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A Study on Acceptability of AI Assistant for Delivering Student Services in Private Universities of Delhi/NCR: A Study Based on the Utaut Model

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ABSTRACT

This study examines how students, faculty, and staff in private universities across Delhi/NCR accept AI assistants for support services, using the UTAUT model framework. The research analyses various effects that influence students' willingness to adopt AI chatbots, including their hopes of performance, ease of use, social influences, and trust considerations. Through quantitative analysis using EFA and SEM techniques, the study presents several key findings. The results indicate that students' aim to use AI chatbots is mainly driven by three factors: their belief in the system's performance benefits, trust in its security and accuracy, and influence from peers. Notably, trust emerged as the intense predictor of adoption intention. Contrary to expectations, the ease of using chatbots and availability of supporting infrastructure did not significantly impact adoption decisions.

This research provides valuable insights for universities planning to implement AI-powered student services, emphasizing the importance of building trust and demonstrating tangible benefits to encourage adoption.

Keywords: *Service quality, Ai assistants, leveraging technologies, educational institutions.*

INTRODUCTION

Artificial intelligence (AI) is quickly shifting many fields, and higher education is no exclusion. AI tools, especially AI assistants like chatbots, offer exciting possibilities for improving student services (Adiguzel et al., 2023; Son et al., 2023). These advanced systems, powered by NLP and ML, can personalize education in ways traditional methods often can't (Srinivasan et al., 2024; Tam et al., 2023). Imagine chatbots like ChatGPT engaging students in complex discussions, generating human-like text, and tailoring educational experiences to individual needs.

The impact of AI in education is a two-edged weapon. While it offers amazing possibilities, we need to be thoughtful about how we use it. Think about it - if students become too dependent on AI tools, they might stop developing their own ability to think critically and solve problems (Tam et al., 2023). It's like giving someone a calculator before they've learned basic math - they might get the right answers, but they won't understand the underlying concepts.

We also can't ignore the temptation for students to misuse AI for plagiarism. And beneath the surface, there are deeper issues we need to grapple with. How do we protect students' personal data? How can we ensure AI systems are transparent about how they work? What about making sure these tools respect and work well for students from all cultural backgrounds? (Nikolopoulou, 2024)

Just like any powerful tool - think of a sharp knife in a kitchen - AI can be incredibly useful when used properly, but potentially harmful if misused. That's why it's crucial for everyone involved in education to come together - teachers, administrators, politicians, and the tech companies themselves. We need to establish clear guidelines and figure out the best ways to harness AI's potential while protecting our students' learning and development (Labadze et al., 2023).

One promising area for AI is improving student support services. Universities face growing pressure to meet diverse student needs efficiently. AI assistants can help by automating common inquiries, providing 24/7 support, and offering more personalized interactions. Previous research has demonstrated AI's potential in higher education for outlining and estimating, adaptive learning, personalized experiences, and streamlined administration (Zawacki-Richter et al., 2019). AI assistants are particularly well-suited for handling routine student queries, which aligns with the expectations of today's tech-savvy students (Winkler & Söllner, 2018). Furthermore, think about how teachers and staff often get buried under mountains of paperwork and repetitive tasks. Here's the exciting part - AI can step in as a helpful assistant, taking care of those time-consuming administrative chores (Popenici & Kerr, 2017).

Despite the potential benefits, implementing AI assistants in higher education raises important ethical questions. Universities must address data privacy, algorithmic transparency, and the need for human oversight (Gao et al., 2020). The effectiveness of AI assistants also depends on how they are implemented, the specific context, and the institution's strategies. This study examines how AI assistants affect student service quality in private universities in the Delhi/NCR region. Service quality is crucial for student satisfaction and institutional success. This research will investigate how AI-driven services impact key aspects of service quality, such as responsiveness, personalization, efficiency, and accessibility. By analyzing how these AI-assisted services work and their outcomes, we hope to provide useful information for improving AI technologies in higher education.

This research extends beyond previous studies on AI assistants and chatbots in educational administration by examining their specific impact on student service quality within private universities in Delhi/NCR. This region's rapidly expanding higher education sector provides an optimal environment for investigating AI implementation in university settings.

Our investigation aims to deliver comprehensive insights for university administrators, policymakers, and technology developers regarding optimal AI deployment strategies. The study addresses critical aspects of AI integration, including operational benefits and potential challenges. While AI demonstrates significant potential for enhancing student satisfaction and operational efficiency, its implementation requires careful management to mitigate risks such as data privacy violations and diminished human interaction.

The findings will contribute significantly to the existing body of education on AI in advanced education while providing actionable guidance for future AI assistant development and implementation. As artificial intelligence technology continues to advance, understanding its comprehensive impact becomes increasingly crucial. This research specifically examines how AI assistants can enhance student service quality, promoting more efficient, responsive, and personalized higher education experiences.

Furthermore, the study's conclusions will inform the improvement of future AI-driven solutions, enabling universities to enhance their student services while maintaining robust ethical standards. This research seeks to advance our understanding of AI's role in meeting evolving student needs within an increasingly digitalized educational landscape. Through systematic analysis of both benefits and challenges, this study trains to establish a framework for responsible AI integration in higher education settings.

Conceptual Background

Evolution and application of AI in Education

Since the 1980s, AIEd has grown into a significant academic field, evolving rapidly with advancements in deep learning. Early chatbots like Eliza (1966), Parry (1972), and Alice (1995) marked the beginning of AI in education but were limited in reliability. Modern AI assistants, such as Siri, Alexa, and Google Assistant, have since emerged, offering robust educational support.

AIEd focuses on two key areas: initiating AI tools for classrooms and using AI to assess and improve learning. Technologies like intelligent tutoring systems, adaptive learning platforms, chatbots, and automated assessment devices personalize learning, enhance engagement, and provide real-time feedback. (Adiguzel et al., 2023)

AI in the field of education has advanced from basic tools like calculators to sophisticated systems that personalize learning and support administration. Innovations like IBM Watson assist with student advising, while AI teaching assistants, such as "Jill Watson" at Georgia Tech, provide feedback, answer questions, and tailor content delivery without replacing human educators.

