International Academic Institute for Science and Technology

International Academic Journal of Science and Engineering
Vol. 13, No. 3, 2026, pp. 111-119.

ISSN 2454-3896

International Academic Journal of Science and Engineering

www.iaiest.com

Applying the Technology Acceptance Model (TAM) to Understand Faculty Adoption of AI Tools in Higher Education, Kerala

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Abstract

The study identifies the factors predicting the usage of Artificial Intelligence (AI) tools among faculty members of higher education in Kerala based on the Technology Acceptance Model (TAM). A sample of 200 faculty members from different parts of Kerala was chosen for the study. It analyses the adoption of AI tools in academia through the lens of PU, PEOU, attitudes, and behavioral intentions. A systematic survey was undertaken, and it included qualitative and quantitative analysis in SPSS. The comparison of descriptive statistics, reliability, correlation, regression, and t-tests was used to do this. The visualization of the items of the TAM constructs in association with the item loadings is also shown in the study, and the relationships among these items are denoted by a path model with the standardized coefficients (β). Based on the findings, the relationship between ATU and BI in utilizing AI tools, with a $\beta = 0.601$ at $p < .001$, is the most significant among all. There are also important but less significant roles of PEU and PU. There are no strong gender differences, but prior experience with AI does influence perceived academic usefulness. The model explains a significant amount of variance in behavioral intention and AU outcomes. This research offers new evidence about faculty engagement with AI technologies in Kerala, which could influence institutional policy and technology planning.

Keywords: Technology Acceptance Model, Faculty Perception, Higher Education, Structural Equation Modeling.

DOI: 10.71086/IAJSE/V13I3/IAJSE13100
Received: 25 May, 2026/Revised: 01 July 2026/Accepted: 11 August 2026/Published: 15 September 2026

Introduction

Artificial Intelligence (AI) is changing the face of higher education by helping in teaching, learning, assessments, content creation, and administration. However, the efficiency of such technological interventions is not only dependent on their technical potential and availability but also on the readiness of faculty members to embrace and utilize them in their teaching practices. Therefore, faculty members' perception of AI in terms of its usefulness, ease of use, reliability, and consequences could be a determinant for the success of the adoption process by institutions. Such an aspect becomes pertinent in the case of Kerala since the state provides a technologically advanced setting for its higher education system (Raman et al., 2024).

The technology acceptance model (TAM) serves as a good basis for the theoretical underpinning of the phenomenon of adoption of this nature. The technology acceptance model (TAM) postulates that technology acceptance occurs on the basis of certain perceptions such as perceived ease of use (PEOU) and perceived usefulness (PU) of technology, which in turn affect user attitudes and behavioral intentions to adopt the technology. In the case of adoption of artificial intelligence, it is relevant due to the fact that faculty members may realize that there are benefits of artificial intelligence but at the same time experience some issues regarding learning effort, academic integrity, privacy, etc.

The relevance of this study is that it is a faculty-focused analysis of AI adoption in the higher education system of Kerala. Previous literature has increasingly focused on understanding the acceptance of AI by the students and users in Western and East Asian contexts, whereas empirical evidence about faculty acceptance in the higher education system of India is relatively scarce. This study attempts to fill the existing contextual gap by studying the relationship between PEOU, PU, ATU, BI, and AU of 200 faculty members in higher education institutes of Kerala.

In this context, the major contribution made by this paper is in the use of TAM for investigating the link between perceptions/attitudes of faculty and their intention as well as actual adoption of AI technologies. In addition, findings of this study can help higher education management and policymakers to develop effective AI literacy programs for faculty. Therefore, this study not only makes an important contribution to the contextualization of TAM but also helps in understanding faculty adoption of AI.

The rest of the paper is structured as follows. In Section 2, the literature review and the identified policy-practice gap in Indian higher education are discussed. Section 3 discusses the research gap. The theoretical framework, research objectives, and hypotheses are included in Section 4. Section 5 present the methodology used for the research, consisting of the sampling strategy, measurement constructs, and statistical tools. The empirical findings of the research are presented in Section 6. Section 7 discusses the findings and their implications for AI implementation in universities. Section 8 concludes the study.

