EPRA International Journal of Environmental Economics, Commerce and Educational Management
Journal DOI: 10.36713/epra0414 |ISI I.F Value: 0.815|SJIF Impact Factor (2025): 8.57 ISSN: 2348 – 814X
Volume: 12 | Issue:10 |October 2025 -Peer Reviewed Journal

INTEGRATING ARTIFICIAL INTELLIGENCE IN HIGHER EDUCATION: A FACULTY-CENTRIC STUDY OF TEACHING TRANSFORMATION

Christy George M.J[1], Riya Mary [2], Akhila Babu [3]
[1] *Department of Commerce, St Pauls College, Kalamassery, Kerala*
[2] *Department of Commerce, St Pauls College, Kalamassery, Kerala*
[3] *Student (M.Com), Department of Commerce, St Pauls College, Kalamassery, Kerala*

ABSTRACT
The rapid advancement of Artificial Intelligence (AI) is transforming multiple sectors, including healthcare, finance, manufacturing, and education. In higher education, AI offers opportunities to enhance learning outcomes, improve administrative efficiency, and enable personalized learning through applications such as tutoring systems, virtual assistants, predictive analytics, automated grading, and smart content creation. While globally AI adoption in education is gaining momentum, in India its implementation remains at an early stage, with limited and uneven uptake among institutions. Faculty members play a critical role in shaping the success of AI integration, as their acceptance and effective utilization of these tools directly influence teaching innovation and student learning. This study investigates key factors influencing AI adoption among faculty at Mahatma Gandhi University, Kerala, focusing on Attitudes, Perceived Risks, Awareness, and Effort Expectancy. By examining faculty readiness, concerns, and expectations, the study provides valuable insights into the enablers and barriers of AI adoption in higher education. The findings are expected to contribute to a faculty-centered understanding of digital transformation in academia and guide strategies for fostering more effective integration of AI technologies in teaching and learning.
KEYWORDS : *Artificial Intelligence, Higher Education Attitudes, Perceived Risks, Awareness, and Effort Expectancy, AI Adoption*

1.1 INTRODUCTION
The advancements in Artificial Intelligence (AI) has changed many sectors worldwide, including healthcare, finance, manufacturing, and, importantly, education. In higher education, AI has emerged as a strong tool that can improve learning outcomes, increase administrative efficiency, and promote personalized learning experiences (Holmes et al., 2019; Zawacki-Richter et al., 2019). Applications like tutoring systems, virtual assistants, predictive analytics, automated grading, and smart content creation are bringing significant changes to the educational sector.

In India, the application of AI is still in its initial stage. While institutions are beginning to recognize its potential, actual implementation and adoption, particularly by faculty, remain limited and inconsistent. Faculty members are vital in delivering education and driving innovation. Their acceptance and effective use of AI technologies are important for successful integration. However, factors such as attitudes toward AI, perceived risks, awareness, and the effort required to learn and use AI tools can greatly affect their willingness to adopt these technologies. This study seeks to examine these important factors among faculty members at Mahatma Gandhi University, Kerala. The research aims to understand their readiness, concerns, and expectations about using AI in teaching. This will provide a faculty-centered perspective on the digital changes in higher education.

1.2 SIGNIFICANCE OF THE STUDY
The use of AI in education is not just a technological improvement; it also represents a change in culture and teaching methods (Luckin et al., 2016). Faculty attitudes and their intentions play a key role in how effective these initiatives are. While there is growing discussion about AI's role in education, there is a gap in research on faculty opinions and the psychological and contextual factors that affect their willingness to adopt AI in Indian universities. The study adds to academic discussions by providing insights into faculty opinions on AI adoption in higher education. The findings will provide insights to university leaders and policy-makers to develop better professional development programs that address faculty and supports the creation of focused strategies for using AI that meet the specific needs and readiness of teaching staff.