Application of AI-Assistant

AI enhances personalized learning and efficiency but must complement human teaching to foster creativity, critical thinking, and problem-solving. Ethical challenges, including privacy, bias, and transparency, remain critical. Emerging technologies, like brain-computer interfaces, will further shape education while preserving the human aspects of learning. (Popenici & Kerr, 2017)

AI-powered virtual assistants are playing transformative roles in higher education by acting as digital tutors, secretaries, motivators, and mentors (Gubareva & Lopes, 2020). These tools offer a range of benefits, such as predicting student performance, providing personalized feedback, and incorporating flawlessly with Learning Management Systems (LMS). While these features improve self-directed learning and motivation, challenges remain in making these systems more adaptive and user-friendly (Okonkwo & Ade-Ibijola, 2021).

AI assistants provide round-the-clock support for tasks such as answering queries, automating routine processes, and delivering accurate, consistent information. These capabilities improve accessibility, streamline administration, and support personalized learning. However, issues like data security, limited contextual understanding, and ethical concerns need to be addressed to enhance their effectiveness in private universities (Oncu & Sural, 2024; Sajja et al., 2024).

Adopting AI assistants involves tackling ethical challenges, including data privacy and biases in AI systems. Ensuring transparency, creating ethical guidelines, and preventing academic dishonesty are essential (Kooli, 2023). There is also a concern that over-dependence on AI could affect students' critical reasoning skills. Balancing AI integration with traditional teaching methods is key to addressing these challenges (Ateeq et al., 2024).

User feedback shows that the accomplishment of AI tools profoundly depends on their ease of use and accessibility. While users appreciate fast and responsive systems, dissatisfaction arises when AI responses lack depth or depend heavily on keyword searches. Enhancing natural language processing capabilities and integrating emotion recognition can significantly improve user experiences (Oncu & Sural, 2024).

Integrating AI assistants with LMS platforms enhances their ability to provide real-time, personalized support and adaptive content. Despite the benefits, scaling such integrations remains a challenge. Private universities must focus on ensuring compatibility across platforms and fostering collaboration between students and faculty to maximize the impact of AI (Sajja et al., 2024).

The application of AI-powered chatbots in education has been gaining attention for their ability to assist students, faculty, and administrators. Research highlights their role in improving communication, providing instant responses, and streamlining administrative processes (Fitria et al., 2023). Chatbots serve as virtual assistants that help with admissions, course navigation, and academic support, enhancing the accessibility of educational services (Debnath & Agarwal, 2020). Their effectiveness in handling student queries has been validated, with studies showing high accuracy and usability scores, reducing wait times and improving student engagement (Aloqayli & Abdelhafez, 2023).

Despite these benefits, challenges remain, including chatbot limitations in providing emotional support, handling ambiguous queries, and maintaining up-to-date information (Sandu & Gide, 2020). Some chatbots struggle with high traffic and require continuous updates to ensure reliability (Susanna et al., 2020). Additionally, integrating chatbots into existing university systems remains a challenge due to privacy concerns and technical constraints (Yang & Evans, 2020). Future research suggests improvements in multilingual capabilities, voice-based interactions, and better adaptability to user needs to enhance the learning experience (Shingte et al., 2021).

Table 1. The detailed literature analysis of AI assistants' utility is shown in the table below:

Aspect/Theme	Methodology Used	Key Findings	Applications/Implications	Citation
Role of virtual assistants	Text mining analysis TF-IDF analysis Content analysis Database search in Scopus and Web of Knowledge	Virtual assistants can be labelled into 4 positions: digital instructor, digital desk, motivator negotiator, and mentor agent. Academic Support: Predictive models for student performance. Learning analytics for early intervention. Personalized feedback systems. Implementation Features: Natural language processing capabilities Emotion recognition through text/facial analysis Multi-agent systems showing better results. Integration with existing platforms (LMS) Student Impact: Improved engagement with avatar-based systems. Better time management Enhanced selfregulated learning. Increased motivation through immediate feedback.	Academic Integration Learning analytics, performance prediction Social Integration Communication support, collaboration tools Institutional Commitment Administrative support, information access Time Management: Scheduling, deadline reminders Personalized Learning: Adaptive content and navigation	(Gubarev a & Lopes, 2020)
Investigation of chatbot technology acceptance among higher education students in Egypt. Application of UTAUT model to understand behavioural intentions- Analysis of demographic factors' influence on technology acceptance	Investigation of chatbot technology acceptance among higher education students in Egypt. Application of UTAUT model to understand behavioural intentions- Analysis of demographic factors' influence on technology acceptance	Meaningful effect found on behavioural intention for Performance expectancy, Effort expectancy, social influence. No significant moderating role found for Age demographics. Gender demographics Model explained 51.9% of variation in behavioural intention	Guidance for implementing chatbot technology in higher education Framework for understanding student acceptance factors. Basis for developing training programs and courses. Support for decision-making in educational technology adoption. Implications For Education: Need for suitable training programs for students and lecturers Importance of considering performance and effort expectations Value of social influence in technology adoption. For Implementation:- Focus on demonstrating clear performance benefits Ensure easy-to-use interface and system Leverage social influence for adoption Design	(Ragheb et al., 2022)

