INNOVARE JOURNAL OF EDUCATION

Vol 14, Issue 2, 2026, 22-30

ISSN: 2347-5528

Research Article

Exploring Faculty Perspectives on Artificial Intelligence Adoption in Higher Education: An Analysis Using the UTAUT Framework

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Abstract

In India, the higher education system is in transition; understanding faculty perspectives on the adoption of artificial intelligence (AI) in teaching and learning is essential. This is especially crucial in India, where a diverse higher education system exists. However, in India, few works focus on AI adoption and its impacts. Addressing this gap empirically is crucial to successful AI adoption in Indian higher education. This paper examined faculty perceptions of AI use in India, including perceived ease of use, performance expectancy, effort expectancy, social influence, and threat perception. A quantitative method was employed, based on data collected from 380 faculty members using a self-developed questionnaire, and a convenience sampling technique was used. The findings indicated that perceived benefits, institutional support, peer influence, and perceived risks positively affected behavioural intentions and the actual use of AI. Ease of use and actual AI adoption were significantly determined by institutional support, whereas ease of use was not a significant factor in behavioural intention. These findings highlight the importance of robust institutional leadership, support, and training in AI. This study provides practical insights for improving AI integration in Indian higher education and drives digital transformation through informed strategies and sound practices.

Keywords: artificial intelligence, higher education, adoption, benefits, risk, faculty perspectives, UTAUT framework

Introduction

The application of artificial intelligence (AI) in higher education is revolutionizing academic activities worldwide and opening new ways for teaching, research, and administration (Kim et al., 2025; Taib et al., 2023). In India, digital adoption in higher education is on the rise, and insights into how faculty perceive AI are important. In India, with its vast range of private and public educational institutions, one area under exploration is how faculty are noticing and working with AI technologies, a study crucial for developing future pedagogical approaches. Higher education has responded to AI with both enthusiasm and scepticism. Educators appreciate that AI can improve efficiency, tailor learning to individual students, and simplify routine administrative tasks (Abouammoh et al., 2023; Alhwaiti, 2023; Fiialka et al., 2023; Lin et al., 2024). Tools such as ChatGPT have the potential to streamline assessments, create educational content, and promote student engagement (Barrett & Pack, 2023; Firat, 2023). The questions of validity and ethical implications not yet answered (Hunting, 2021), and the concerns that AI can gradually destroy traditional pedagogical practices (Pisica et al., 2023) remain problematic. The acceptance of AI by faculty is influenced by perceived usefulness, organizational support, and individual digital competencies (Amron et al., 2022; Du & Gao, 2022).

However, despite the growing demand, limited research is available on faculty views on AI adoption from an Indian perspective. Although worldwide studies identify trends and problems, the regional perspective is limited. This gap needs to be addressed, as the higher education context in India differs culturally, institutionally, and technologically from that in Western countries. The same issues regarding displacement, ethical concerns, and the reliability of AI content are also faculty concerns that underscore the importance of context-specific work (Tan et al., 2025). This research is important as it provides insight into faculty perceptions of AI in India's higher education. This research helps inform institutional policies, professional development programs, and ethical guidelines that promote the responsible integration of AI. The study will examine how Unified Theory of Acceptance and Use of Technology (UTAUT) factors, including ease of use, perceived usefulness, facilitation conditions, social influence, and risk perception, would affect faculty adoption of AI technologies.

The primary objective of the present study is to explore the influence of ease of use, perceived benefits, institutional support, social influence, and perceived risk on faculty behavioural intentions and actual use of AI adaptation in higher education. It aims to examine how institutional support and peer influence shape faculty experiences and practices related to AI integration in teaching and research. Additionally, the study seeks to provide policy recommendations to enhance AI adoption in higher education, ensuring ethical usage, adequate support, and alignment with India's educational objectives. This research is expected to contribute to improvements in teaching and learning experiences by providing insights into how AI can be best integrated to support personalised, effective academic experiences. It seeks to advance the study's knowledge area by extending the technology acceptance phenomenon in the Indian higher education setting. It is also intended to contribute to policy-making by providing recommendations for institutional policies and training programmes that promote responsible AI adoption in academia. Faculty views on AI adoption are important for formulating effective strategies aligned with educational objectives and technological developments. The

DOI: https://dx.doi.org/10.22159/ijoe.2026v14i2.58362. Journal homepage: https://journals.innovareacademics.in/index.php/ijoe.