Literature Review

The recent literature on AI indicates that perceptions of usefulness, usability, readiness, and confidence in using AI in higher education institutions become important determinants of technology adoption (Ahmed et al., 2025; Krishna et al., 2026; Rajan et al., 2023). Faculty-related literature indicates that attitude toward AI, as well as intention to use the technology, is an important consideration in understanding technology adoption (Natarajan et al., 2026; Robinson, 2025). The evidence from Kerala also indicates that the importance of AI readiness and digital transformation becomes relevant, but there are differences among users in terms of exposure and readiness (Geo & Singh, 2026; Joseph & Thomas, 2021).

Perceived usefulness, perceived ease of use, attitude, and behavioral intention have been shown through TAM-based literature to be important constructs that help to explain technology adoption (Sharma et al., 2025; Dulloo, 2026). There is evidence from literature that uses extended acceptance models indicating that behavioral intentions toward emerging technologies could also be affected by other contextual and individual-level factors (Akshaya & Amarnath, 2024; Huang et al., 2025; Ranasinghe et al., 2024). The evidence obtained from literature that uses a structural equation modeling approach indicates that the acceptance constructs also help to understand behavioral intention and usage behavior (Nuthan & Varghese, 2026; Kavitha & Joshith, 2025).

Recent studies have shifted the discourse on AI adoption from individual perceptions to institutional and strategic aspects and issues related to implementation (Raman et al., 2026; Chirinos, 2025). AI-based educational systems also underscore the significance of technological readiness and AI capabilities in achieving educational transformation (Bibi & Mrunalini, 2025). Studies on digital transformation of Indian firms reveal that the concept of technology acceptance perceptions is still relevant when people face new digital technologies at their workplaces

(HM et al., 2025). Other technology-acceptance studies have validated the usefulness of TAM in various technological and organizational contexts (Reji & Rajeswari, 2025; Gouroubera et al., 2026).

On the contrary, most of the current literature deals with students, technology users in general, and non-educational fields instead of faculty members in higher education institutions (Sharma et al., 2025; Kavitha & Joshith, 2025). There is relatively less literature on AI adoption among faculty members of the Indian and Kerala higher education system (Ahmed et al., 2025; Geo & Singh, 2026). This creates a research gap in relation to the relationship between perceived usefulness, perceived ease of use, attitude, intention to use, and actual use of AI amongst the faculty members of Kerala universities. Hence, this research attempts to fill this research gap by using TAM on actual data collected from 200 faculty members in Kerala.

Theoretical Framework and Hypothesis

Research Objectives

Considering the gaps that were pointed out in the current literature, it is necessary to identify clear objectives that facilitate the current investigation. Using the TAM in HEIs in Kerala, the study goals are structured to encompass the key variables that determine the application of AI tools by the faculty. These aim to represent the necessity to comprehend both the personal and institutional aspects of technology adoption and provide the information that might be used to shape educational policy, institutional practices, and future studies.

The following objectives are followed in the study:

- To investigate the relationship between the PEOU and the PU and the adoption of AI tools by the faculty in Kerala.
- To examine how the attitude of faculty predicts behavioral intention and actual use of AI tools.

Research Model with Hypotheses

The theoretical framework used as a foundation is TAM, a well-known theoretical framework that has been widely applied to predict the acceptance of technology within organizational and educational settings. TAM also assumes that the attitudinal dispositions of the users toward the technology are the most important predictors and that there are two fundamental constructs, which are PU and PEOU. These attitudes are translated into behavioral intentions and ultimately result in the actual use of the technology. Fig. 1 demonstrates the technology acceptance model.