			universal approach rather than demographic-specific strategies	
Acceptance of Chat-bot Technology in Higher Education	Acceptance of Chat-bot Technology in Higher Education	Performance expectancy, effort expectancy, and social influence significantly affect students' behavioural intentions to use chat-bots. No significant moderating effects of gender or age were observed.	Training for students and faculty to utilize chat-bots effectively. Encouraging the integration of AI technologies in higher education to develop learning results and resourcefulness.	Ragheb, Tantawi, Farouk, Hatata (2022)
Chatbots in Education	Systematic Literature Review of 53 articles from recognized digital databases like Scopus, IEEE, and SpringerLink.	Chatbots enhance teaching, learning, administration, assessment, and advisory tasks. Key challenges include ethical issues, user attitudes, and technical limitations.	Integration of Chatbots promotes personalized learning, quick information access, and reduced administrative workload in education. Further research needed on usability and ethical principles	Okonkwo & Ade-Ibijola (2021)
ChatGPT chatbot usage and academic performance	ChatGPT chatbot usage and academic performance	Strong positive correlation between ChatGPT chatbot usage and academic performance. Traditional textbooks showed significant positive impact on academic performance. Model explained 29.2% of variance in academic performance. Both hypotheses regarding ChatGPT's effectiveness and technology reliance were supported	Supports integration of AI chatbots like ChatGPT alongside traditional teaching methods. Highlights need for balanced approach combining digital and traditional resources. |Emphasizes importance of focusing ethical worries like data secrecy and equal access. Suggests need for policy development to regulate AI use in education. Recommends multidisciplinary collaboration between educators, technologists and policymakers.	(Ateeq et al., 2024)
Interpretation of ChatGPT's capabilities in education	Qualitative exploratory study using expert analysis and interpretation of existing literature	Study provides foundational understanding of chatbots in education and research. Chatbot can perfectly answer multiple-choice questions. Raises concerns about academic integrity. May decrease critical thinking skills Creates uneven playing field between students. Chatbots offer 24/7 availability for data collection. Can automate repetitive tasks. Provide consistent, accurate information. Lack contextual understanding and empathy. Data privacy issues. Bias in training data. Lack of transparency	Research design can inform future studies examining AI/chatbot implementation in academic settings. Traditional assessment methods need redesign; shift toward creative, hands-on evaluations required. Chatbots should complement, not replace human researchers; require close supervision. Need for clear regulations, ethical guidelines, and verification processes. Educational institutions must adapt assessment strategies and policies to new AI reality.	Kooli (2023)

		Potential for misuse/manipulation. Accuracy and reliability concerns		
Leveraging AI for user satisfaction	Sequential explanatory design (mixed methods)	Moderate satisfaction among users; positive feedback on design adherence; dissatisfaction with detail and utility of information.	Insights for user-centered development of AI tools; recommendations for enhancing virtual assistant functionality in open education settings.	(Öncü & Süral, 2024)
Virtual Assistant in Open Education	Surveys (quantitative) and focus group discussions (qualitative)	High importance placed on usability; users experience lower satisfaction due to limited information detail and keyword dependence.	Enhances AI-based tools for real-time support; potential for improved service quality and alignment with user expectations in education technology.	Öncü & Süral (2024)
Focus group insights	Focus group insights	Lack of academic counseling via AI; non-academic support (e.g., student affairs) is relatively better rated.	Integration of academic advisory services in virtual assistants to support broader educational needs; AI can complement traditional support roles in large-scale education systems.	Öncü & Süral (2024)
AI-Enabled Intelligent Assistants in Education	Mixed-methods research; system architecture design	Improved learning engagement and outcomes through personalized support and real-time assistance.	Enhances integration of AI in education for personalized, adaptive learning environments.	Sajja et al. (2024)

Importance of Utaut Model in the Study

Performance expectancy, effort expectancy, and social influence are key factors inducing the acceptance of AI tools in education, as highlighted by studies using the UTAUT model. (Ragheb et al., 2022). These factors strongly impact user behavior, while demographic variables like age and gender show minimal influence. Training initiatives and intuitive interfaces are crucial for boosting acceptance and ensuring effective usage of these tools (Ateeq et al., 2024).

The UTAUT model serves as a powerful tool for studying know-how acceptance by integrating multiple existing models into a single comprehensive framework. Its strength lies in systematically analyzing key factors affecting user adoption while remaining flexible enough to adapt to specific contexts. The model's proven effectiveness in educational settings and its ability to support robust statistical analysis makes it particularly valuable for researchers studying how and why users embrace new technologies. (Ragheb et al., 2022)

The UTAUT model has confirmed to be a significant framework in technology acceptance research, demonstrating its value through widespread adoption across various domains like e-government, e-banking, and e-learning. Its importance stems from its methodological versatility, supporting multiple analytical approaches, and its strong predictive power in understanding technology adoption behaviors. The model's flexibility in incorporating external variables and its successful implementation across 41 countries highlights its robust capability as a research tool for understanding how and why users accept new technologies. (Williams, Rana, & Dwivedi, 2015)

Research Gaps

1. Limited Regional Focus: While much research has examined AI adoption in education globally, there is a lack of region-specific studies.
2. Customization and Inclusivity: Current literature lacks emphasis on developing AI systems tailored to the socio-economic and cultural diversity of students in Indian private universities, which might influence acceptability.

3. The scalability and usability of AI assistants in the existing infrastructure of private universities have not been comprehensively studied.

Research Questions

1. What issues influence students' willingness to apply AI chatbots for support services?
2. How does user satisfaction influence the behavioural intention to adopt AI chatbot support services?

Research Objectives

1. This study examines the effect of performance expectancy, effort expectancy, social influence, and facilitating conditions on students' intentions to adopt AI chatbots for support services within higher education.
2. To investigate the relationship between trust-related factors (Trust & Security) and user experience factors (Satisfaction & Feedback) on students' behavioural intention to apply and recommend AI chatbots for academic support services.
3. To develop a validated framework that identifies the relative significance of key determinants (PE, EE, SI, FC, Trust & Security, and Satisfaction) in predicting students' behavioural intention to adopt AI chatbot support services.