EPRA International Journal of Environmental Economics, Commerce and Educational Management
Journal DOI: 10.36713/epra0414 |ISI I.F Value: 0.815|SJIF Impact Factor (2025): 8.57 ISSN: 2348 – 814X
Volume: 12 | Issue:10 |October 2025 -Peer Reviewed Journal

1.3 STATEMENT OF THE PROBLEM

More people are recognizing the benefits of AI in higher education, but many faculty members still hesitate or feel unprepared to use AI technologies in their teaching (Holmes et al., 2019)). This concern may come from several factors, including the belief that learning to use AI tools is too complex, worries about ethical issues, doubts about the accuracy and usefulness of AI, and a general lack of training or familiarity. At Mahatma Gandhi University, one of the top universities in Kerala, there is little empirical data on faculty opinions about AI and what influences their decision to accept or reject these technologies. Without this information, efforts to implement AI across the institution may face resistance or limited adoption. This research aims to address this gap by examining how faculty attitudes, perceived risks, awareness levels, and expectations about effort affect their willingness to adopt AI in their teaching. The goal is to identify what helps or hinders AI adoption from the perspective of those most involved in the educational process (Umar & Zubairu, 2022).

1.4 OBJECTIVES

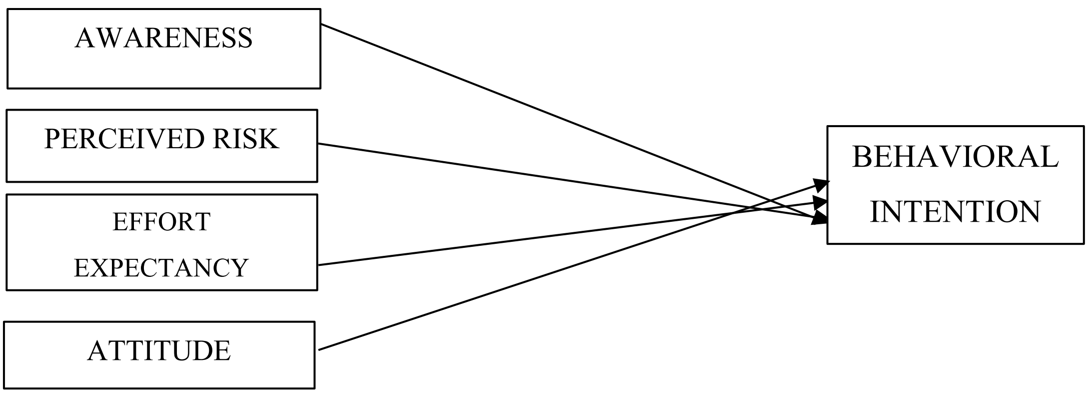
1. To assess the level of drivers of AI adoption towards the behavioural intention of college teachers.
2. To measure the behavioural intention of college teachers concerning AI adoption.
3. To analyse the relationship between drivers of AI adoption and behavioural intention towards adopting AI among college teachers.
4. To analyse effect of drivers of AI adoption on the behavioural intention towards adopting AI among college teachers.

1.5 THEORETICAL FRAMEWORK AND KEY CONSTRUCTS

To explain AI adoption in higher education, this study draws on three theoretical perspectives: the Theory of Planned Behaviour (TPB), Innovation Diffusion Theory (IDT), and Risk Perception Theory. TPB highlights the role of attitude, perceived risk, and behavioural intention in shaping technology use (Ajzen, 1991). IDT emphasizes the adoption process, particularly the importance of awareness, effort expectancy (perceived ease of use), and uncertainty tied to risk (Rogers, 2003). Risk Perception Theory further explains how concerns related to ethics, privacy, and job security influence attitudes and reduce the likelihood of adoption (Slovic, 1987).

Based on these perspectives, five key constructs are central to this study. Awareness reflects faculty familiarity with AI applications in education and serves as the first step toward adoption. Perceived risk captures concerns about job displacement, data privacy, and ethical challenges. Effort expectancy refers to the perceived ease of using AI tools, which shapes willingness to adopt. Attitude reflects the overall evaluation of AI adoption, shaped by both benefits and risks, while behavioural intention represents the likelihood of actual use and is considered the strongest predictor of behaviour. The measurement scales for these constructs are adopted from Rahiman and Kodikal (2024).

1.6 CONCEPTUAL MODEL OF THE STUDY



The conceptual model for this study is developed to examine the relationship between faculty perceptions of AI adoption and their behavioural intention to use AI in higher education. Drawing on prior research in technology adoption, the model proposes that four key constructs—awareness, perceived risk, effort expectancy, and attitude—influence behavioural intention toward AI adoption. Awareness and attitude are hypothesized to have a positive effect on behavioural intention, while perceived risk is expected to have a negative effect, and effort expectancy is expected to have a positive effect. This model provides a faculty-centered perspective for understanding AI adoption in higher education, capturing both enabling and inhibiting factors that shape behavioural intention.