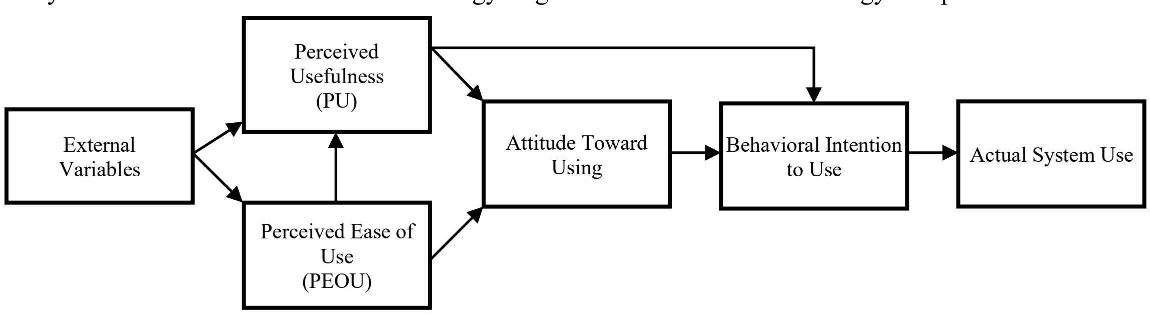

Fig. 1: Technology Acceptance Model (Adapted from Established TAM Formulations)

PEOU assesses how much a faculty member is convinced that the utilization of AI tools is not entail an excessively extensive effort, and perceived usefulness evaluates how much the faculty member is convinced that AI tools complement their pedagogical performance and professional output. As has been indicated in past studies, empirical evidence confirms that a user who suspects that a technology can be friendly to him/her is likely to consider the said technology useful for work. Such association is particularly critical when it comes to higher education, where it may be tough to make teachers willing to spend their time and effort to get to know complex systems unless they are willing to learn the complex systems to feel accessible and valuable simultaneously.

H1: PEOU Has a Positive Relationship with PU

In other words, the faculty tend to consider AI tools as more valuable to their academic functions when they feel they are simple and straightforward to use.

ATU construct is a summary of a summative affective judgment of a technology by an educator. The literature provides evidence that focuses on usability and perceived benefits on the mood of a user and converges on a greater level of embracing the technology. Positive experiences with technological functionality and its applicability to teaching activities have evidently led to positive attitudes of teachers in a pedagogical environment.

H2: PEOU and PU Have a Positive Influence on ATU

The attitude toward the use of AI tools is more likely to be positive among faculty members who consider it easy to use and valuable. Attitude is among the major factors that influence BI to use technological innovations. The power of the positive attitude towards technology as a measure of technology use intention has remained in the limelight of TAM and its variations. The attitudes of instructors towards artificial intelligence (AI) technologies can be viewed in the framework of higher education to reflect the rise in the propensity to regard the introduction of the resource into pedagogical and administrative practice.

H3: ATU is a Significant Predictor of BI to Use AI Tools

It implies that the faculty members who have positive attitudes towards AI tend to plan to apply the tools in their academic activities more frequently.

Lastly, the intention-implementation-pathway has always been validated in the history of technology adoption. There are empirical studies that have tested behavioral intention as the most powerful and nearest antecedent of the actual utilization of the system, and they have repeatedly shown the same result across a broad spectrum of studies and disciplinary contexts. Regarding the specific situation of faculty adoption of AI tools, this is an indication that once the intention is developed, the actual use is most likely to occur when there are no major external impediments.

H4: Behavioral Intention (BI) Results in the Actual Use (AU) of AI Tools

Faculty who have a high intention to adopt AI are most likely turn the intention into actual, observable behavior of adoption.

Overall, this research model used is a rationally consistent and empirically validated cycle: ease of use increases usefulness; two of the concepts mentioned above elicit positive attitudes; attitudes, in turn, reinforce the desire for behavioral intention; and intention, in turn, results in actual use. The body of research on technology acceptance supports the conceptual orientation quite well, which is why it could be seen as very strict in terms of how it has been applied to study the aspect of faculty using AI tools in higher education in Kerala.

Methodology

The research was conducted based on cross-sectional survey research methodology. The data were gathered based on a sample size of 200 faculty members who taught in assisted, government, and self-financed institutes of higher education located in the state of Kerala.