Acknowledgment: The authors sincerely thank all the faculty members who voluntarily participated in this study and generously shared their time, experiences, and insights. Their contributions were invaluable in enhancing the understanding of faculty perspectives on the adoption of artificial intelligence in higher education. The authors also acknowledge the institutional support that facilitated ethical data collection and the smooth conduct of the research. **Authors' Contribution:** The first author conceived the study and drafted the manuscript, while the second author reviewed the results, provided critical feedback, made grammatical and language corrections, and approved the final version of the manuscript. **Conflicts of Interest:** The authors declare that there are no conflicts of interest regarding the research, authorship, and publication of this article. **Funding Source:** No financial support was received for the research, authorship, or publication of this article.

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proposed research will provide practical guidelines to facilitate the implementation of AI in higher educational institutions across India, based on the identified gaps.

Review of the Related Literature

Perceived Benefits of AI Adoption in Higher Education

AI adoption in higher education has significantly enhanced faculty efficiency in teaching, research, and administrative tasks (Abouammoh et al., 2023; Fiialka et al., 2023; Livberber & Ayvaz, 2023). Faculty members recognize AI's capacity to generate content, summarize complex information, and automate repetitive processes, reducing workload and enabling greater academic focus (Abouammoh et al., 2023; Antony & Ramnath, 2023; Fiialka et al., 2023; Livberber & Ayvaz, 2023). Tools like AI-assisted grading, scheduling, and data management streamline academic operations (Alhwaiti, 2023; Alnasib, 2023; Al-Riyami et al., 2023; Du & Gao, 2022). Generative AI supports research through automated literature reviews, academic writing assistance, and report generation, boosting faculty productivity (Firat, 2023; Kohnke et al., 2023). Additionally, data-driven insights from AI help faculty track student progress and refine teaching strategies (Barrett & Pack, 2023). AI has also transformed teaching and learning by enabling personalized instruction, increasing engagement, and enhancing accessibility. According to another study, AI-enabled systems enhance learning engagement, motivation, and academic performance through personalized learning mechanisms (Mallillin, 2024). Faculty report using AI for adaptive content delivery and real-time feedback (Alhwaiti, 2023; McGrath et al., 2023), while AI tutors and virtual mentors improve learning outcomes (Fiialka et al., 2023; Wood et al., 2021). AI fosters inclusivity through multilingual and disability support (Abouammoh et al., 2023; Alnasib, 2023; McGrath et al., 2023) and encourages interactive, gamified learning (Roy et al., 2022). However, structured training, ethical guidelines, and institutional backing remain essential to mitigate concerns around integrity, reliability, and bias (Du & Gao, 2022; Singh et al., 2023; Wang et al., 2021).

Perceived Risk of AI Adoption in Higher Education

Perceived risk refers to users' belief that adopting new technology may lead to negative consequences or losses (Klein et al., 2024). Faculty concerns regarding transparency, algorithmic bias, and data privacy continue to influence trust and adoption of AI in education (Pandey, 2025). In higher education, faculty often voice concerns about behavioral insecurity stemming from unfamiliarity with AI and environmental insecurity arising from the unpredictable nature of AI-generated content (Velez-Cruz & Holstun, 2022). A key issue is academic integrity, with fears that AI may facilitate plagiarism, misinformation, and biased content, undermining the credibility of academic work (Barrett & Pack, 2023; Firat, 2023). Faculty also expressed concern over decision-making autonomy, fearing AI may reduce their control over curriculum and assessment (Alhwaiti, 2023; Pisica et al., 2023). Privacy and data security risks, especially regarding the misuse of personal and student data by AI systems, further heighten hesitancy (Alhwaiti, 2023; McGrath et al., 2023; Wang et al., 2021). Beyond ethical concerns, fears of job displacement, dehumanisation of education, and diminished student critical thinking contribute to resistance (Fiialka et al., 2023; Firat, 2023; McGrath et al., 2023; Ruiz-Rojas et al., 2023; Wood et al., 2021). Barriers such as lack of training, resource demands, and institutional limitations also impede adoption (Alhwaiti, 2023; Du & Gao, 2022; Wang et al., 2021). Reducing perceived risk through institutional support, AI literacy programs, and transparent policies can improve faculty trust and promote responsible AI integration (Alajmi et al., 2020; Du & Gao, 2022).

