Determinants of AI adoption among College Students in Kerala – An Integrated Model with PLS SEM NCA approach

Dr. Vineesh A K
Associate Professor, Department of Commerce C K G M Govt college Perambra Kozhikode -Kerala

Abstract—**The present study employed the Unified Theory of Acceptance and Use of Technology (UTAUT) constructs to investigate the dimensions of artificial intelligence (AI) adoption intention among arts and science college students in Kerala. The determinants influencing users' intention to adopt AI were identified as performance expectancy, effort expectancy, facilitating conditions, and perceived trust. The mediation effect of attitude was also investigated. A sample of 489 responses was analyzed using partial least squares structural equation modeling (PLS-SEM) in conjunction with the Necessary Condition Analysis (NCA) approach. The findings revealed that performance expectancy, effort expectancy, facilitating conditions, and perceived trust positively influenced students' attitudes towards AI adoption. However, facilitating conditions and perceived trust did not positively affect students' intentions to adopt AI technology. Furthermore, the indirect effect of attitude demonstrated a significant impact of various dimensions of AI adoption on intention. The NCA results indicated that performance expectancy, effort expectancy, and attitude were necessary conditions for the intention to adopt AI technology in higher education. This research provides actionable insights for both technology designers and higher education institutions to facilitate AI-enabled transformation in learning.**

Index Terms—**AI adoption, Higher education, Attitude, AI adoption intention**

1. INTRODUCTION

Technological advancements have revolutionised the frequency of human interactions since the advent of artificial intelligence (AI). AI-driven chatbots have become popular because of their added features, such as interactive capabilities and personalised assistance (Hasan et al., 2024). In recent years, OpenAI, ChatGPT, and Google Bard have sparked vigorous debates within academic communities (Ivanov et al., 2024). Given their importance, scholars and policymakers are increasingly relying on AI applications across various disciplines. Moreover, studies have contended that AI-driven teaching and learning offer significant potential in higher education (Hwang & Chang, 2023; Ivanov et al., 2024; Mogavi et al., 2023; Saihi et al., 2024). For instance, Kamalov et al. (2023) argued that AI-driven chatbots provide instant responses, anytime availability, and offer personalised learning support for both students and teachers, thereby fostering active academic engagement. The extant literature has focused on the education domain of AI research, such as teaching methods (Gill et al., 2024), assessment and feedback processes (Smolansky et al., 2023), and user experience in educational chatbots (Lim et al., 2021).

Despite its potential, scholars have posited that security, reliability, and ethics remain major concerns regarding the adoption and acceptance of AI in higher education (Hoi 2023; Hwang and Chang 2023). However, AI is relatively new, and few studies have explored various dimensions of AI adoption for learning purposes in the context of higher education. (Lund et al., 2023). This has established AI-supported higher education as a dynamic area of research by exploring various dimensions of adoption and its subsequent impact on students' intention to adopt AI technology (Saih et al., 2024). The current research employs the UTAUT model (Venkatesh et al., 2012) to predict various drivers of AI adoption among higher-education students in Kerala. The extensive use of the UTAUT model in technology adoption has been widely established (Chatterjee & Bhattacharjee, 2020; Osei et al., 2022; Yang et al., 2022). This study seeks to investigate the various dimensions of attitudes towards AI adoption and the behavioural intentions of arts and science college students in Kerala. Moreover, this study proposes a hybrid methodology by combining PLS-SEM and Necessary Condition Analysis (NCA) in the domain of technology in higher education. This study addresses the following research questions:

RQ1: What are the dimensions of AI adoption intention among higher education students in Kerala?

RQ2: Does attitude mediate the relationship between dimensions of AI adoption and higher education students' intention to adopt AI technology?

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1. AI Adoption in Higher education