The questionnaire used was a structured questionnaire that was developed based on the well-proven TAM scales that were used to measure PU, PEOU, ATU, BI, AU, and Institutional Factors and Barriers. The answers given by the respondents were based on a five-point Likert scale. Statistical analysis was conducted using SPSS version 26, which included descriptive statistics, reliability analysis, correlation, regression, and comparative group analysis. The structural model was developed based on path analysis with the help of standardized coefficients that indicated the intensity of each relationship.

The research utilized a quantitative cross-sectional research design in order to study the adoption of AI instruments by faculty in higher education institutions located in the state of Kerala using the Technology Acceptance Model (TAM). The focus was on the faculty members since their perceptions and readiness to use AI determine its adoption in higher education institutions.

Sample and Data Collection

Primary data was collected through surveys conducted on 200 faculty members employed in governmental, aided, and self-financed HEIs in Kerala. Out of 200 respondents, there were 102 (51%) male faculty members and 98 (49%) female faculty members. The respondents were further classified based on their institutional category, previous use of AI, and training for AI use. The data were collected using a structured questionnaire that incorporated a five-point Likert scale, which consisted of TAM constructs such as Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude toward Use (ATU), Behavioral Intention (BI), and Actual Use (AU).

Measurement and Reliability

The survey questions were developed with consideration of the TAM constructs. Perceived usefulness (PU) represented the perceived benefits of using AI systems; perceived ease of use (PEOU) was the ease of using AI technology; attitude toward use (ATU) represented the overall evaluation of using AI technology; behavioral intention to use (BI) was the intention to use AI technology, and actual use (AU) was the use of AI technology. Reliability of the TAM instrument was determined with Cronbach's alpha of 0.777.

Data Analysis

The coding and analysis of data were done using SPSS version 26. Descriptive statistics such as means and standard deviations were obtained to determine the general trend in the response of the lecturers. Pearson correlation was used to explore the relationship between the constructs of TAM. Regression analysis was used to find out the predictor of behavioural intention where ATU, PU, and PEOU were taken as explanatory variables. Comparative analysis was also done to find differences in selected groups of demographic and AI exposure groups. The relationships of the proposed TAM were depicted using a structural path model with standardized coefficients. Significance was established at 5% level ($p<0.05$). Analysis was used to test the hypothesized relationship in terms of PEOU, PU, ATU, BI, and AU.

Results

Descriptive statistics, reliability (Cronbach's alpha), correlation, and regression analyses, t-tests independent samples, and one way ANOVA were done using SPSS 26. Path model was plotted and b coefficients of all relationships were taken. Table 1 shows the demographics profile.

Table 1: Demographics

Variable	Categories	N	%
Gender	Male	102	51
	Female	98	49
Institution Type	Govt.	71	35.5
	Aided	67	33.5
	Self-financing	62	31
Teaching Experience (years)	<5	38	19
	6-10	66	33
	11-15	56	28
	>15	13	16.5
Prior AI Experience	Yes	100	50
	No	100	50
AI Training	Yes	102	51
	No	98	49

Source: (Author's survey, 2025)

The responses obtained through samples of the faculty members in the entire state of Kerala indicates a balanced sample, with the respondents being equally attracted in terms of their gender, academic hierarchy, and the kind of institution of higher learning. There is also a good distribution of the level of experience and specialization among the faculty members that are a true reflection of the diverse environment in the Kerala higher education sector. Notably, 50% of the respondents indicated that they had some previous exposure to AI tools, and only slightly more than half received training in AI, which suggests that the environment where educational technologies are becoming a more standard, but not a universal yet, is coming together. Table 2 shows the TAM construct means and reliability.