Application of AI and UTAUT in Higher Education

Integrating AI in higher education has transformed teaching, research, and administrative processes, making it an essential tool for faculty. Understanding faculty adoption of AI-based technologies is crucial for ensuring effective implementation in academic institutions. The UTAUT provides a widely accepted framework for analysing the factors influencing AI adoption among educators (Venkatesh et al., 2003). UTAUT identifies four key constructs, performance expectancy, effort expectancy, social influence, and facilitating conditions, that shape faculty decisions to integrate AI into their professional activities. Research suggests that faculty members view AI as a powerful tool that enhances productivity, streamlines academic tasks, and improves student learning experiences (Sharma & Singh, 2024; Strzelecki, 2023).

Performance Expectancy

Performance Expectancy refers to the perception that AI enhances academic performance and effectiveness. Teachers recognise that AI-based applications help automate grading, produce course materials, examine research papers, reduce the burden of administrative duties, and make activities easier than in the early days (Abouammoh et al., 2023; Barrett & Pack, 2023; Fiialka et al., 2023). AI also increases productivity in research, as faculty can analyze large amounts of data, provide literature reviews with greater precision, and develop research hypotheses more effectively (Firat, 2023; Livberber & Ayvaz, 2023). In learning, AI-based adaptive learning technologies enable educational institutions to adopt personalised teaching strategies, real-time grading, and individualised testing, thereby enhancing student engagement and academic performance (Al-Riyami et al., 2023; Ruiz-Rojas et al., 2023). These benefits indicate that AI adoption in higher education could significantly increase the efficiency of faculty work and, therefore, support teaching and research activities more effectively (Nikolic et al., 2024; Strzelecki, 2023).

Effort Expectancy

Effort Expectancy is the expectation of how easy AI tools are to use in an academic context. In general, faculty members perceive AI-based ed-tech as user-friendly and intuitive, particularly for performing tedious tasks such as grading, creating content, and providing student feedback (Guo & Wang, 2023). Generative AI tools such as ChatGPT can help educators rapidly develop class materials, prepare exam reviews and supplementary materials, and support students' academic writing (Alyoussef, 2021; Ruiz-Rojas et al., 2023). Whilst some faculties needed more time to familiarise themselves with AI tools, there is evidence that AI has the potential to reduce workload, expand access to knowledge, and simplify academic complexities (Livberber & Ayvaz, 2023). The easier it is for AI to be integrated into existing workflows, the more faculty and academicians will use it without a high level of computational knowledge (Ruiz-Rojas et al., 2023).

Social Influence

Social influence is a key factor in faculty adoption of AI technologies, as peers' testimonials, institutional guidelines, and student-driven expectations shape faculty conceptions of AI's use in education. The findings indicate that colleagues' success in using AI in teaching and research encourages faculty to utilise AI providers (Crompton & Burke, 2023; Pang & Wei, 2025). The support from colleagues, professional networks, and the institution's leadership also significantly impacts the integration process, as faculty peer groups gain confidence in the utility of AI for academic activities (Jang & Kim, 2024). Students' growing use of AI-driven learning experiences (e.g., AI tutors, automated research assistants) also adds to faculty members' impetus to innovate with AI in their teaching practices (Mollick & Mollick, 2024). Faculty participants who have opportunities for collective discussions on AI adoption and share best-practice experiences could be more successful in mitigating initial curiosity, scepticism, and fears in favour of AI inclusion in education (Chan & Colloton, 2024; Oc et al., 2024).