Teaching, learning, and pedagogical approaches have been reshaped since the advent of artificial intelligence in the educational domain (Wang & Zhang, 2023). In this context, AI tools have emerged as potential solutions for students and teachers seeking to enhance their educational competence (Chatterjee & Bhattacharjee, 2020). Students can benefit from AI tools such as ChatGPT, Google Bard, and Gemini to complete their homework, assignments, and projects to learn more effectively (Khalil & Er, 2023). Additionally, researchers have extensively explored AI in various academic disciplines, such as economics and finance (Lee & Chen, 2022; Ruiz-Real et al., 2021) and medical education (Beldad & Hegner, 2018). For instance, Ivanov et al. (2024) examined AI adoption among teachers and students in higher education institutions across various countries through the lens of the theory of planned behaviour (TPB). They investigated the relationship between TPB variables and the intention to use generative AI tools in higher education. Furthermore, Saihi et al. (2024) explored the perceptions of students and teachers regarding chatbot adoption using a comprehensive research model. Studies have also indicated that AI technology can improve students writing capabilities, real-time interactive learning, creativity, and self-efficacy, thus enhancing students' engagement and satisfaction (Shen et al., 2022; Wang et al., 2023). However, studies (Dwivedi et al., 2023; Khademi, 2023; Wang et al., 2023) have provided evidence regarding the drawbacks of AI in higher education, such as issues of academic integrity, ethical concerns, cultural considerations, language proficiency, accuracy, and reliability.

2.2. Theoretical framework

The UTAUT model is the most frequently applied theoretical framework for predicting technology adoption. According to Venkatesh et al. (2003), user intention and behaviour in technology adoption are determined by factors such as performance expectancy, effort expectancy, social influence, and facilitating conditions. The UTAUT has been employed to explain user acceptance of technology in various contexts, including meta-education, e-learning (Osei et al., 2022), AI adoption, and blended learning (Andrews et al., 2021; Wu et al., 2022). In this context, the UTAUT Model is an important tool for understanding the AI technology adoption process of students in higher education institutions. It is also presumed that students are not expected to be influenced heavily by societal forces; hence, social influence was omitted. Furthermore, attitude has been extensively used for user intention in technology acceptance. This study also incorporated an additional variable, perceived trust, based on the works of Biswas et al. (2021) and Aslam et al. (2023).

2.3. Performance expectancy, Attitude and Intention towards AI adoption

Performance expectancy refers to the level at which one perceives that using a system will help to attain objectives (Camilleri, 2024; Venkatesh et al., 2003). According to An et al. (2023), using AI technology can improve students' learning outcomes through enhanced teaching methodologies. This means that AI tools enable students to improve their learning processes. Previous studies (Camilleri, 2024; Wu et al., 2022) have empirically shown that performance expectancy significantly influences users intention to adopt AI technology. AI tools such as Chat GPT, Google Bard, and Quillbot can provide auto-generated learning resources to students. Therefore, students would be confident that using AI tools would improve their academic performance. Users' favourable or unfavourable appraisals of technology are often reflected in their attitudes. When students perceive that AI's potential enhances their productivity and competence, they tend to develop a positive attitude toward its extensive application. Empirical studies provided evidences on the linkage between performance expectation and attitudes toward technology (Chatterjee & Bhattacharjee, 2020; Emon

et al., 2024; Helmiatin et al., 2024). Based on the above, the following hypotheses were proposed:
H1: Performance expectancy positively influences attitude
H2: Performance expectancy positively influences intention to AI adoption

2.4. Effort expectancy, Attitude and Intention towards AI adoption

Effort expectancy is conceptualised as the degree of ease that one feels while using technology (Rahiman & Kodikal, 2024; Venkatesh et al., 2003). Chatterjee and Bhattacharjee (2020) found that effort expectancy significantly and positively influenced higher education stakeholders' attitudes toward AI technology adoption. Foroughi et al. (2024) argued that students would be more selective about new technology, evaluating whether the benefits outweigh the costs based on the effort required. When people are more confident in using AI technologies, they may perceive them as more comfortable to use, thereby influencing their attitudes and intentions to adopt such technologies (Wang et al., 2021). The literature suggests that users' attitudes toward AI adoption are positively influenced by effort expectancy (Helmiatin et al., 2024; Rahiman & Kodikal, 2024). In view of the above discussion, the following hypotheses were proposed for the study:
H1: Effort expectancy positively influences attitude
H2: Effort expectancy positively influences intention to AI adoption

2.5. Facilitating conditions, Attitude and Intention towards AI adoption

The technical and allied infrastructure that supports new technology adoption is referred to as the facilitating conditions (Venkatesh et al., 2003). Facilitating conditions in the educational context encompass resources, technical assistance and instructions, and students' compatibility with the new system and its usage (Foroughi et al., 2024). In the e-learning context, facilitating conditions were statistically significant in interpreting students' attitudes and intentions regarding new technology adoption (Chatterjee & Bhattacharjee, 2020). Studies (Emon et al., 2024; Kwak et al., 2022) further indicate that the degree of comfort in facilitating conditions improves users' attitudes, which in turn influences their intention to adopt and use the technology. Considering the discussion above, the following hypotheses were proposed:
H1: Facilitating conditions positively influences attitude
H2: Facilitating conditions positively influences intention to AI adoption