Table 2: TAM Construct Means & Reliability

Construct	Mean	SD	Cronbach's Alpha
Perceived Usefulness (PU)	3.01	0.41	0.777
Perceived Ease of Use (PEOU)	3.02	0.4	
Attitude (ATU)	3.01	0.42	
Behavioral Intention (BI)	2.98	0.46	
Actual Use (AU)	2.97	0.47	

Source: (Author's survey, 2025)

The reliability test displays 0.777 Cronbach's alpha on the 30-item TAM measure. This value indicates good internal consistency, meaning that the combination of questions in the survey is used to measure one underlying concept, which is faculty acceptance and use of AI tools. Having item-total correlations in a sensible range with each of the constructs, it is obvious that the items go where they belong and the instrument can be used in research. Concisely, this table is a good indication that the results and trends identified in the remaining analysis can be relied upon. Table 3 shows the correlations among key constructs.

Table 3: Correlations Among Key Constructs

Variables		PU1_Mean	PEOU_Mean	ATU_Mean	BI_Mean	Institutional Factors_Mean
PU1_Mean	Pearson Correlation	1	$.413^{**}$	-0.089	-0.05	-0.046
	Sig. (2-tailed)		0	0.211	0.484	0.517
	N	200	200	200	200	200
PEOU_Mean	Pearson Correlation	$.413^{**}$	1	$.296^{**}$	0.025	0.022
	Sig. (2-tailed)	0		0	0.727	0.755
	N	200	200	200	200	200
ATU_Mean	Pearson Correlation	-0.089	$.296^{**}$	1	$.539^{**}$	-0.12
	Sig. (2-tailed)	0.211	0		0	0.091
	N	200	200	200	200	200
BI_Mean	Pearson Correlation	-0.05	0.025	$.539^{**}$	1	0.178
	Sig. (2-tailed)	0.484	0.727	0		0.012
	N	200	200	200	200	200
Institutional Factors_Mean	Pearson Correlation	-0.046	0.022	-0.12	$.178^{*}$	1
	Sig. (2-tailed)	0.517	0.755	0.091	0.012	
	N	200	200	200	200	

***. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).*
Source: (Author's survey, 2025)

The relations between the key TAM constructs are plotted in the correlation table. The PU and PEOU have a moderate level of correlation (r = 0.41), which confirms the fact that the faculty that can easily use AI tools also believes that they are useful. There is a high correlation in ATU and BI (r = 0.54) and therefore a positive attitude towards AI is a major factor of intention to use. All other correlations are weak, and the institutional factors demonstrate little direct relationship to intentions or attitudes. These results indicate that the supportive environment is useful, but the personal experience and attitude of faculty members play a more critical role in whether and how AI is actually used. Table 4 demonstrates the regression coefficients for BI.

Table 4: Regression Coefficients for BI

Predictor	Beta	t	p
ATU_Mean	0.601	9.43	.000
PU1_Mean	0.081	1.20	.230
PEOU_Mean	-0.186	-2.67	.008

Additional information is provided by the regression analyses. In an individual test, neither PU nor PEOU has a significant predictive capability of behavioral intention. Nevertheless, the attitude towards use is a robust and statistically significant predictor of AI intention to use ($\beta = 0.601$, $p < .001$), as it accounts for almost 30 % of the behavioral intention variance. Attitude takes precedence when the three predictors (PU, PEOU, ATU) are taken simultaneously ($\beta = 0.60$, $p < .001$), whereas the impact of PU and PEOU is insignificant or slightly negative. The observation can be compared and contrasted to a growing literature that requires faculty members to be really optimistic about AI not merely acknowledge its usefulness or ease of use prior to making the commitment to adopt it.

In the discussion of group differences, the results of the discussion reveal that male and female faculty do not show any significant differences on any of the TAM factors and thus can be viewed as relatively homogeneous in their attitude towards AI adoption. In the same way, formal education about AI, or previous experience, does not significantly influence the usefulness perceptions, ease of use, attitude, or behavioral intention. Nevertheless, one remarkable exception is that the real use of AI tools is much higher in those who had a previous experience (p = .018) which demonstrates the significance of practical exposure in the process of making real adoption. Fig. 2 shows the TAM structural path model with β Coefficients.