Facilitating Conditions

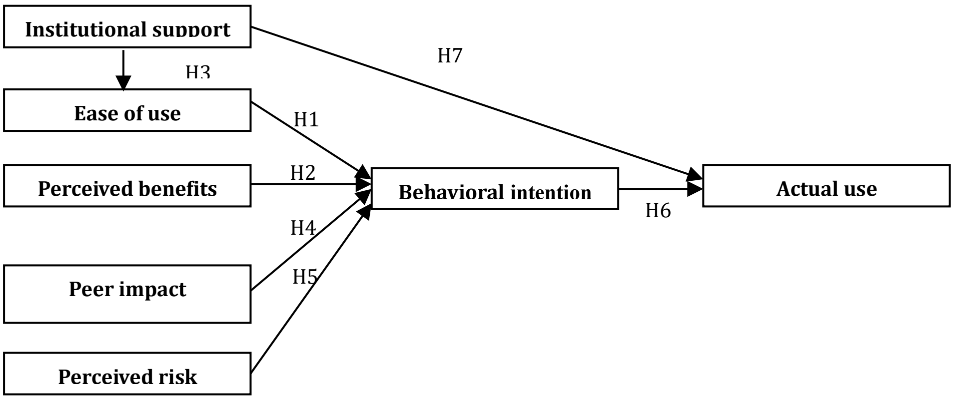
Facilitating condition refers to the ease and availability of using AI in training. Institutional support and ethical guidelines significantly influence faculty Adoption of AI. Those institutions and universities that offer organised AI training programs, policy frameworks, infrastructure, etc., are better able to help their faculty members integrate AI more effectively into teaching activities (Dubey et al., 2024). Research has shown that faculty will embrace it more when institutions offer an AI literacy curriculum, professional development workshops, and clear guidelines on the ethical use of AI. Additionally, findings reveal that faculty trust in AI tools increases when it is assured that concerns related to academic integrity, data privacy, and AI accuracy are taken into account (Hodges & Kirschner, 2024). Universities must provide the necessary institutional support and access to AI-driven resources if they are to move towards a more seamless integration of AI into education, ensuring that faculty have the skills and knowledge to embed AI in their teaching and research with confidence (Chan & Colloton, 2024).

Hypothesis

Based on the literature review, the following hypothesis was formulated, and Figure 1 illustrates the proposed research model:

1. Ease of Use (EU) positively influences faculty's Behavioural Intention (BI) to adopt AI
2. Perceived Benefits (PB) positively influence faculty's Behavioral Intention (BI) to adopt AI
3. Institutional Support (IS) positively influences faculty's Ease of Use (EU) of AI tools
4. Institutional and Peer Impact (PI) positively influence faculty's Behavioral Intention (BI) to adopt AI
5. Perceived Risk (PR) negatively influences faculty's Behavioral Intention (BI) to adopt AI
6. Behavioral Intention (BI) positively influences faculty's Actual Use (AU) of AI in higher education
7. Institutional Support (IS) positively influences faculty's Actual Use (AU) of AI in teaching and research

Figure 1
Proposed Research Model



Methodology

Design

This study employed a quantitative research method and utilised a survey for data collection. The structured questionnaire was designed based on existing literature to capture faculty perspectives on AI adoption in higher education. Convenience sampling was used to collect data from 380 faculty members across public and private universities in India. The survey comprised sections that measured factors such as ease of use, perceived benefits, institutional support, peer influence, perceived risk, behavioural intention, and actual AI use. Structural Equation Modeling (SEM) was employed to analyze the data, examine relationships among the identified variables, and validate the proposed research model. The demographic profile of the respondents is presented in Table 1.

Table 1
Demographic Profile of the Respondents

Baseline characteristic	*f*	%
Gender		
Male	190	50.00
Female	190	50.00
Age		
<35	46	12.10
35-40	108	28.40
41-45	37	9.70
46-50	88	23.20
51-55	42	11.10
>55	59	15.50
Years of experience		
< 1 year	9	2.40
1-5	61	16.10
6-10	66	17.40
11-15	124	32.60
16-20	55	14.50
> 20 years	65	17.10
Type of institution		
Public	192	50.50
Private	188	49.50
Level of proficiency with AI technologies		
Beginner	131	34.50
Intermediate	138	36.30
Advanced	111	29.20

Note. N = 380.

Data Collection

Data were collected from 380 faculty members across public and private Indian universities using a structured questionnaire based on existing literature. The instrument comprised eight sections: demographics (age, gender, institution type, teaching experience), Ease of Use (perceived simplicity of AI tools), Perceived Benefits (AI's impact on teaching and research efficiency), Institutional Support (availability of training and resources), Peer Impact (influence of colleagues and institutional encouragement), Perceived Risk (concerns over academic integrity and data privacy), Behavioral Intention (willingness to adopt AI), and Actual Use (current engagement with AI tools). This comprehensive design ensured a systematic evaluation of factors influencing AI adoption.