2.6. Perceived trust, attitude and intention towards AI adoption

Trust influences perceptions of the credibility, reliability, and security of AI technology (Bilquise et al., 2024). Trust often comes when users are concerned about security and privacy issues in technology adoption (Biswas et al., 2021). Aslam et al. (2023) explored how trust determines the level of confidence that students have in the capabilities of AI technology. Perceived trust in AI has a positive effect on attitudes, underlining the relevance of credibility in shaping favourable attitudes toward technology adoption (Choung et al., 2023). Moreover, studies have indicated that trust is a significant factor in predicting users' behavioural intention to use technology (Hamidi & Chavoshi, 2018; Pesonen, 2021). Therefore, the following hypotheses were proposed for the study:
H1: Perceived trust positively influences attitude
H2: Perceived trust positively influences intention to AI adoption

2.7. Attitude and intention to adopt AI technology

Individuals' behavioural intention to adopt new technology is often influenced by their cognitive evaluations or attitudes (Chatterjee & Bhattacharjee, 2020). In the context of higher education, students' intention to adopt AI technology was predicted based on their attitudes. Hence, a strong association was found between students' attitudes toward technology adoption and their intention (Helmiatin et al. (2024). Empirical studies have shown that students' attitudes are essential for predicting their intention to adopt technology (Chatterjee & Bhattacharjee, 2020; Helmiatin et al., 2024; Wang et al., 2021). Through this discourse, the following hypothesis was proposed:
H2: Attitude positively influences intention to AI adoption

3. MEDIATING ROLE OF ATTITUDE

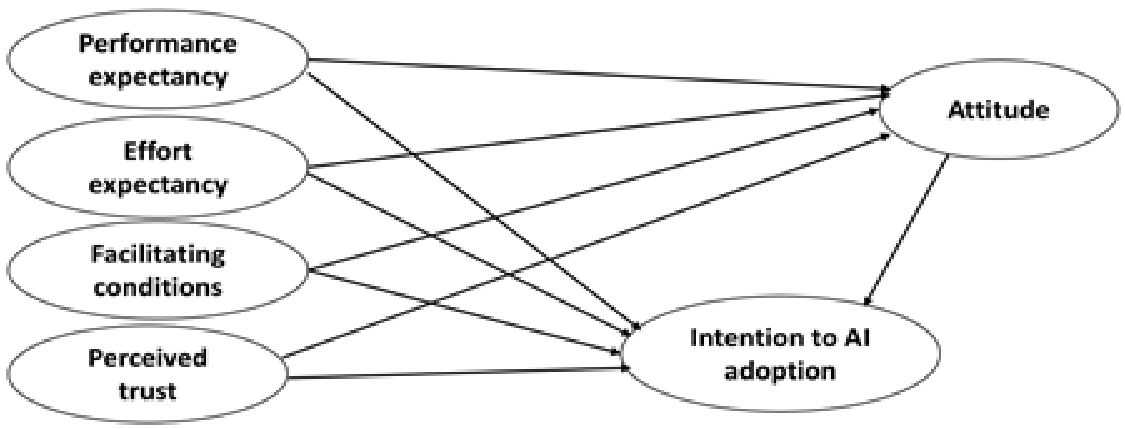
According to Fang and Alam (2025), perceptions related to usefulness and ease of use can influence technology adoption through an attitude framework. Emon et al. (2024) observed a significant mediating effect of attitude on the relationship between perceived ease of use and AI technology adoption behaviors among professionals. This suggests that users' personal evaluations may not lead to adoption behaviour in the absence of a mediating attitude. Ho et al. (2020) highlighted the indirect effect of attitude on the relationship between facilitating conditions and the intention to adopt new technologies. Choung et al. (2023) found that attitude significantly mediated the relationship between trust and the intention to adopt AI voice assistants among college students. Collectively, these studies underscore the mediating role of attitude in the relationship between the drivers of AI adoption and behavioural intentions. Based on the above, the following hypotheses were proposed:

H6: Attitude significantly mediates the relationship between performance expectancy and intention to AI adoption

H6: Attitude significantly mediates the relationship between effort expectancy and intention to AI adoption

