort expectancy, perceived trust, social influence, perceived risk, and perceived intelligence when deciding whether to adopt AI-powered chatbots.

Table 4: Discriminant Validity (HTMT Ratio)

	PE	EE	SI	PI	PT	PR	CAI
PE							
EE	0.593						

SI	0.367	0.267					
PI	0.560	0.368	0.490				
PT	0.304	0.168	0.383	0.683			
PR	0.035	0.109	0.003	-0.084	-0.175		
CAI	0.645	0.345	0.478	0.632	0.417	0.085	

The Heterotrait-Monotrait Ratio (HTMT) was used to assess discriminant validity further, as shown in Table 4. HTMT is considered a more robust method for evaluating "discriminant validity in structural equation modelling, particularly when constructs are conceptually similar" (Henseler et al., 2015). According to the recommended threshold, HTMT values should ideally be below 0.90 to confirm that constructs are distinct.

Performance expectancy (PE) shares moderate HTMT values with several constructs, notably with AI-powered chatbot Adoption Intention (CAI) = 0.645, Perceived Intelligence (PI) = 0.560, and Effort Expectancy (EE) = 0.593. These values, well below 0.85, indicate sufficient discriminant validity while reflecting theoretical relationships between these constructs. The moderate association between PE and CAI suggests that students' perceived academic benefits of AI-powered chatbots contribute to their intention to use them, aligning with prior findings by Bilquise et al. (2023) and Pillai et al. (2023).

Effort Expectancy (EE) shows relatively low HTMT values with Social Influence (SI) = 0.267 and Perceived Trust (PT) = 0.168, indicating these constructs are empirically distinct. Its value with Perceived Intelligence (PI) = 0.368 and CAI = 0.345 is moderate but still well within acceptable limits, suggesting that although perceived ease of use supports adoption, it operates independently from social and trust-based drivers of behaviour.

Social Influence (SI) also meets discriminant validity requirements across all comparisons. Its highest HTMT value is with CAI (0.478), indicating that while peer and faculty influence may shape intention, it remains conceptually separate from direct motivation. Other values, such as Perceived Intelligence (0.490) and PT (0.383), remain moderate and acceptable.

Perceived Intelligence (PI) shows a notably high HTMT with Perceived Trust (PT) of 0.683, which, while still below 0.85, suggests a relatively strong relationship between the two constructs. This shows that the intelligence of the AI-powered chatbots is influencing users to be more likely to trust them. However, the values remain below the benchmark level, suggesting that PI and PT are statistically distinct despite their conceptual overlap.

Perceived Trust (PT) maintains discriminant validity with all other constructs. It has its highest HTMT ratio with CAI (0.417), reflecting that trust is positively linked to adoption intention but does not statistically merge with it. This supports previous research showing that trust is a mediator or moderator in AI adoption models (Pillai et al., 2023).

Perceived Risk (PR) shows very low or even negative HTMT values with all other constructs (e.g., with PI = –0.084 and PT = –0.175), confirming that it is empirically and conceptually distinct. These results highlight that risk is perceived as an opposing factor to trust and intelligence, consistent with findings from Shuhaiber (2024) and Chatterjee & Bhattacharjee (2020).

AI-powered chatbot Adoption Intention (CAI) shows moderate HTMT values with PE (0.645), PI (0.632), SI (0.478), and PT (0.417), all well below 0.85. These results confirm that these constructs influence adoption intention but remain a distinct outcome variable.

All HTMT values in the model are within the conservative threshold of 0.85, indicating that each construct exhibits strong discriminant validity. None of the values approach the critical boundary, suggesting minimal conceptual overlap among the measured constructs. These findings complement the Fornell-Larcker criterion results, collectively reinforcing the robustness of the measurement model.

Interpretation of Model Fit and Hypothesis Testing:

The model demonstrates a strong overall fit based on multiple goodness-of-fit indices. The GFI (0.919) and AGFI (0.900) meet the ideal threshold (>0.90), indicating an appropriate model-data alignment. RMSEA is excellent at 0.04, suggesting minimal approximation error. Indices such as IFI (0.927), TLI (0.915), and CFI (0.926) further confirm the high model quality. Although NFI (0.869) is slightly below 0.90, it still falls within acceptable limits. The CMIN/DF value of 2.103 is within the recommended range (<3), reflecting model parsimony. These values suggest that the hypothesised model fits the observed data robustly and reliably.

Hypothesis testing provides a comprehensive view of how Perceived Trust (PT) mediates the relationships between the independent and dependent antecedents of the conceptual model. The model was evaluated using AMOS SEM and the PROCESS macro, which are particularly useful for assessing complex models with latent constructs and mediation effects (Hair et al., 2016). The key direct and indirect effects are explained below:

Performance expectancy (PE) → AI-powered Chatbot Adoption Intention (CAI) ($\beta = 0.4729$, $p < 0.001$): This is the most substantial direct effect in the model, suggesting that students who perceive AI-powered chatbots as enhancing academic performance and efficiency are inclined to adopt them. This result affirms the TAM (Davis, 1989), which posits that perceived usefulness is a major driver of technology adoption. It reinforces earlier work (Venkatesh et al., 2003), highlighting productivity as a central factor in acceptance decisions.