Processor

The study used validated measures to assess constructs influencing AI adoption in higher education. Perceived Benefits (PB) included AI's role in teaching efficiency, grading automation, content creation, personalized feedback, and accessibility. Ease of Use (EU) assessed the simplicity of AI tools, effectiveness, user-friendly interfaces, chatbot usefulness, and access to academic resources. Peer Impact (PI) covered institutional encouragement, peer influence, student expectations, AI normalization, and discussions about AI's usefulness. Institutional Support (IS) examined AI training, policy, and resource support, funding, and technical assistance. Perceived Risk (PR) addressed concerns about academic integrity, grading bias, faculty-student interaction, time demands, and data privacy. Behavioral Intention (BI) evaluates willingness to adapt, explore, and recommend AI. Actual Use (AU) reflected current AI integration, tool exploration, and adoption trends. For consistency, all constructs were measured using a Likert scale.

Results

Exploratory Factor Analysis

Factor analysis was employed to identify a smaller set of latent factors underlying a larger number of observed variables. Table 2 presents the results of the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity. The KMO statistic, which ranges from 0 to 1, assesses the suitability of the data for factor analysis, with higher values indicating greater adequacy. According to Kaiser's classification, KMO values between 0.90 and 1.00 are considered *marvellous*, 0.80 to 0.89 *meritorious*, 0.70 to 0.79 *middling*, 0.60 to 0.69 *mediocre*, and 0.50 to 0.59 *miserable*. The obtained KMO value of 0.972 indicates *marvellous* sampling adequacy.

Additionally, Bartlett's Test of Sphericity was significant (χ^2 = 27,324.349, p < .001), further supporting the appropriateness of factor analysis. Rotated factor loadings, representing the correlations between the observed variables and the extracted factors, are reported in Table 4. These loadings range from -1 to +1, with higher absolute values indicating stronger relationships. For an optimal factor solution, each item should load highly on a single factor and minimally on others (Ajai & Sanjaya, 2006). As shown in Table 4, all items demonstrated factor loadings greater than 0.50, indicating a strong association with their respective underlying constructs. Based on these results, all 35 items were retained for subsequent analysis.

Table 2
KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.972
Bartlett's Test of Sphericity	Approx. Chi-Square	27324.349
	df	595
	Sig.	.000

Table 3
Rotated Component Matrix[a]

Items	Factor loading						
	1	2	3	4	5	6	7
AI tools are easy to use for academic tasks	.853						
AI improves teaching effectiveness without extra effort	.862						
AI-based chatbots are useful for quick academic assistance	.864						
AI learning platforms provide user-friendly interfaces	.852						
AI helps faculty quickly retrieve academic resources	.863						
I intend to use AI in my academic activities		.843					
I plan to integrate AI tools into my teaching and research		.855					
I am willing to explore new AI tools for educational purposes		.862					
I expect to use AI in my classroom within the next year		.857					
I will recommend AI adoption to my colleagues		.842					
AI improves faculty efficiency in teaching and research			.827				
AI helps automate grading and reduces workload			.836				
AI facilitates content creation and research writing			.825				
AI enables better student learning through personalized feedback			.826				
AI improves accessibility by offering assistive technologies			.839				
My institution encourages faculty to integrate AI into teaching				.834			
My colleagues' use of AI influences my willingness to adopt AI				.834			
Student expectations push me to explore AI-powered tools				.821			
AI adoption is becoming a norm in higher education				.814			
Faculty discussions about AI impact my perception of its usefulness				.824			
My institution provides adequate training on AI use					.807		
AI-related policies and guidelines support faculty adoption					.801		
Sufficient resources are available to integrate AI into teaching					.817		
My institution provides financial support for AI adoption					.832		
Technical support is available to assist faculty with AI					.816		
I currently use AI tools in my academic activities						.814	
AI is part of my regular teaching and research process						.802	
I have applied AI to at least one course or research project						.810	
I actively explore AI-driven learning tools for students						.813	
My AI adoption has increased over the last year						.819	
AI raises concerns about academic integrity							.802
AI tools can introduce biases in grading and feedback							.810
AI reduces faculty-student interaction in learning							.789
AI adoption requires additional time and effort							.778
Privacy and data security concerns limit my AI adoption							.793

Note. N = 380. Extraction method: Principal component analysis, Rotation method: Varimax with Kaiser Normalization. [a] = Rotation converged in 7 iterations.

Measurement Model

Convergent validity was established as all composite reliabilities exceeded 0.70 and all average variance extracted (AVE) values exceeded 0.50, meeting the criteria of Hair et al. (p. 785, 2010). Discriminant validity was also confirmed; correlations between constructs were low, and the square root of each construct's AVE was more significant than its correlations with other constructs, satisfying Fornell and Larcker's (1981) condition, as shown in Table 4.