H6: Attitude significantly mediates the relationship between facilitating conditions and intention to AI adoption

H6: Attitude significantly mediates the relationship between perceived trust and intention to AI adoption



Conceptual model proposed for the study

4.. MATERIALS AND METHODS

This study employed a quantitative approach using a survey method to investigate the dimensions of students' intention to adopt AI in the higher education context. Data were collected from students at arts and sciences colleges in Kerala through both offline and online questionnaires. The participants comprised students pursuing final-semester undergraduate and postgraduate courses in the arts, science, and commerce streams, as they had experienced AI-driven learning environments in higher education institutions. The study used a purposive sampling strategy (Etikan et al., 2016) to collect responses while ensuring representation across different academic streams. This also enabled an improvement in the response rate and the elimination of non-response bias. Higher education institutions were randomly selected to serve as the basis for the respondent selection. Furthermore, with the prior permission of the institutional heads and the support of the tutors, a questionnaire was distributed via students' personal email addresses and WhatsApp groups.

Filter questions were included as inclusion criteria. A pilot study was conducted following the procedures outlined by Teare et al. (2014) to test the survey instrument's internal consistency, reliability, and construct validity. Initially, 535 responses were obtained, of which 489 were retained for analysis after data cleaning. A five-point Likert-type scale, ranging from strongly disagree to strongly agree, was utilized in the questionnaire. Partial least squares structural equation modeling (PLS-SEM) was employed to validate the research model.

5. RESULTS

Profile of the respondents

The results (Table 1) indicated that 57.7% of the respondents were female and 42.3% were male. Self-financing colleges had the highest number of respondents, based on their strength in Kerala; hence, 42.94% of the respondents belonged to the self-financing college category. The number of undergraduate (UG) students was higher than that of postgraduate (PG) students; therefore, 64.82% of the respondents were from UG courses. A total of 39.3% of the respondents were from the science stream, 33.1% belonged to commerce, and the rest were from the arts. Furthermore, 55.64% of the respondents opined that ChatGPT was their most preferred AI tool for learning. Moreover, 72.2% were frequent users of AI tools for educational purposes.

Table 1: Demographic Profile of respondents(N=489)

	Frequency	Percentage
Gender		
Male	207	42.30
Female	282	57.70
Category		
Government	144	29.44
Aided	135	27.60
Self-financing	210	42.94
Academic Level		
UG	317	64.82
PG	172	35.17
Course stream		
Arts	135	27.60
Science	192	39.30
Commerce	162	33.10
Most preferred AI tools in learning		
Chat GPT	272	55.64
Grammarly	55	11.22
Others	162	33.13
Frequency of using AI		
Always	181	37.00
Occasionally	172	35.20
Sometimes	136	27.80

Source: Author's own compilation

Measurement model evaluation

The measurement model was evaluated using Cronbach's alpha (Nunnally & Bernstein, 1994) outer loadings, Average Variance Extracted (AVE), composite reliability (CR), and discriminant validity (Hair et al., 2017). The results (Table 2) indicate that the Cronbach's alpha and CR values were higher than the threshold of 0.7, as suggested by Hair et al. (2021). The outer loading values of all constructs and their measures exceeded the minimum threshold of 0.78 (Hair et al., 2017; Hair et al., 2021), and the AVE scores were also above 0.50, demonstrating the measurement model's internal consistency and reliability. Discriminant validity was evaluated using the HTMT (heterotrait-monotrait ratio), and the results (Table 3) demonstrated that the values were below the threshold of 0.85, as suggested by Henseler et al. (2015) and Hair et al. (2017). Therefore, the reliability and validity of the model were confirmed.

Table 2: Measurement Model

Components	Items	Loadings	Composite Reliability	AVE	Cronbach's alpha
Performance expectancy	PE1	0.736	0.895	0.631	0.853
	PE2	0.742			
	PE3	0.813			
	PE4	0.831			
	PE5	0.843			
Effort expectancy	EE1	0.801	0.905	0.656	0.869
	EE2	0.793			
	EE3	0.826			
	EE4	0.837			
	EE5	0.795			
Facilitating conditions	FC1	0.892	0.917	0.786	0.865
	FC2	0.891			
	FC3	0.877			
Perceived rust	PTR1	0.859	0.921	0.796	0.872
	PTR2	0.902			
	PTR3	0.916			
Attitude	ATT1	0.766	0.862	0.610	0.787
	ATT2	0.756			
	ATT3	0.779			
	ATT4	0.821			
Intention to AI adoption	INT1	0.824	0.892	0.675	0.839
	INT2	0.783			
	INT3	0.828			
	INT4	0.849			