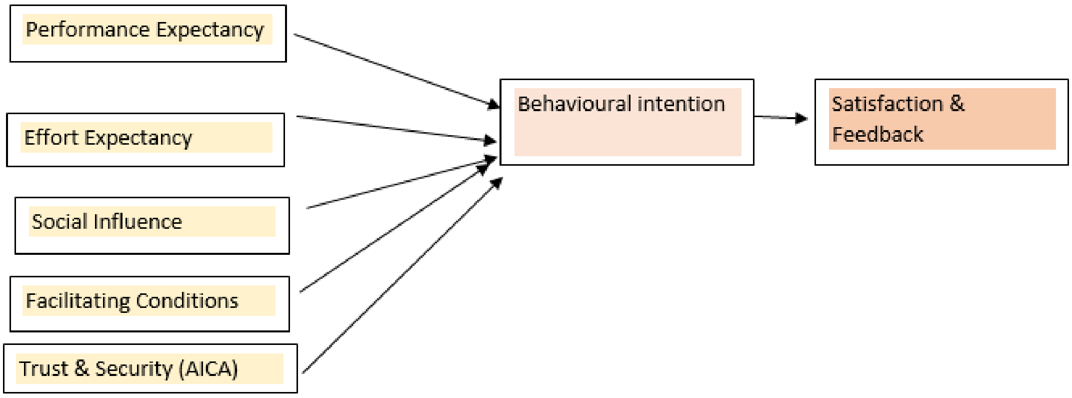

Figure 1. Conceptual framework

Based on above model, the key constructs are as follows:

Key construct 1: Performance Expectancy (PE): Measures perceived efficiency gains from AI chatbot use in student support.
Under key construct 1 the variables are as follows:
V1: Support efficiency
V2: Query handling Efficiency
Key construct 2: Effort Expectancy (EE): Evaluates the perceived usability and learnability of AI chatbots
The construct variables are as follows:
V3: Ease of interaction
V4: Ease of Learning
Key Construct 3: Social Influence (SI): Measures the influence of peer recommendations on AI chatbot adoption.
The construct variables are as follows:
V4: Peer Endorsement
V5: Social Persuasion
Key construct 4: Facilitating Conditions (FC): Effective chatbot usage depends on readily available resources and accessibility.
V6: Accessibility of Resources
V7: Usage resource support
Key construct 5: Trust and Security (AICA): Emphasizes trust in chatbot accuracy and security.

V8: Trust & accuracy
V9: Security & Accuracy
Key construct 6: Behavioural Intention (BI): Examines the willingness to adopt AI chatbots for student support services.
V10: Future usage Intent
V11: Recommendation Intention
Satisfaction and Feedback: Assesses overall user satisfaction with AI chatbots, incorporating user experiences and feedback to understand adoption outcomes.

Hypothesis Development

Performance Expectancy (PE) and Behavioural Intention (BI)

Null Hypothesis (H_o1): There is no statistically significant positive relationship between Performance Expectancy (PE) and behavioural Intention (BI) to use AI chatbots for student support services.

Alternate Hypothesis (H_11): There is a statistically significant positive relationship between Performance Expectancy (PE) and behavioural Intention (BI) to use AI chatbots for student support services.

Effort Expectancy (EE) and behavioural Intention (BI)

Null Hypothesis (H_o2): There is no statistically significant positive relationship between Effort Expectancy (EE) and behavioural Intention (BI) to use AI chatbots for student support services.

Alternate Hypothesis (H_12): There is a statistically significant positive relationship between Effort Expectancy (EE) and behavioural Intention (BI) to use AI chatbots for student support services.

Social Influence (SI) and behavioural Intention (BI)

Null Hypothesis (H_o3): Social Influence (SI) does not demonstrate a statistically significant relationship with behavioural Intention (BI) to use AI chatbots for student support services.

Alternate Hypothesis (H_13): Social Influence (SI) demonstrates a statistically significant relationship with behavioural Intention (BI) to use AI chatbots for student support services.

Facilitating Conditions (FC) and behavioural Intention (BI)

Null Hypothesis (H_o4): Facilitating Conditions (FC) do not demonstrate a statistically significant relationship with behavioural Intention (BI) to use AI chatbots for student support services.

Alternate Hypothesis (H_14): Facilitating Conditions (FC) demonstrate a statistically significant relationship with behavioural Intention (BI) to use AI chatbots for student support services.

Trust and Security (AICA) and behavioural Intention (BI)

Null Hypothesis (H_o5): There is no statistically significant positive relationship between Trust and Security (AICA) and behavioural Intention (BI) to use AI chatbots for student support services.

Alternate Hypothesis (H_15): There is a statistically significant positive relationship between Trust and Security (AICA) and behavioural Intention (BI) to use AI chatbots for student support services.

Satisfaction and Feedback and behavioural Intention (BI)

Null Hypothesis (H_o6): Satisfaction and Feedback do not demonstrate a statistically significant relationship with behavioural Intention (BI) to use AI chatbots for student support services.

Alternate Hypothesis (H_16): Satisfaction and Feedback demonstrate a statistically significant relationship with behavioural Intention (BI) to use AI chatbots for student support services.

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Research Design

This study explored how students in private universities in the Delhi/NCR region feel about using AI assistants for student services. We used a survey to collect data and a framework based on the UTAUT model but adapted it to better understand what influences students to accept or reject this technology. Our research looked at several factors beyond the original UTAUT model to get a more complete picture of AI assistant adoption in this specific context.

Research Approach

This research used a descriptive-correlational design to explore how different things are connected to whether students are likely to use AI assistants. We chose this approach for three main reasons: First, we wanted to see how strongly these factors are related to each other and in what direction (positive or negative). Second, we aimed to test our ideas about which factors are most important for predicting whether students will use AI assistants. Finally, we wanted to see if our proposed model for AI assistant adoption holds up in the real world.

Sampling Design

Population: The target population consisted of stakeholders from private universities in the Delhi/NCR region, including students, faculty members, and administrative staff who interact with or potentially could interact with AI-powered student support services.

Sample Size: The study included 200 respondents, distributed as follows:

- Students: 140 respondents (70%)
- Faculty members: 40 respondents (20%)
- Administrative staff: 20 respondents (10%)

Sampling Technique: A convenience sampling technique was employed.

Data Collection

Instrument: A structured questionnaire was developed based on the UTAUT model and modified to include items measuring:

- Performance Expectancy (PE)
- Effort Expectancy (EE)
- Social Influence (SI)
- Facilitating Conditions (FC)
- Trust and Security (AICA)
- Behavioural Intention (BI)
- User Satisfaction and Feedback

Scale: The questionnaire used a 5-point Likert scale ranging from "Strongly Disagree" (1) to "Strongly Agree" (5) to measure respondents' attitudes and perceptions.