Table 4
Results of CFA for the Measurement Model

Construct	Item	Internal reliability: Cronbach's Alpha	Convergent validity		
			Factor loading	Composite reliability	Average variance extracted
Institutional support	IS1	0.986	0.807	0.978	0.9
	IS2		0.801		
	IS3		0.817		
	IS4		0.832		
	IS5		0.816		
Perceived risk	PR1	0.985	0.802	0.977	0.895
	PR2		0.81		
	PR3		0.789		
	PR4		0.778		
	PR5		0.793		
Peer impact	PI1	0.989	0.834	0.983	0.922
	PI2		0.834		
	PI3		0.821		
	PI4		0.814		
	PI5		0.824		
Perceived benefits	PB1	0.988	0.827	0.98	0.909
	PB2		0.836		
	PB3		0.825		
	PB4		0.826		
	PB5		0.839		
Ease of use	EU1	0.988	0.853	0.981	0.911
	EU2		0.862		
	EU3		0.864		
	EU4		0.852		
	EU5		0.863		
Behavioral intention	BI1	0.986	0.843	0.978	0.9
	BI2		0.855		
	BI3		0.862		
	BI4		0.857		
	BI5		0.842		
Actual use	AU1	0.989	0.814	0.982	0.919
	AU2		0.802		
	AU3		0.81		
	AU4		0.813		
	AU5		0.819		

Note. A Composite reliability = (square of the summation of the factor loadings)/ {(square of the summation of the factor loadings) + (square of the summation of the error variances).
b Composite reliability = (summation of the square of the factor loadings)/ {(summation of the square of the factor loadings) + (summation of the error variances).

Table 5
Discriminant Validity of Constructs

Constructs	IS	PR	PI	PB	EU	BI	AU
IS	0.949						
PR	0.44756	0.946					
PI	0.35522	0.40704	0.96				
PB	0.34692	0.43296	0.3969	0.953			
EU	0.31472	0.30581	0.33063	0.3014	0.954		
BI	0.39063	0.31697	0.3181	0.27984	0.29703	0.949	
AU	0.3576	0.41732	0.38688	0.3844	0.3721	0.34928	0.959

Note. Diagonals represent the square root of the average variance extracted, while the other entries represent the squared correlations.

Structural Model

The structural model was estimated using the maximum likelihood method. Figure 2 presents the results. The fit statistics are presented in Table 6. The SEM results indicate that six out of seven hypotheses were supported (see Table 8). EU did not significantly influence BI (β = 0.052, p = .434). Thus, H1 was not supported. However, PB positively affected BI (β = 0.208, p < .001), supporting H2**.** IS significantly influenced EU (β = 0.894, p < .001), supporting H3. PI also positively affected BI (β = 0.256, p < .001), supporting H4. PR showed a significant positive relationship with BI (β = 0.305, p < .001), supporting H5. Furthermore, BI significantly influenced AU (β = 1.517, p < .001), supporting H6. Lastly, IS also positively impacted AU (β = 0.351, p = .012), supporting H7. Overall, the results highlight the critical role of perceived benefits, institutional support, peer influence, and perceived risks in shaping behavioral intentions and actual AI usage in higher education.

Table 6
Model Fit Indices

Fit measures	Observed value	Recommended values
df	5	
Chi-square	1.450	≤ 5.00
GFI	.995	≥ 0.90
AGFI	.970	≥ 0.90
NFI	.995	≥ 0.90
CFI	.999	≥ 0.90
TLI	.994	≥ 0.90
RMSEA	.034	≤ 0.08