1.7 RESEARCH HYPOTHESIS

H1: There is a significant effect of level of awareness on behavioural intention
H2: There is a significant effect of perceived risk on behavioural intention.
H3: There is a significant effect of effort expectancy on behavioural intention
H4:There is a significant positive effect of attitude towards AI adoption on behavioural intention.

1.8 RESEARCH METHODOLOGY

The present study employed a quantitative survey method to examine how faculty-related factors—such as awareness, perceived risk, effort expectancy, and attitude—influence the intention to adopt Artificial Intelligence (AI) in higher education. Primary data was collected from 100 faculty members of Mahatma Gandhi University (MG University), Kerala, using a structured online questionnaire. The sampling method adopted for the study was a convenience sampling method. The research design was predictive in nature, aimed at testing hypotheses on the relationships between key constructs and behavioural intention. The collected data was systematically arranged, classified, and analyzed with the help of the Statistical Package for the Social Sciences (SPSS). Descriptive statistics, including percentages, mean, mode, and standard deviation, were employed to summarize faculty responses, while correlation and regression analyses were conducted to test the hypotheses and evaluate the predictive strength of the model.

1.9 LITERATURE REVIEW

The adoption of artificial intelligence (AI), particularly generative AI (GenAI), in higher education has become a growing focus of research, with studies investigating factors shaping acceptance, behavioural intentions, and challenges across diverse contexts. A range of theoretical frameworks, including the Theory of Planned Behaviour (TPB), Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and structural equation modelling (SEM), have been applied to explain adoption dynamics.

Ivanov et al. (2024) applied TPB and demonstrated that perceived strengths and benefits of GenAI positively influence attitudes, subjective norms, and perceived behavioural control, ultimately driving intention and actual use, whereas perceived risks are less influential. Ofosu-Ampong (2024) found high lecturer acceptance of AI in Ghana, with organizational policies, pedagogical affordances, and usability playing key roles, though concerns over privacy, job security, and training remained. Edwards et al. (2024) reported positive educator attitudes in a U.S. context, with benefits and ease of integration influencing adoption, though concerns persisted regarding critical thinking and academic dishonesty. By contrast, O'Dea and O'Dea (2023) argued that AI's role in universities remains largely administrative, hindered by infrastructural and training barriers.

Building on this, Perez (2024) used the UTAUT framework to show that behavioural intention is strongly shaped by performance expectancy, effort expectancy, social influence, and facilitating conditions, with peer support particularly influential. Mah and Groß (2024) identified four faculty profiles—optimistic, critical, critically reflective, and neutral—finding that optimism moderated the link between AI self-efficacy and use, with equity in education viewed as a key benefit but AI literacy a major challenge. Dotan et al. (2024) advanced a "points to consider" framework for responsible AI integration, emphasizing governance aligned with academic values, while Rahiman and Kodikal (2024) highlighted varied levels of awareness and a positive link between AI use, faculty learning, and engagement.

UTAUT- and TAM-based studies further reinforced these findings. Chatterjee and Bhattacharjee (2020) showed AI's potential to improve governance, teaching, and decision-making in India. Srivastava et al. (2025) integrated UTAUT with information systems constructs, revealing the importance of performance expectancy, system quality, and self-efficacy for e-learning adoption. Almogren et al. (2024) reported that ease of use and usefulness strongly predicted ChatGPT adoption, while Poenaru et al. (2024) identified determinants of acceptance through a systematic review, pointing to gaps in contextual understanding. Roy et al. (2025) found that students and faculty in India expressed readiness for AI-based robots, shaped by attitudes, readiness, and behavioural intentions. Eldakar et al. (2025) emphasized the importance of ethics, self-efficacy, and social influence for GenAI adoption in academic research, with perceived risks proving less significant.