Data Analysis Techniques

In conducting our rigorous statistical analysis, we employed a comprehensive three-stage approach to examine the collected data. Initially, we performed Exploratory Factor Analysis (EFA) to establish and validate our measurement constructs, ensuring the fundamental structure of our variables was sound. Following this foundational step, we proceeded with Confirmatory Factor Analysis (CFA), which allowed us to meticulously evaluate the measurement model's validity and reliability. Finally, to examine the complex interrelationships proposed in our hypotheses, we utilized Structural Equation Modelling (SEM), enabling us to assess both direct and indirect relationships among our variables while accounting for measurement error. This methodical analytical progression ensured a thorough and robust examination of our theoretical framework.

Result & Interpretation

EFA results:

Table 2. Factor Loadings

	Factor				
	1	**2**	**3**	**4**	**Uniqueness**
FC3					0.83
PE1			0.923		0.281
PE2			0.816		0.307
EE1				0.668	0.279
EE2				0.736	0.315
SI1	0.551				0.54
SI2	0.668				0.479
FC1	0.922				0.224
FC2	0.97				0.197
AICA1		0.872			0.407
AICA2		0.914			0.326
BI1		0.535			0.444
BI2					0.541

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FC1	0.922				0.224
FC2	0.97				0.197
AICA1		0.872			0.407
AICA2		0.914			0.326
BI1		0.535			0.444
BI2					0.541

NOTE: Principal axis factoring' extraction method was used in combination with a 'promax' rotation

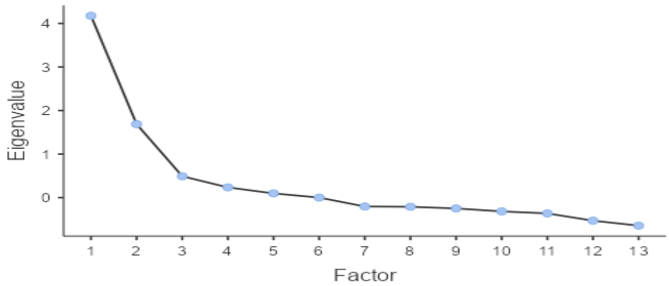

Figure 2. Factor Loadings

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The loadings indicate how strongly each item correlates with the extracted factors. Higher loadings on a specific factor suggest a strong association between the item and that factor. As per the results the following findings are analysed:

Facility Conditions (FC): FC1 and FC2 have high loadings, indicating their strong representation of this factor.

Performance Expectancy (PE): PE1 and PE2 have significant loadings.

Effort Expectancy (EE): EE1 and EE2 load on this factor.

Social Influence (SI): SI1 and SI2 show substantial loading values.

AICA: AICA1 and AICA2 contribute notably to this factor.

Behavioral Intention (BI): BI1 and BI2 were identified under this factor.

S1, S2, FC1 and FC2 were loaded on factor 1 with significant loading values whereas AICA1, AICA2, BI1 and BI2 were loaded on factor 2 and subsequently PE1, PE2 loaded on factor 3 with EE1 and EE2 loaded on factor 4.

Table 3. Model Fit Measures

RMSEA 90% CI			Model Test				
RMSEA	**Lower**	**Upper**	**TLI**	**BIC**	**χ^2**	**df**	**p**
0.101	0.0786	0.124	0.867	-71.7	98.8	32	< .001

Model Fit Measures Analysis

The model's fit indices reveal several key insights regarding its statistical validity. The Root Mean Square Error of Approximation (RMSEA) yielded a value of 0.101 (CI: 0.0786 - 0.124), indicating a moderate level of estimation error in the model. The Tucker-Lewis Index (TLI) produced a value of 0.867, suggesting an acceptable, though not optimal, model fit. Additionally, the Bayesian Information Criterion (BIC) value of -71.7 demonstrates relatively low model complexity, which is favorable for interpretation purposes. The Chi-Square analysis resulted in a value of 98.8 (df = 32, $p < 0.001$), indicating a significant deviation from perfect fit, though this is not uncommon in complex models. Collectively, these indices suggest that while the model demonstrates adequate fit characteristics, there may be room for refinement in future iterations.

Table 4. Barlett's Test of Sphericity

χ^2	df	p
1322	78	< .001

Bartlett's Test of Sphericity ($\chi^2 = 1322$, $p < 0.001$) confirms the appropriateness of factor analysis for this dataset.

Table 5. KMO Measure of Sampling Adequacy

MSA	
Overall	0.817
FC3	0.899
PE1	0.752
PE2	0.806
EE1	0.81
EE2	0.806
SI1	0.874
SI2	0.838

FC1	0.729
FC2	0.707
AICA1	0.836
AICA2	0.866
BI1	0.891
BI2	0.893

The overall Kaiser-Meyer-Olkin (KMO) value of 0.817 indicates sampling adequacy, which is considered very good. Individual measures also reflect high adequacy for each item.

Reliability Analysis: Cronbach's Alpha values for different scales show their internal consistency. The individual scores of scale reliability were:

Performance Expectancy (PE): $\alpha = 0.805$, indicating good reliability.

Facility Condition: $\alpha = 0.710$, acceptable reliability.

Effort Efficiency: $\alpha = 0.795$, good reliability.

Social Influence: $\alpha = 0.715$, acceptable reliability.

AICA: $\alpha = 0.769$, indicating acceptable reliability.

Behavioral Intention (BI): $\alpha = 0.799$, showing good reliability.

From the following values the Interpretation: A higher Cronbach's alpha (typically above 0.7) suggests that the items are correlated and consistent with each other.

A significant result supports the use of the scale for research or measurement purposes.

A significant alpha suggests the construct has a stable measurement structure.