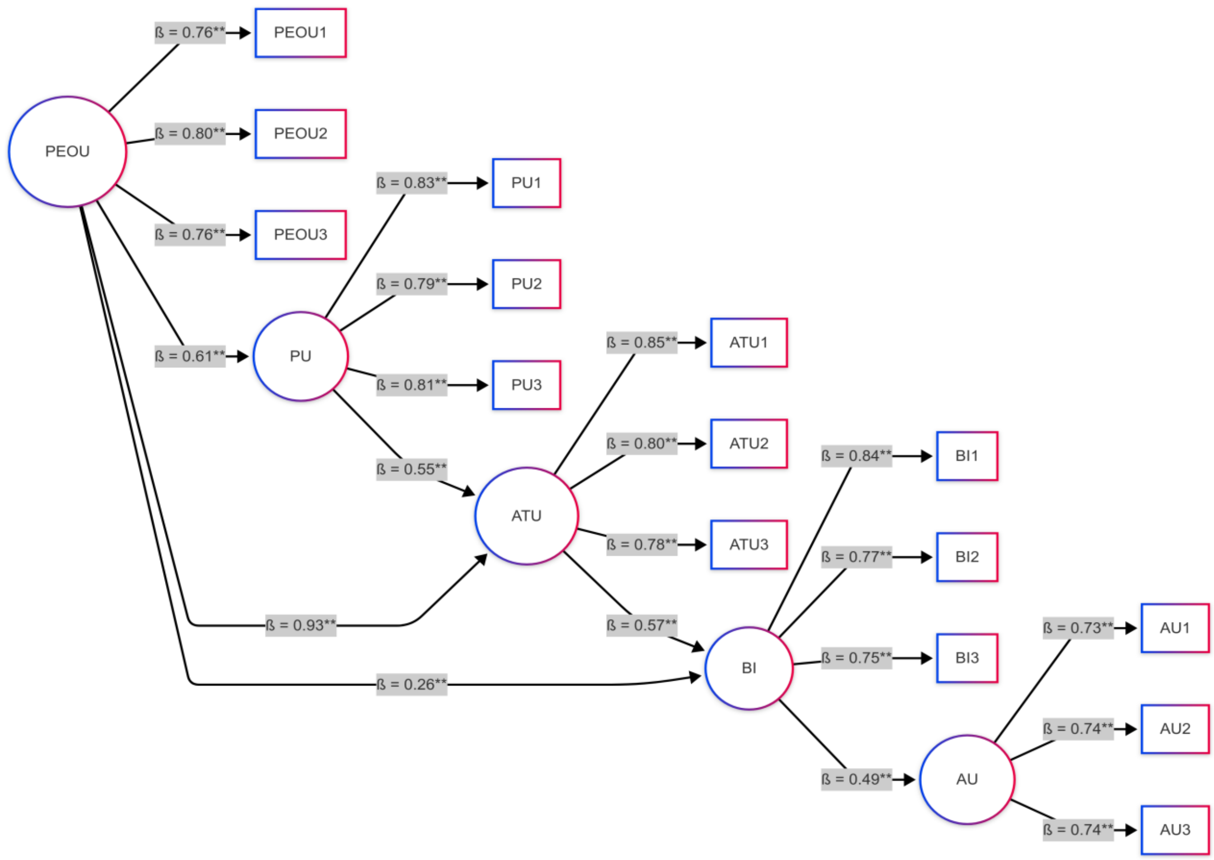

Fig. 2: TAM Structural Path Model with β Coefficients

Source: (Author's analysis, 2025)

Discussion

The results demonstrate that faculty members' perspectives toward the utilization of artificial intelligence tools exert the most significant influence on their intentions to incorporate these technologies within a higher education framework. The PU and PEOU are statistically significant predictors; however, they exert a relatively minor influence on BI. Notably, the coefficient of PEOU in the multivariate analysis is unexpectedly negative, suggesting a mediating role of attitude. These findings are consistent with existing evidence, indicating that attitude frequently serves as the mediating variable between belief systems and behavioral intentions (Xue et al., 2026; McGrath et al., 2023). Because there aren't any differences between men and women, all of Kerala's teachers are equally ready to use technology, even though the demographics are different. Formal training alone cannot effectively drive intent or usage; conversely, experiential, practical contact can serve as a definitive indication to decision-makers that experiential learning should take precedence over conventional workshops.