Other studies identified additional drivers and barriers. Nguyen et al. (2025) highlighted performance expectancy and personal innovativeness as the strongest adoption predictors, with information accuracy moderating intention. Xu et al. (2025) found effort expectancy and performance expectancy shaped behavioural intention, while habit and facilitating conditions drove actual use. Mostafavi (2025) confirmed AI's positive role in improving assessment and faculty engagement, while Kizilcec (2024) observed that predictive analytics has yet to achieve its potential due to non-technical barriers. Dewar Rico-Bautista et al. (2025) identified fear and lack of knowledge as adoption barriers, underscoring the role of IT organizational units in institutional integration. Finally, Sunil Kumar et al. (2025) stressed AI's transformative potential for personalized learning while raising concerns about ethics, privacy, bias, and the need for new educator skills and interdisciplinary collaboration.

Overall, the literature converges on the view that perceived usefulness, ease of use, self-efficacy, and social influence are consistent drivers of AI adoption in higher education, while barriers include limited AI literacy, privacy and ethical concerns, infrastructural constraints, and institutional readiness. Collectively, these studies suggest that successful integration requires not only technical affordances but also supportive policies, governance aligned with academic values, and sustained faculty development initiatives.

1.10 RESULTS AND DISCUSSION

1.10.1. Demographic Profile: - Majority of the respondents (83%) were between 25 and 44 years of age. Assistant Professors constituted the largest group (43%), followed by Guest Faculty (35%). In terms of qualifications, 38% of respondents held a PhD, while 29% had a postgraduate degree. A majority (60%) had less than 10 years of teaching experience, indicating that younger and mid-career faculty formed the dominant segment of participants.

1.10.2. Reliability Analysis: - The data was collected using structured questionnaire to measure the constructs using adopted scales. Constructs measured in this study exhibited high internal consistency, with Cronbach's Alpha values above 0.87. This confirmed the reliability of the scales adopted for assessing awareness, perceived risk, effort expectancy, attitude, and behavioural intention.

Faculty perceptions of AI in higher education reveal a balanced outlook, with moderate awareness of AI tools and their potential benefits for enhancing teaching and learning. While respondents acknowledged ethical, reliability, and control-related concerns, these perceived risks did not overshadow the generally positive attitude toward AI. Faculty recognized the usefulness of AI but highlighted the learning effort required for effective adoption. Despite these challenges, their overall perceptions were favourable, and a strong willingness to adopt AI emerged, suggesting that with adequate support and training, AI integration in higher education has promising prospects. Normality and One-Sample t-Test :- All constructs were approximately normally distributed. Results of the one-sample t-test showed significant deviations from the neutral midpoint, indicating strong opinions across all measured constructs.

ANOVA Results Analysis of variance showed no significant differences in perceptions based on age, designation, or teaching experience. However, educational qualification produced significant differences in both attitude ($p = .006$) and behavioural intention ($p = .017$), highlighting that faculty with different qualifications hold varied views about AI adoption.

Correlation Analysis indicated that independent variables awareness, perceived risk, effort expectancy, and attitude—showed strong positive correlations with behavioural intention. The regression model confirmed strong predictive ability, with an R^2 value of 0.825. This indicates that the constructs explained 82.5% of the variance in behavioural intention to adopt AI tools.

Table 1.10.1 Shapiro- Wilk Test

Constructs	Statistic	Shapiro- Wilk df	P Value	Inference
Awareness	.903	100	.000	Reject H0
Perceived Risk	.953	100	.001	Reject H0
Effort Expectancy	.931	100	.000	Reject H0
Attitude	.937	100	.000	Reject H0
Behavioural Intention	.931	100	.000	Reject H0

The Shapiro–Wilk test was conducted to assess the normality of the constructs—awareness, perceived risk, effort expectancy, attitude, and behavioural intention. The results (Table 1.10.1) show that all constructs recorded p-values below 0.05 (0.000 or 0.001), indicating significant deviations from normality. Hence, the null hypothesis of normal distribution was rejected for all constructs. This implies that caution must be exercised when applying parametric tests, and the results should be interpreted in light of this deviation from normality.

Subsequently, one-sample t-tests were applied to evaluate the hypothesized relationships between independent variables (awareness, perceived risk, effort expectancy, and attitude) and the dependent variable (behavioural intention).