Confirmatory Factor Analysis

Confirmatory analysis was carried out with the assistance of Jamovi software to do structural equation modelling and assess the overall construct validity. Following results were drawn:

Table 6. Factor Loadings

Factor	Indicator	Estimate	SE	Z	p	Stand. Estimate
facility condition	FC3	0.18	0.0546	3.31	< .001	0.238
	FC1	0.848	0.0506	16.76	< .001	0.946
	FC2	0.918	0.0582	15.78	< .001	0.908
Performance expectancy	PE1	0.437	0.0344	12.72	< .001	0.825
	PE2	0.619	0.0467	13.26	< .001	0.856
Effort expectancy	EE1	0.568	0.0447	12.71	< .001	0.869
	EE2	0.547	0.0493	11.1	< .001	0.762

social influence	SI1	0.591	0.0594	9.94	< .001	0.722
	SI2	0.707	0.0667	10.6	< .001	0.775
AICA	AICA1	0.549	0.0491	11.17	< .001	0.755
	AICA2	0.699	0.0561	12.45	< .001	0.836
Behaviorial Intention	BI1	0.534	0.0464	11.5	< .001	0.802
	BI2	0.46	0.0479	9.61	< .001	0.67

Factor Covariances

Factor	Indicator	Estimate	SE	Z	p	Stand. Estimate
facility condition	facility condition	1[a]				
	Performance expectancy	-0.107	0.0826	-1.3	0.195	-0.107
	Effort expectancy	0.4	0.0724	5.52	< .001	0.4
Social influence	social influence	0.704	0.0539	13.05	< .001	0.704
	AICA	0.281	0.0777	3.62	< .001	0.281
	Behavioural Intention	0.289	0.0871	3.32	< .001	0.289
Performance expectancy	Performance expectancy	1[a]				
	Effort expectancy	0.545	0.0659	8.28	< .001	0.545
	social influence	0.129	0.1034	1.25	0.212	0.129
	AICA	0.478	0.0752	6.36	< .001	0.478
	Behaviorial Intention	0.623	0.0657	9.48	< .001	0.623
Effort expectancy	Effort expectancy	1[a]				
	social influence	0.454	0.0901	5.04	< .001	0.454
	AICA	0.527	0.0746	7.07	< .001	0.527

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	Behaviorial Intention	0.578	0.0714	8.09	< .001	0.578
social influence	social influence	1[a]				
	AICA	0.504	0.0772	6.53	< .001	0.504
	Behaviorial Intention	0.586	0.0874	6.71	< .001	0.586
AICA	AICA	1[a]				
	Behaviorial Intention	0.8	0.0562	14.24	< .001	0.8
Behaviorial Intention	Behaviorial Intention	1[a]				

Table 7. Test for Exact Fit

χ^2	df	p
164	50	< .001

Table 8. Fit Measures

RMSEA 90% CI			
TLI	**RMSEA**	**Lower**	**Upper**
0.862	0.105	0.0874	0.123

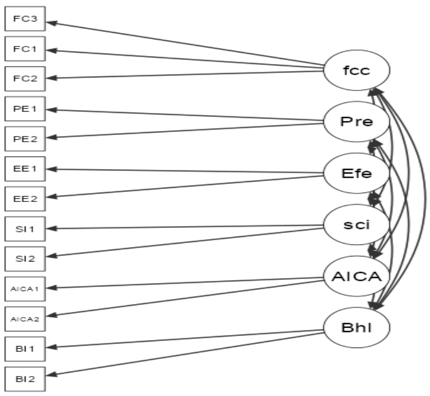

Figure 3. Path Diagram

Interpretation of the Results

Confirmatory Factor Analysis (CFA)

The CFA results show that the model successfully identifies the relationships between the observed indicators and the latent factors.

Factor Loadings and Standardized Estimates: The high factor loadings for indicators FC1 and FC2 under the Facility Conditions factor suggest that these indicators are strong and reliable measures of the Facility Conditions factor. Similarly, the Performance Expectancy and Effort Expectancy factors also show high factor loadings, supporting the validity and strong representation of these factors in the model.

Factor Covariances: The factor covariances show the relationships between the different factors:

A positive correlation of 0.400 between Facility Conditions and Effort Expectancy suggests a moderate relationship between these two factors. This indicates that as the conditions of the facility improve, the expectancy for easier effort is likely to increase as well.

The positive correlation of 0.623 between Performance Expectancy and Behavioral Intention shows a strong relationship, implying that as people expect better performance, their intention to engage in the behavior increases.

Model Fit for CFA

Our analysis of the Confirmatory Factor Analysis (CFA) model's fit indices reveals nuanced insights regarding its alignment with the empirical data. The Root Mean Square Error of Approximation (RMSEA) demonstrated a value of 0.105, with a confidence interval spanning from 0.0874 to 0.123. While this exceeds the conventional threshold of 0.08 for optimal fit, it suggests a moderately acceptable model fit. This moderate RMSEA value indicates some discrepancy between the theoretical model and observed data structure, though remaining within interpretable bounds.

Further examination of the Tucker-Lewis Index (TLI) provides additional context regarding the model's performance. Given that TLI values approach optimality as they near 1.0, our results suggest potential areas for model refinement to better capture the underlying data patterns. These fit indices, when considered collectively, indicate that while our model demonstrates adequate explanatory power, there may be opportunities for structural improvements to enhance its representation of the empirical relationships.

Overall Interpretation

The CFA results suggest that the proposed model has reasonable validity with strong factor loadings, confirming that the factors (such as Facility Conditions, Performance Expectancy, and Effort Expectancy) are adequately measured. The model fit is moderate. These findings suggest that the model explains a good portion of the data.

Structural Equation Modeling

The Structural Equation Modeling (SEM) results provide a comprehensive analysis of the relationships among various latent constructs, their indicators, and the overall model fit. The estimation was performed using the Maximum Likelihood (ML) method, optimized with the NLMINB approach. The model successfully converged after 65 iterations, suggesting reliable parameter estimates. With 206 observations and 59 free parameters, the results offer a robust basis for interpretation.