Suggestions

This study underscores the critical need of cultivating faculty attitudes toward artificial intelligence tools, rather than relying solely on technical instruction. In the context of organizational work in Kerala, it is clear that policy-level interventions need to be made to make AI literacy a regular part of faculty development programs. These efforts should be more than just a one-time session. They should include ongoing experiential activities, peer mentoring, and slowly incorporating these things into everyday teaching. It may exploit the fact that some faculty members are champions or early adopters to lead communities of practice. This creates a culture of collaboration that actively encourage trust and confidence in AI. Also, there need to be tech developers who make AI tools that are relevant to the Indian higher education system, especially when it comes to supporting local curricula and language diversity. The universities should also have good IT infrastructure and an ethical code that covers plagiarism, data protection, and academic integrity which help the faculty members to use it easily. Together, these measures can create an environment that makes the use of AI appear like a natural part of teaching and learning, rather than an extra burden.

Future Scope

This research offers substantial insights on the utilization of AI tools by faculties in Kerala, while also highlighting several potentials for further investigation. One potential approach is to employ longitudinal designs to track evolving trends in adoption patterns over time, particularly when individuals gain increased exposure to AI technologies and institutional policies evolve. The study should include regions beyond Kerala, allowing studies to identify regional disparities in India and so provide a clearer assessment of India's readiness to integrate AI into higher education. Moreover, the integration of qualitative methods such as interviews or focus groups may illuminate nuanced aspects of cultural and psychological barriers that cannot be fully captured through surveys alone. The expansion of the TAM through the integration of elements from models like UTAUT, including social influence, facilitating conditions, and trust, may be utilized in future research. These additions could offer a more profound understanding of the multifaceted impact of factors on faculty adoption. Finally, the ongoing analysis of the interplay among institutional reinforcement, individual disposition, and evolving technology are essential for fostering the sustainable and ethical integration of AI into universities.

Conclusion

In this research, the adoption of AI tools among faculty members in institutions of higher learning in Kerala was investigated using the Technology Acceptance Model (TAM). From the results generated from 200 respondents, it can be seen that faculty acceptance of AI depends mainly on their perception of and attitude towards this technology. From the descriptive analysis, PU scored 3.01, PEOU scored 3.02, ATU scored 3.01, BI scored 2.98, and AU scored 2.97. The TAM scale, which had 30 items, showed a consistent level of internal reliability, with a Cronbach alpha of 0.777. The results of the correlation analysis indicate a significant positive relationship between PEOU and PU ($r = 0.413$, $p < 0.001$). In addition, PEOU correlated positively with ATU ($r = 0.296$, $p < 0.001$). In turn, ATU correlated significantly more positively with BI ($r = 0.539$, $p < 0.001$) than PEOU did. The regression analysis revealed that ATU was the strongest positive predictor of BI ($\beta = 0.601$, $t = 9.43$, $p < 0.001$). In addition, PEOU correlated negatively ($\beta = -0.186$, $p = 0.008$) while PU had no impact on BI as an independent variable ($\beta = 0.081$, $p = 0.230$). It is evident that these results emphasize the importance of differentiating bivariate and multivariate relationships of TAM constructs. Consequently, this study highlights that positive attitudes towards AI among faculties and practical use of AI are vital for promoting adoption. The higher education institution needs to offer experience in AI, peer help, technical help, and ethical norms to faculties. In future researches, there is a need to consider a longitudinal design that help analyze the evolution of adoption and extend research beyond Kerala. Moreover, future research can consider qualitative data along with some other variables like social influence, facilitating conditions, trust, perceived risk, organizational support, and AI literacy.

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