Table 1.10.2 One sample T- test

Construct	Item Acronym	Mean	Standard Error	T Value	P Value	Inference
Awareness	AW	3.5275	.10975	4.807	.000	Reject H0
Perceived Risk	PR	3.4060	.09996	4.098	.000	Reject H0
Effort Expectancy	EE	3.6000	.10602	5.659	.000	Reject H0
Attitude	ATT	3.6060	.10326	5.869	.000	Reject H0
Behavioural Intention	B	3.5900	.10607	5.562	.000	Reject H0

Source: *Compiled from primary data*

The one-sample t-test results (Table1.10.2) indicate that for all constructs—awareness, perceived risk, effort expectancy, attitude, and behavioural intention—the mean values significantly differ from the test value of 3 (p = 0.000 in all cases). This demonstrates that respondents' opinions regarding these constructs are not average, reflecting clear and distinct perceptions across the factors studied.

Table No. 1.10.3. Correlations between Independent and Dependent Variables

Constructs	Awareness	Perceived Risk	Effort Expectancy	Attitude	Behaviour
Awareness	1	.844** .000	.794** .000	.785** .000	.823** .000
Perceived Risk		1	.871** .000	.843** .000	.810** .000
Effort Expectancy			1	.854** .000	.812** .000
Attitude				1	.883** .000
Behaviour					1

Source: Calculated by researcher

**. Correlation is significant at the 0.01 level (2-tailed).

Awareness shows a strong positive correlation (Table 1.10.3) with all other variables namely Perceived Risk (r = 0.844), Effort Expectancy (r = 0.794), Attitude (r = 0.785), and Behaviour (r = 0.823). This indicates that higher awareness is associated with greater effort expectancy, more positive attitudes, and stronger behavioural intentions toward the subject (AI adoption/sustainable practice etc., depending on the study).The variable Perceived Risk exhibits a strong correlation with Effort Expectancy (r = 0.871), Attitude (r = 0.843), and Behaviour (r = 0.810), implying that perceptions of risk are closely linked with how much effort individuals expect and their overall attitude and behavioural responses.Effort Expectancy correlates strongly with Attitude (r = 0.854) and Behaviour (r = 0.812), suggesting that when tasks are perceived as easier to perform, individuals tend to develop more favourable attitudes and behaviours. The strongest correlation is observed between Attitude and Behaviour (r = 0.883), highlighting that attitude plays a crucial mediating role in shaping behavioural intentions or actions.

Regression analysis, hypothesis testing and model validation

Table 1.10.4 Model Summary of Multiple Regression Analysis

Method	Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
Enter	1	.908	.825	.817	.45327

a. Predictors: (Constant), Attitude, Awareness, Effort Expectancy, Perceived Risk

The multiple regression model (Table 1.10.4) was used to examine the combined effect of Awareness, Perceived Risk, Effort Expectancy, and Attitude on the dependent variable — Behaviour. The multiple correlation coefficient (R) is 0.908, indicating a very strong positive relationship between the set of independent variables and the dependent variable. The R Square value (0.825) reveals that 82.5% of the variance in Behaviour is explained by the four independent variables included in the model. The Adjusted R Square (0.817), which accounts for the number of predictors and sample size, confirms that the model is a

EPRA International Journal of Environmental Economics, Commerce and Educational Management
Journal DOI: 10.36713/epra0414 |ISI I.F Value: 0.815|SJIF Impact Factor (2025): 8.57 ISSN: 2348 – 814X
Volume: 12 | Issue:10 |October 2025 -Peer Reviewed Journal

good fit, with a minimal reduction from R^2, indicating strong model reliability. Given the strong R and R^2 values, it can be inferred that the independent variables Awareness, Perceived Risk, Effort Expectancy, and Attitude collectively have a significant impact on Behaviour.

Table 1.10.5 ANOVA Table - Regression Model Fit

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	91.872	4	22.968	111.790	.000**
	Residual	19.518	95	.205		
	Total	111.390	99			

**Significant at 0.01 level
a. Dependent Variable: Behaviour
b. Predictors: (Constant), Attitude, Awareness, Effort Expectancy, Perceived Risk

The ANOVA table (Table 1.10.5) evaluates the overall significance of the regression model and determines whether the independent variables collectively explain a significant proportion of variance in the dependent variable (Behaviour).The F-value of 111.790 is considerably high, indicating that the regression model fits the data well.The significance value (Sig. = .000) is less than the 0.01 level, confirming that the model is statistically significant. This implies that the set of independent variables — Awareness, Perceived Risk, Effort Expectancy, and Attitude — jointly exert a significant influence on the dependent variable (Behaviour).