Figure 2
Structural Model

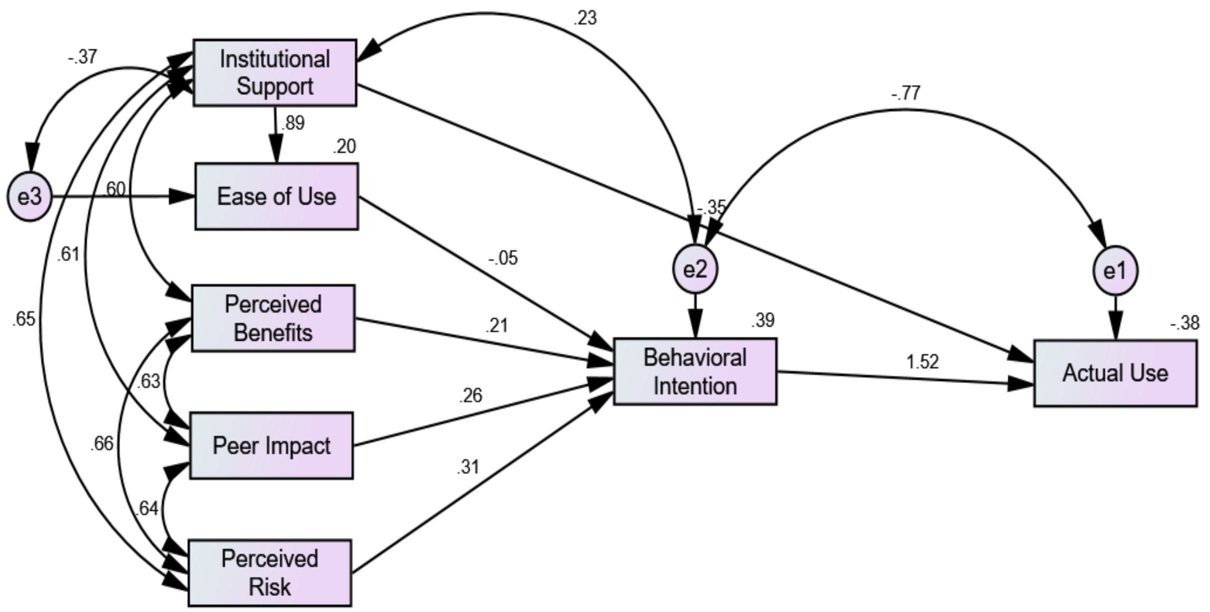


Table 7
Hypothesis Testing

Hypothesis				Estimate	CR	p-value	Decision
H1	EU	→	BI	0.052	0.783	.434	Not Supported
H2	PB	→	BI	0.208	5.365	.000	Supported
H3	IS	→	EU	0.894	13.919	.000	Supported
H4	PI	→	BI	0.256	6.452	.000	Supported
H5	PR	→	BI	0.305	6.996	.000	Supported
H6	BI	→	AU	1.517	7.512	.000	Supported
H7	IS	→	AU	0.351	2.504	.012	Supported

Discussion

The results of this study emphasise the critical factors that affect faculty adoption of AI in Indian academia. The findings revealed five antecedents of AI adoption: perceived usefulness, institutional support, peer influence, perceived risk, and behavioral intention. Perceived benefits, institutional pressure, interpersonal influence, and perceived risk were found to have significant positive effects on behavioural intention to use AI systems. If we see it through the lens of individual perspective, ease of use, and actual use of AI, we see that institutional support is directly affected by ease of use and actual use of AI, whereas behavioural intention has a significant influence on the actual use of AI tools. Interestingly, ease of use did not have a significant effect on behavioral intention, suggesting that other factors (institutional support and perceived advantages) may better explain why faculty members adopt or do not adopt AI.

These findings substantiate that the positive effect of perceived benefit on behavioural intention is consistent with Abouammoh et al. (2023) and Fiialka et al. (2023), who found that faculty members use AI tools when they perceive practical benefits, such as increased efficiency and academic productivity. The central role of institutional support in promoting use is consistent with studies that have highlighted the significance of structured assistance and resources for technology adoption (Du & Gao, 2021). Likewise, the effect of peer influence is consistent with Crompton and Burke (2023), who found that social influence was one of the most powerful factors in adopting educational technologies.

However, the study supports previous work; at the same time, it deviates from those findings. The lack of significance of ease of use, unlike prior research, where ease of use was a significant determinant of technology usage intention (Ruiz-Rojas et al., 2023), is also noteworthy. In the Indian higher education system, faculty members are likely to value institutional support and perceived advantages over the ease of use of AI tools. Another interesting discovery in this study is the positive effect of perceived risk on behavioural intention. In contrast with prior studies that presented perceived risk as a barrier (Alhwaiti, 2023; Wang et al., 2021), this study indicates that faculty in Tamil Nadu recognise the potential risks of AI but are responsible for adopting it when they see clear academic benefits and institutional support.