Table 9. Models Info

Estimation Method	ML
Optimization Method	NLMINB
Number of observations	206
Free parameters	59

Standard errors	Standard
Scaled test	None
Converged	TRUE
Iterations	65
Model	PE=~PE2+PE1
	EE=~EE2+EE1
	SI=~SI2+SI1
	FC=~FC2+FC1
	AICA=~AICA2+AICA1
	BI=~BI2+BI1
	overall=~OS

Table 10. Models Test

Label	**X²**	**df**	**p**
User Model	136	45	< .001
Baseline Model	1419	78	< .001

Table 11. Fit indices

		95% Confidence Intervals		
SRMR	**RMSEA**	**Lower**	**Upper**	**RMSEA p**
0.066	0.099	0.080	0.118	< .001

Table 12. User Model Versus Baseline Model

Model	
Comparative Fit Index (CFI)	0.932
Tucker-Lewis Index (TLI)	0.882
Bentler-Bonett Non-normed Fit Index (NNFI)	0.882
Relative Noncentrality Index (RNI)	0.932

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Bentler-Bonett Normed Fit Index (NFI)	0.904

Table 13. Measurement model

Latent	Observed	Estimate	SE	95% Confidence Intervals		β	z	p
				Lower	Upper			
PE	PE2	1.000	0	1	1	0.86		
	PE1	0.698	0.0624	0.576	0.821	0.821	11.19	< .001
EE	EE2	1.000	0	1	1	0.76		
	EE1	1.046	0.1082	0.834	1.258	0.873	9.67	< .001
SI	SI2	1.000	0	1	1	0.776		
	SI1	0.833	0.0945	0.648	1.018	0.721	8.82	< .001
FC	FC2	1.000	0	1	1	0.914		
	FC1	0.913	0.053	0.809	1.016	0.94	17.23	< .001
AICA	AICA2	0.913	0	1	1	0.828		
	AICA1	0.799	0.0824	0.638	0.961	0.762	9.7	< .001
BI	BI2	1.000	0	1	1	0.689		
	BI1	1.099	0.1166	0.87	1.327	0.781	9.43	< .001
overall	OS	1.000	0	1.000	1.000	1.000		

Table 14. Variances and Covariances

95% Confidence Intervals								
BI	BI	0.2237	0.0433	0.1389	0.3086	1	5.17	< .001
overall	overall	0.5145	0.0507	0.4151	0.6138	1	10.15	< .001
PE	EE	0.1855	0.0349	0.1172	0.2539	0.547	5.32	< .001
PE	SI	0.0574	0.04	-0.0209	0.1358	0.13	1.44	0.151
PE	FC	-0.0668	0.046	-0.1569	0.0234	-0.116	-1.45	0.147
PE	AICA	0.2085	0.0416	0.127	0.2901	0.484	5.01	< .001
PE	BI	0.1822	0.0327	0.1181	0.2463	0.619	5.57	< .001
PE	overall	0.1821	0.037	0.1095	0.2546	0.408	4.92	< .001
EE	SI	0.1743	0.04	0.096	0.2526	0.452	4.36	< .001

EE	FC	0.1980	0.0454	0.1089	0.287	0.393	4.36	< .001
EE	AICA	0.1986	0.0393	0.1216	0.2755	0.526	5.06	< .001
EE	BI	0.1496	0.0297	0.0915	0.2078	0.58	5.04	< .001
EE	overall	0.1383	0.0331	0.0733	0.2033	0.354	4.17	< .001
SI	FC	0.1383	0.0697	0.3231	0.5963	0.703	6.6	< .001
SI	AICA	0.2466	0.051	0.1467	0.3465	0.503	4.84	< .001
SI	BI	0.2028	0.0392	0.1259	0.2796	0.606	5.17	< .001
SI	overall	0.1935	0.0447	0.1059	0.2811	0.381	4.33	< .001
FC	AICA	0.1725	0.0545	0.0656	0.2794	0.27	3.16	0.002

Table 15: Variance and Covariance

95% Confidence Intervals								
FC	BI	0.1329	0.0399	0.0547	0.2111	0.304	3.33	< .001
FC	overall	0.1870	0.0501	0.0888	0.2852	0.282	3.73	< .001
AICA	BI	0.2636	0.0412	0.1827	0.3444	0.804	6.39	< .001
AICA	overall	0.2593	0.0444	0.1723	0.3462	0.522	5.84	< .001
BI	overall	0.2236	0.0354	0.1542	0.2930	0.659	6.31	< .001

Table16: R^2

Variable	R^2
BI	0.788
overall	0.437

Table 17: Parameters estimates

Dep	**Pred**	**Estimate**	**SE**	**95% Confidence Intervals**		**β**	**z**	**p**
				Lower	**Upper**			
BI	PE	0.3005	0.0838	0.13625	0.465	0.3889	3.586	< .001
BI	EE	-0.0464	0.0932	-0.22902	0.136	-0.0531	-0.498	0.618
BI	SI	0.1882	0.0923	0.00732	0.369	0.2783	2.039	0.041
BI	FC	0.0438	0.0607	-0.07506	0.163	0.0852	0.722	0.470
BI	AICA	0.3308	0.0773	0.17938	0.482	0.4776	4.282	< .001
overall	BI	0.9879	0.1186	0.75554	1.220	0.6611	8.332	< .001

Table 18: Realities indices

Variable	**α**	**ω_1**	**ω_2**	**ω_3**	**AVE**
PE	0.805	0.830	0.830	0.830	0.716
EE	0.795	0.795	0.795	0.795	0.660
SI	0.715	0.721	0.721	0.721	0.566
FC	0.921	0.924	0.924	0.924	0.859

AICA	0.769	0.779	0.779	0.779	0.641
BI	0.699	0.701	0.701	0.702	0.540
overall	.	.	.	.	.

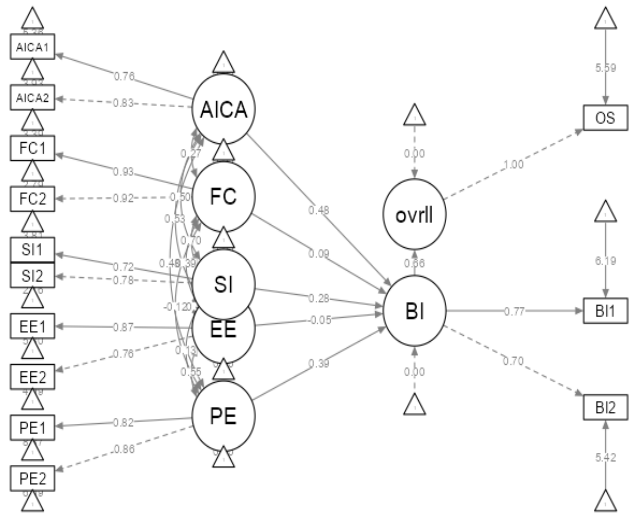

Figure 4.