Table 1.10.6 Regression Coefficients- Significance of drivers of AI adoption factors on the Behaviour intention of College Teachers

Construct/dimension	Unstandardized Coefficients		Standardized Coefficients	T value	Sig.
	B	Std. Error	Beta		
(Constant)	.133	.172		.772	.442
Awareness	.309	.081	.320	3.829	.000**
Perceived Risk	-.014	.113	-.013	-.124	.901
Effort Expectancy	.074	.099	.074	.748	.456
Attitude	.596	.094	.580	6.369	.000**

** Correlation Coefficient significant at 0.01 level
a. Dependent Variable: Behaviour Intention

The results of a regression study conducted to evaluate the influence of the independent variables—Awareness, Perceived Risk, Effort Expectancy, and Attitude—on the dependent variable, Behavioural Intention, are shown in Table 1.10.6. With a correlation coefficient (R) of 0.908, the model shows that behavioural intention and the independent variables have a very strong positive relationship. This set of independent variables accounts for 82.5% of the variance in behavioural intention, according to the R-square value of 0.825. Furthermore, the model remains robust even when taking the number of predictors into account, as evidenced by the Adjusted R-square value of 0.817. The regression analysis provides further insights into the predictors of behavioural intention. The results reveal that awareness ($T = 3.829$, $p = 0.000$) and attitude ($T = 6.369$, $p = 0.000$) significantly and positively influence behavioural intention. However, perceived risk ($T = -0.124$, $p = 0.901$) and effort expectancy ($T = 0.748$, $p = 0.456$) do not exhibit statistically significant relationships ($p > 0.05$). Therefore, the null hypothesis is rejected for awareness and attitude, while it is accepted for perceived risk and effort expectancy.

The results revealed that awareness and attitude exert a significant positive effect on behavioural intention, supporting H1 and H4. In contrast, perceived risk and effort expectancy were not found to have significant effects on behavioural intention, leading to the acceptance of H0 in these cases and the rejection of H2 and H3. Overall, while all constructs deviated from normality, the findings demonstrate that awareness and attitude are the strongest predictors of behavioural intention to adopt AI in higher education.

Implications

These findings suggest that although respondents acknowledge and form opinions about all the constructs under study, awareness and attitude are the strongest determinants of behavioural intention to adopt AI in higher education. This underscores the importance of:

1. Awareness-building initiatives – Universities and policymakers should prioritize training, workshops, and knowledge-sharing platforms to enhance faculty awareness of AI's role, benefits, and applications in teaching and learning.

2. Shaping positive attitudes – Efforts should focus on addressing skepticism, highlighting success stories, and demonstrating the value of AI tools in improving pedagogy and student engagement.
3. Risk and effort perception management – Even though perceived risk and effort expectancy are not significant predictors in this study, strategies to minimize concerns about workload, complexity, and potential drawbacks can indirectly support adoption.

In conclusion, fostering greater awareness and cultivating favourable attitudes among faculty are essential for strengthening behavioural intention, thereby accelerating the adoption of AI in higher education contexts.

CONCLUSION

The findings highlight a growing readiness among faculty to embrace AI in higher education. Despite moderate concerns about risks and the effort required to learn new tools, these issues did not significantly deter adoption intentions. Instead, awareness and positive attitudes emerged as the strongest predictors of behavioural intention, underscoring the importance of building AI literacy and fostering favourable perceptions.

The positive correlation between perceived risk and behavioural intention is particularly noteworthy. This suggests that faculty who are more aware of risks are not necessarily discouraged but may instead develop a proactive interest in adopting AI, provided risks are managed through ethical guidelines and institutional support. The lack of significant differences based on age, designation, or teaching experience indicates that AI adoption is broadly relevant across faculty demographics. However, the significant role of educational qualification suggests that strategies for AI integration should be tailored to academic backgrounds, ensuring that faculty with lower qualifications receive targeted training and support.

Overall, findings of the study confirms that AI adoption in higher education is strongly influenced by psychological and cognitive factors such as awareness, effort expectancy, and attitudes, rather than demographic characteristics. Institutions can therefore accelerate adoption by focusing on training, risk management, and confidence-building measures, rather than solely on demographic-based interventions.