Source: PLS SEM results

Table: 3. HTMT Ratio

		PE	EE	FC	PTR	ATT	INT
PE		--					
EE		0.779	--				
FC		0.351	0.276	--			
PTR		0.368	0.315	0.512	--		
ATT		0.776	0.794	0.447	0.459	--	
INT		0.760	0.740	0.349	0.353	0.836	--

Source: PLS SEM results

Structural model assessment

The relationship between latent variables was examined through the assessment of the structural model, which followed the estimation of path coefficients, coefficient of determination (R^2), and predictive relevance (Q^2 predict, RMSE, and MAE) (Hair et al., 2019). Initially, collinearity issues were assessed using the inner VIF values, and the results indicated that all values were within the threshold of 3.3.(Kock, 2015; Hair et al., 2020). For hypothesis testing, a bootstrapping procedure with 10000 sub samples was used (Hair et al., 2017). The path coefficient results (Table 4) revealed that performance expectancy ($\beta = 0.241$, $t = 5.425$, $p < 0.001$), effort expectancy (β = 0.175, t = 3.145, $p < 0.001$), and attitude (β = 0.445, t = 7.644, $p < 0.001$) were significant drivers of the intention to adopt AI. However, perceived trust (β = 0.023, t = 0.011, $p > 0.10$) and facilitating conditions (β = 0.018, t = 0.475, $p > 0.10$) did not exhibit statistically significant effects on the intention to adopt AI. Therefore, H1, H2, H3, H5, H6, H7, and H9 were accepted, whereas H4 and H8 were rejected.

Table. 4: Path coefficient estimates

Hypotheses	PATHS	β	T statistics	2.5% CI	97.5%CI	Results
H1	EE -> ATT	0.401	0.044	9.074	1.838	Accepted
H2	EE -> INT	0.175	0.056	3.145	2.193	Accepted
H3	FC -> ATT	0.132	0.036	3.721	1.298	Accepted
H4	FC -> INT	0.018	0.038	0.475	1.337	Rejected
H5	PE -> ATT	0.292	0.050	5.804	1.921	Accepted
H6	PE -> INT	0.241	0.043	5.425	2.110	Accepted
H7	PTR -> ATT	0.117	0.037	3.205	1.316	Accepted
H8	PTR -> INT	0.023	0.039	0.011	1.347	Rejected
H9	ATT -> INT	0.445	0.058	7.644	2.206	Accepted

Source: PLS SEM results

Table. 5: Co-efficient of Determination

Paths	R^2	Adjusted R^2
Attitude	0.547	0.543
Intention to AI adoption	0.594	0.590

The model demonstrated robust R^2 values for both the endogenous constructs. The R^2 values (Table 5) for attitude and intention to adopt AI were 0.547 and 0.594, respectively. Thus, the model exhibited moderate explanatory power, as suggested by Hair et al. (2011). The predictive relevance of the model was estimated using the PLS prediction procedure suggested by Shmueli et al. (2019). The outcomes (Table 6) demonstrated that Q2 Predict Value of both endogenous constructs attitude and intention to AI adoption were found to be positive (Hair et al., 2017). Furthermore, the Mean Absolute Error (MAE) values (as shown in Table 7) of items of both constructs were less than the Root Mean Squared residual error (RMSE) values of the path model. Therefore, the model indicated a high predictive relevance.

Table. 6: PLS predict assessment of Attitude and Online Purchase intention

Constructs	Items	Q^2 Predict	$RMSE_{PLS\text{-}SEM}$	$RMSE_{LM}$
Attitude	ATT1	0.266	0.660	0.651
	ATT2	0.255	0.655	0.664
	ATT3	0.394	0.583	0.591
	ATT4	0.380	0.586	0.589
Intention to AI adoption	INT1	0.315	0.643	0.656
	INT2	0.286	0.658	0.659
	INT3	0.402	0.608	0.617
	INT4	0.318	0.648	0.653

Source: PLS SEM results

Mediation effect

A mediation analysis was conducted to examine the mediating role of attitude in the relationship between the drivers of AI adoption and students' intention to adopt AI. The results (Table 7) indicate that attitude effectively mediates the impact of various dimensions of AI adoption on intention. The indirect effects of PE → ATT → INT (β = 0.130, t = 4.246, p < 0.001), EE → ATT → INT (β = 0.178, t = 6.51, p < 0.001), FC → ATT → INT (β = 0.59, t = 3.447, p < 0.005), and PTR → ATT → INT (β = 0.52, t = 2.981, p < 0.005) were statistically significant. Since both the direct effect and the total indirect effect were significant, it was concluded that complementary partial mediation occurred in the cases of PE → ATT → INT and EE → ATT → INT. However, the direct effects of FC → INT and PTR → INT were not significant; therefore, partial mediation was observed.