Effort Expectancy (EE) → AI-powered Chatbot Adoption Intention (CAI) ($\beta = 0.2283$, $p < 0.001$): This significant and positive effect indicates that when they find chatbots user-friendly, the students are prone to adopt them. This aligns with TAM and UTAUT theories, emphasising the significance of usability in driving behavioural intention (Venkatesh et al., 2003; Teo, 2011).

Social Influence (SI) → Perceived Trust (PT) → AI-powered Chatbot Adoption Intention (CAI) ($\beta = 0.0724$, $p < 0.001$): This result confirms that peer influence and faculty encouragement positively influence chatbot adoption indirectly by building trust. As a mediator, trust plays a crucial role in translating social norms into behavioural intention, in line with UTAUT extensions (Venkatesh & Bala, 2008).

Perceived Intelligence (PI) → Perceived Trust (PT) → AI-powered Chatbot Adoption Intention (CAI) ($\beta = 0.0656$, $p < 0.001$): Those who understand chatbots as intelligent and similar to human-like, relevant responses tend to develop more trust in them, which encourages adoption. This aligns with prior findings (Ghazali et al., 2018; Pillai et al., 2023) that chatbot intelligence enhances trust and satisfaction.

Perceived Risk (PR) → Perceived Trust (PT) → AI-powered Chatbot Adoption Intention (CAI) ($\beta = –0.0979$, $p = 0.001$): This negative, significant mediation recommended that perceived risk, such as concerns about data privacy or misinformation, reduces trust in chatbots, which in turn lowers the intention to use them. This supports earlier research highlighting trust as a fragile factor easily influenced by risk perception (Chatterjee & Bhattacharjee, 2020; Shuhaiber et al., 2024).

5. DISCUSSIONS AND CONCLUSION

This study explored the determinants of students' intention to adopt AI-powered chatbots in Indian higher education institutions. Grounded in the TAM and UTAUT, the model incorporated classical predictors, perceived and effort expectancy, and emerging constructs such as social influence, intelligence, risk, and trust. The results revealed that PE and EE directly and significantly affect adoption intention, suggesting that students value the utility and usability of AI chatbots.

Notably, perceived trust emerged as a critical mediator between social, cognitive, and risk-related variables and adoption intention. Trust was positively impacted by social influence and perceived intelligence but negatively affected by perceived risk, reinforcing that emotional and ethical factors can either enhance or hinder technology acceptance. These results are consistent with prior research (Bilquise et al., 2023; Pillai et al., 2023; Chatterjee & Bhattacharjee, 2020) and extend them within the Indian academic context.

In conclusion, students are strongly inclined to use chatbots when they perceive them as beneficial, eco-friendly, trustworthy, and socially endorsed. Conversely, perceived risks significantly undermine trust and reduce the likelihood of adoption. The study findings highlight the dual importance of functionality and psychological safety in designing AI tools for education.

Theoretical Implications

This research advances technology adoption theories by integrating perceived intelligence and perceived trust as mediators of AI-powered chatbot adoption. While TAM and UTAUT have traditionally emphasised usefulness and ease of use, this research reveals the growing relevance of trust and risk perception, especially in human-AI interaction contexts. It aligns with recent literature (Almahri et al., 2024; Strzelecki, 2024) in calling for the inclusion of socio-emotional constructs and design features when examining user acceptance. Trust as a mediating mechanism adds depth to behavioural modelling and extends the predictive capacity of classical models in a rapidly evolving digital learning environment.

Practical Implications

The findings guide higher education educators, developers, and administrators. Institutions should prioritise chatbots' user-friendliness and academic value while investing in features that boost perceived intelligence, such as natural language processing and adaptive responses. Additionally, trust-building mechanisms must be integrated, including clear data privacy policies, transparent functionality, and ethical usage practices.

Developers should consider designing chatbots that communicate in emotionally intelligent and culturally relevant ways, particularly for Indian students. Peer-led training, awareness campaigns, and faculty endorsement can enhance social influence and increase adoption. Lastly, proactively addressing perceived risks, improving system reliability, and explaining how user data is handled will be key in overcoming psychological barriers.

LIMITATIONS AND FUTURE DIRECTIONS

While the study offers robust findings, a few limitations should be noted. First, the sample was constrained to higher education students in India, which may limit the applicability of the outcomes to other educational or cultural contexts. Second, the data were self-reported and cross-sectional, limiting the ability to infer causality or observe long-term adoption patterns. Third, although the model includes classical and emerging variables, other potential influences, such as gender, course type, or personality traits, were not examined.

Future studies could utilise longitudinal approaches to examine how chatbot adoption evolves. It would also be beneficial to compare chatbot use across diverse educational levels (e.g., undergraduate vs. postgraduate) and institutional types (e.g., private vs. public universities). Researchers should explore the emotional and relational dynamics of chatbot interactions in greater depth, potentially through mixed-methods approaches. Further, experimental designs involving real-time chatbot usage data could enrich our understanding of the intention-behaviour gap.

Lastly, extending the model to include factors such as user motivation, AI literacy, and adaptive learning outcomes would add valuable nuance to the growing research on AI in education.

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