REFERENCES

1. *Ajzen, I. (1991). The theory of planned behaviour. Organizational Behaviour and Human Decision Processes, 50(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T*
2. *Almogren, A., Al-Rahmi, W., & Dahri, A. (2024). Factors influencing the adoption of ChatGPT in smart education: A structural equation modeling approach. Smart Learning Environments, 11(1), 1–22.*
3. *Chatterjee, S., & Bhattacharjee, K. (2020). Adoption of artificial intelligence in Indian higher education: A UTAUT model perspective. Education and Information Technologies, 25(5), 3443–3463.*
4. *Dewar Rico-Bautista, J., Gómez, M., & Herrera, C. (2025). Challenges and opportunities in AI adoption in universities: Toward a contextual model. Journal of Educational Technology Systems, 54(2), 89–108.*
5. *Dotan, R., Parker, L., & Radzilowicz, M. (2024). Points to consider for responsible adoption of generative AI in higher education. AI & Society, 39(3), 577–594.*
6. *Edwards, M., Ghimire, S., & Prather, J. (2024). University educators' awareness, attitudes, and influencing factors regarding generative AI and LLMs in higher education. Journal of Higher Education Research, 45(2), 112–130.*
7. *Eldakar, S., Hassan, N., & Salem, M. (2025). Generative AI adoption in academic research: Insights from Egyptian scholars. Research Policy, 54(1), 104837.*
8. *Ivanov, D., Petrov, A., & Lee, J. (2024). Factors influencing the adoption of generative AI tools in higher education: A Theory of Planned Behaviour approach. Computers & Education, 205, 104874.*
9. *Kizilcec, R. (2024). The rise of AI and predictive learning analytics in education: Opportunities and challenges. British Journal of Educational Technology, 55(1), 23–41.*
10. *Mah, D., & Groß, O. (2024). Faculty perspectives on AI in higher education: Profiles, benefits, challenges, and professional development needs. International Journal of Educational Research, 125, 102236.*
11. *Mostafavi, S. (2025). Impact of AI on faculty engagement and learning experiences in higher education: A SEM approach. Interactive Learning Environments. Advance online publication.*
12. *Nguyen, T., Le, Q., & Tran, P. (2025). Factors influencing the intention to use AI technologies in higher education. Education and Information Technologies, 30(2), 2145–2168.*
13. *O'Dea, T., & O'Dea, M. (2023). Artificial intelligence in higher education: Unrealized potential and persistent barriers. Higher Education Studies, 13(4), 25–36.*
14. *Ofosu-Ampong, K. (2024). University lecturers' acceptance of AI tools for student use in Ghana: Opportunities and concerns. International Journal of Educational Technology in Higher Education, 21(3), 1–18.*
15. *Perez, R. (2024). Faculty perspectives on AI adoption in higher education: A UTAUT framework analysis. Educational Technology & Society, 27(1), 45–59.*

16. *Poenaru, A., Matei, M., & Ionescu, L. (2024). AI technology acceptance in higher education: A systematic review from the service sector perspective. Education Sciences, 14(2), 76.*
17. *Rahiman, H., & Kodikal, R. (2024). Faculty awareness, applicability, and adoption of AI in higher education: Implications for learning and engagement. Journal of Applied Research in Higher Education, 16(4), 789–804.*
18. *Rogers, E. M. (2003). Diffusion of innovations (5th ed.). Free Press.*
19. *Roy, S., Sharma, R., & Das, K. (2025). Adoption of AI-based robots in Indian universities: Integrating TAM, TPB, and TRI. Asian Journal of Education and Development, 17(1), 52–70.*
20. *Slovic, P. (2020). Perception of bisk. In Emerging Technologies (pp. 141-146). Routledge.*
21. *Srivastava, A., Mehta, P., & Singh, R. (2025). Factors influencing learners' AI adoption in e-learning: Integrating UTAUT and IS models. Journal of Computer Assisted Learning. Advance online publication.*
22. *Sunil Kumar, P., Menon, A., & George, R. (2025). The transformative impact of AI on higher education: Opportunities, skills, and ethical concerns. Education and Information Technologies, 30(4), 2890–2912.*
23. *Xu, F., Chen, Y., & Zhang, H. (2025). University educators' behavioural intention and actual use of AI tools in teaching: Insights from UTAUT. Interactive Technology and Smart Education, 22(1), 67–85*