Table. 7: Specific Indirect effects

Hypotheses	PATHS	β	T statistics	2.5% CI	97.5% CI	Results
H10	EE -> ATT -> INT	0.178	6.510	0.130	0.239	Accepted
H11	FC -> ATT -> INT	0.059	3.447	0.029	0.097	Accepted
H12	PE -> ATT -> INT	0.130	4.246	0.078	0.201	Accepted
H13	PTR -> ATT -> INT	0.052	2.981	0.021	0.089	Accepted

Source: PLS SEM results

Necessary condition analysis

To further explore the relationship between constructs, this study supplemented PLS-SEM with Necessary Condition Analysis (NCA) based on the procedures of Dul (2016). Initially, unstandardised latent variable scores were computed from the PLS-SEM analysis to be used as inputs for the NCA (Richter et al., 2020). Necessary conditions were established using three criteria: theoretical support for the relationship between predictor and outcome constructs; the effect size (d) should exceed zero to be considered significant; and conditions were tested against null hypotheses using a permutation-based test with a bootstrapping procedure, and statistical significance was assessed based on p-values (Basco et al., 2022; Dul, 2016). The analysis is based on the Ceiling Regression–Free Disposal Hull (CR-FDH) technique, the default method for NCA working with both discrete and continuous data at numerous levels (Basco et al., 2022). To gain more insight, a bottleneck analysis was performed. In this study, NCA was used to highlight combinations of minimum levels of performance expectancy, effort expectancy, facilitating conditions, perceived trust, and attitude necessary to obtain a certain level of intention to adopt AI among arts and science college students in Kerala. The NCA results(Table 8) revealed that performance expectancy (d = 0.209) and effort expectancy (d = 0.102) are necessary conditions for students' attitudes toward AI adoption, both of which are meaningful ($d \geq 0.1$) and statistically significant ($p < 0.05$). In addition, performance expectancy (d = 0.166), effort expectancy (d = 0.095), and attitude (d = 0.184) were necessary conditions for students' intention to adopt AI, which were also meaningful ($d \geq 0.1$) and significant ($p < 0.05$).

Table 8: NCA effect sizes

Dimensions	Attitude		Intention to AI adoption	
	CR-FDH	P-value	CR-FDH	P values
Performance expectancy	0.209	0.000**	0.166	0.000**
Effort expectancy	0.102	0.000**	0.095	0.001**
Facilitating conditions	0.029	0.119	0.029	0.122
Perceived trust	0.025	0.142	0.025	0.192
Attitude	---	---	0.184	0.000**

Source: PLS SEM results

Table. 9: Bottleneck analysis: Attitude					
	ATT	EE	FC	PE	PTR
0%	1.960	NN	NN	NN	NN
10%	2.264	NN	NN	NN	NN
20%	2.568	NN	NN	NN	NN
30%	2.872	NN	NN	NN	NN
40%	3.176	NN	NN	2.076	NN
50%	3.480	2.050	NN	2.398	NN
60%	3.784	2.236	1.041	2.720	1.083
70%	4.088	2.422	1.214	3.042	1.214
80%	4.392	2.608	1.388	3.363	1.345
90%	4.696	2.794	1.561	3.685	1.476
100%	5.000	2.980	1.735	4.007	1.607

Source: PLS SEM results

Table.10: Bottleneck analysis: Intention to AI adoption						
	INT	ATT	EE	FC	PE	PTR
0%	1.00	NN	NN	NN	NN	NN
10%	1.40	NN	NN	NN	NN	NN
20%	1.80	2.002	NN	NN	NN	NN
30%	2.20	2.144	NN	NN	NN	NN
40%	2.60	2.286	NN	NN	NN	NN
50%	3.00	2.428	1.989	NN	NN	NN
60%	3.40	2.570	2.167	NN	2.337	NN
70%	3.80	2.713	2.344	1.015	2.734	1.001
80%	4.20	2.855	2.522	1.237	3.130	1.242
90%	4.60	2.997	2.700	1.460	3.527	1.483
100%	5.00	3.139	2.878	1.682	3.924	1.724