Based on the major findings of the present study, Indian higher education needs policy recommendations to effectively adopt AI among faculty. Institutions should focus on developing strong institutional support for AI, including AI literacy, continuous training, and faculty development workshops. Ensuring that teachers have the necessary resources and technical support will increase their confidence in using AI tools. Promoting a climate of cooperation in which academics can share experiences and best practices will foster peer influence and reduce fears about AI integration. In Addition, institutions need to develop ethical standards, such as in academic integrity, data privacy, and reliability, to ensure that AI is introduced in accordance with institutional norms and national educational policies. Efforts to mitigate perceived risks, including transparent data governance and ongoing monitoring of AI-generated content, may also help build trust with faculty.

The development of successful AI applications related to the objectives of teaching, learning, and research needs is an important aspect in the educational context. Institutions need to support the application of AI in personalised learning, automated assessment, and research assistance to enhance educational productivity. Faculty mentoring programmes may be set up to support cautious faculty members in AI adoption by learning from experienced early adopters. Additionally, AI awareness and training should be included in faculty development programs to foster greater knowledge and acceptance of AI tools.

Conclusion

This research adds to the body of knowledge on the factors influencing AI adoption among faculty members in higher education institutions in Tamil Nadu. The study finds that perceived benefits, institutional support, peer influence, and perceived risk are the most significant antecedents of faculty intention and use of AI tools. Although the risks associated with AI were acknowledged, they were not significant enough to discourage faculty from adopting AI for educational use when weighed against perceived benefits, institutional support, and peer influence. This illustrates the increasing integration of AI tools into academia, provided sufficient institutional support and training. The results indicate that a single-pronged strategy is insufficient to promote AI assimilation within organizations. Enhancements in institutional support through ongoing training, the formulation of ethical protocols, and the nurturing of collegial peer context are key. Institutions also need to consider ethical risks, data security, and academic integrity to build faculty confidence in the responsible use of AI.

Another highlight is that further studies are necessary to expand knowledge of AI assimilation across other regions and disciplines over longer time periods. As AI technologies evolve, so too will the need to understand their influence on teaching, research, and administration. This study provides a basis for formulating evidence-based policy and educational strategies to enable AI in Indian higher education. Finally, the study concludes with some policy suggestions to boost AI adoption and propel India's digital transformation in higher education. Responsible use of AI can enable better-quality teaching, accelerate research and innovation, and make administrative processes more efficient, ensuring that India continues its trailblazing path toward universal education on a global scale.

Limitations

This study also has several limitations. First, the application of the convenience sampling method in Indian faculty may introduce selection bias, as faculty who are more technology-savvy, have practical knowledge, and have a positive attitude towards AI may have been more likely to participate. This may, in part, account for the high perceived benefits and usage intentions reported, and therefore, generalizes to other contexts with caution. Moreover, the generalizability of the findings is limited by the study's focus on Indian faculty, particularly given differences in attitudes and experience with AI across institutional cultures, technological infrastructure, and regional educational policies. Second, the research did not account for differences in faculty members' disciplines; a STEM faculty member might have different academic experiences and attitudes toward AI than a faculty member from a non-science or social science discipline. Third, although the questionnaire was formulated based on existing literature, using a self-developed tool may introduce bias into the measurements. Lastly, this is a cross-sectional study that measures faculty perceptions of AI use at a single point in time, and we do not know how faculty attitudes and AI use would change over time.

Future Research Directions

Further studies may consider encompassing the faculties of all regions across India's geography and exploring regional differences in AI adoption. Research might also explore disciplinary distinctions to analyse how academics across disciplines understand and incorporate AI. Longitudinal investigations are advised to examine the evolution of faculty attitudes and behaviour regarding AI. In Addition, such studies should include the student perspective to explore how students' expectations and experiences influence faculty adoption of AI tools. In Addition, examining the effectiveness levels and comparing various institutional supports and training programs would deepen understanding of how to better promote AI integration in higher education. Moreover, one possible line of research would focus on developing standardised, non-biased measurement procedures to reduce data-collection vagueness. Finally, qualitative investigation (interviews and focus group discussions) could supplement the quantitative results by providing a more nuanced, location-specific understanding of the challenges and opportunities for AI adoption.

AI Use Statement

The authors used Grammarly for grammar checking, improving sentence clarity, and language improvement. The authors reviewed and edited the output and takes full responsibility for the final content.

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Received: 15 January 2026
Revised: 10 February 2026
Accepted: 23 February 2026