Model Fit and Evaluation

Our comprehensive evaluation of the model's fit indices reveals a nuanced assessment of its statistical adequacy. The Comparative Fit Index (CFI) demonstrates a commendable value of 0.932, indicating robust model performance. However, the Tucker-Lewis Index (TLI) value of 0.882 suggests potential opportunities for enhancing the model's capacity to account for data variance.

The Root Mean Square Error of Approximation (RMSEA) yielded a value of 0.099, marginally exceeding the conventional threshold of 0.08, indicating areas where the model's representation of the underlying data structure could be refined. Notably, the Standardized Root Mean Square Residual (SRMR) value of 0.066 falls well within acceptable parameters (≤0.08), providing evidence of satisfactory residual discrepancies.

Collectively, these fit indices demonstrate that while the model exhibits acceptable statistical properties and practical utility, there exists potential for structural refinements to enhance its explanatory power. The combination of these metrics suggests a model that is fundamentally sound yet amenable to optimization through targeted modifications of its theoretical framework.

Measurement Model Insights

The latent constructs examined include Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), AICA, Behavioral Intention (BI), and an overall outcome measure (OS). Each construct is represented by at least two indicators. The factor loadings for these indicators are statistically significant ($p < .001$), demonstrating their reliability in measuring the intended constructs. For instance, PE1 and PE2 show strong loadings (β = 0.821 and 0.860, respectively), underscoring their critical role in defining Performance Expectancy. Similarly, indicators for EE, such as EE1 (β = 0.873), highlight the relevance of this construct in influencing behavioral outcomes.

Reliability and Validity Assessment

The reliability indices indicate that the constructs are measured consistently across items. Facilitating Conditions (FC) exhibit exceptional internal consistency with a Cronbach’s alpha (α) of 0.921 and an Average Variance Extracted (AVE) of 0.859. This implies that a substantial portion of variance in FC is attributable to the construct itself rather than measurement error. Other constructs, such as Performance Expectancy (PE) and Behavioral Intention (BI), also demonstrate high reliability and acceptable AVE, supporting convergent validity. The consistency of these measurements reinforces the robustness of the constructs in the model.

Structural Model Relationships

The structural model highlights several significant pathways. Performance Expectancy (PE) has a positive and significant impact on Behavioral Intention (BI) ($\beta = 0.3889$, $p < .001$), illustrating that individuals' perception of improved performance due to a system significantly influences their intention to use it. AICA also has a strong and positive effect on Behavioral Intention ($\beta = 0.4776$, $p < .001$), emphasizing its pivotal role in shaping user behavior. In contrast, Effort Expectancy (EE) does not significantly impact BI ($\beta = -0.0531$, $p = 0.618$), suggesting that the ease of use may not directly influence users' intentions in this context. This non-significance might point to other mediating factors that warrant exploration.

Covariances and Interactions

The covariances among the constructs provide further insights into their interrelations. Strong positive correlations exist between constructs such as Social Influence (SI) and Facilitating Conditions (FC) ($\beta = 0.703$, $p < .001$), indicating that social support and infrastructural facilitation are closely linked in influencing behavior. However, negative or weak correlations, such as between Performance Expectancy (PE) and Facilitating Conditions ($\beta = -0.116$, $p = 0.147$), suggest limited direct interaction, which could reflect distinct roles these constructs play in the model.

Findings

1. Performance Expectancy strongly influences Behavioural Intention to use AI chatbots. Users believe that chatbots enhance efficiency and improve support services, leading to higher willingness to adopt them. The hypothesis that Performance Expectancy positively impacts Behavioural Intention is supported.

2.Effort Expectancy, or the ease of using chatbots, does not have a significant impact on users' intentions to adopt them. This suggests that other factors outweigh the simplicity of interaction when deciding to use AI chatbots. The hypothesis that Effort Expectancy positively impacts Behavioural Intention is not supported.

3.Social Influence, including recommendations and peer feedback, plays an important role in shaping Behavioural Intention. People are more likely to use chatbots if their peers endorse or recommend them. The hypothesis that Social Influence significantly affects Behavioural Intention is supported.

4.Facilitating Conditions, such as the availability of resources and support, do not directly impact Behavioural Intention. While these conditions are crucial for effective use, they might not directly motivate users to adopt chatbots. The hypothesis that Facilitating Conditions significantly influence Behavioural Intention is not supported.

5.Trust in the chatbot's reliability and security strongly influences Behavioural Intention. Users value the chatbot's ability to provide accurate and safe services, making trust a key factor in their decision to adopt the technology. The hypothesis that Trust and Security positively impact Behavioural Intention is supported.

Interconnections: Social Influence and Facilitating Conditions are closely linked, suggesting that social support and accessibility go hand in hand in influencing behaviour.

CONCLUSION

This study sheds light on the acceptability of AI assistants in delivering student services within private universities in Delhi/NCR, utilizing the UTAUT framework. The findings underscore the pivotal role of performance expectancy, trust, and social influence in shaping students' behavioural intentions toward adopting AI chatbots. Among these, trust emerged as the most influential factor, highlighting the necessity of ensuring secure, accurate, and reliable chatbot systems to gain users' confidence.

Interestingly, while effort expectancy and facilitating conditions are often associated with technology adoption, their lack of significant impact in this context suggests that students prioritize perceived benefits and peer recommendations over ease of use and resource availability. This highlights the importance of demonstrating tangible value and leveraging social networks to drive adoption.

Universities can leverage these insights to enhance their AI-powered student services by focusing on building trust and showcasing clear performance benefits. However, institutions must also address ethical concerns such as data privacy and transparency to ensure sustainable and responsible integration of AI technologies.

Overall, this research provides a foundational understanding of factors influencing AI chatbot adoption in higher education, offering actionable insights for administrators and technology developers. Future studies could further explore mediating variables and examine region-specific challenges to enrich the understanding of AI integration in diverse educational settings.

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