Source: PLS SEM results

The necessary conditions for different levels of AI adoption intention were determined using a bottleneck analysis (Table 9 and 10). The results indicated that to achieve a 50 % level of attitude toward AI adoption, two conditions must be satisfied: at least 2.050 effort expectancy and at least 2.398 performance expectancy. Similarly, to achieve a high level of attitude (100 percent), four conditions must be satisfied: at least 2.980 effort expectancy; at least 1.735 facilitating conditions; at least 4.007 performance expectancy; and at least 1.607 perceived trust.

The results also revealed that to achieve a 50 % level of intention to adopt AI, two conditions must be satisfied: at least 1.989 effort expectancy and at least 2.428 attitude. Similarly, to achieve a high level of intention to adopt AI (100 percent), four conditions must be satisfied: at least 2.878 effort expectancy, at least 1.682 facilitating conditions, at least 3.924 performance expectancy, at least 1.724 perceived trust, and at least 3.139 attitude. These findings highlight the importance of ensuring performance expectancy, effort expectancy, facilitating conditions, and perceived trust while leveraging the intention to adopt AI in higher education.

6. DISCUSSION

This study investigated how various dimensions of AI adoption influence the intention to adopt AI among arts and science college students in Kerala using UTAUT constructs. Moreover, this study included perceived trust as an additional variable to predict students AI adoption intentions. A research model was developed considering various dimensions of AI adoption, such as performance expectancy, effort expectancy, facilitating conditions, and perceived trust, with the mediating role of attitude on students' intention to adopt AI. To examine the association between constructs, a sample of 489 responses was analysed using partial least squares structural equation modelling (PLS-SEM) with the Necessary Condition Analysis (NCA) approach. The study also conducted a necessary condition analysis to determine whether the dimensions of AI adoption were necessary for college students' intention to adopt AI.

The results of the Partial Least Squares Structural Equation Modeling (PLS SEM) analysis demonstrated that performance expectancy, effort expectancy, facilitating conditions, and perceived trust exerted a positive influence on students' attitudes towards the adoption of AI. However, facilitating conditions and perceived trust did not positively influence students' intentions to embrace AI technology. Moreover, attitude mediates the relationship between the various dimensions of AI adoption and intention. Additionally, the NCA findings revealed that performance expectancy, effort expectancy, and attitude qualify as the necessary conditions for the intention to adopt AI technology in higher education.

Although facilitating conditions and perceived trust were found to have a statistically significant influence on students' attitudes toward AI adoption, neither exhibited dominant predictors of attitude according to the NCA results. This suggests that facilitating conditions and perceived trust were not necessary to predict students' attitudes towards AI adoption. This is in line with the results of (Chatterjee and Bhattacharjee (2020) and Choung et al. (2023) and Dwivedi et al. (2023), Emon et al. (2024), and Zhao et al. (2024), who suggested that students are more willing to adopt AI in their learning when they have positive feelings towards AI technology, which, in turn, increases their intention. If college students perceive AI tools as user-friendly and easy to operate, along with tangible benefits, higher education institutions can cultivate a positive attitude toward AI adoption and its user intention. In contrast, other studies (Cao et al., 2021; Emon & Khan, 2025) have reported inconsistent results regarding these relationships.

In addition, performance and effort expectancy positively affected students' intention to adopt AI. This supports the NCA results, which suggest that performance expectancy and effort expectancy are the critical necessary conditions to predict students' intention to adopt AI. These results are consistent with the findings of Foroughi et al. (2024), who suggested that AI can improve learning potentials in higher education by providing a personalised learning experience with a user-friendly interface.

Furthermore, facilitating conditions and perceived trust were found to have an insignificant association with students AI adoption intention, which corroborates the findings of (Beldad and Hegner (2018) and Foroughi et al. (2024). The NCA results also validated these results. This implies that providing the necessary infrastructure support or solving security concerns may not be sufficient to drive AI adoption. Moreover, students might feel apprehension or distrust regarding data privacy, security risks, and lack of infrastructure support while embracing new technology.

However, the effects of facilitating conditions and perceived trust through attitude could enhance students AI adoption intention. These results are consistent with those of Foroughi et al. (2024). This means that the availability of infrastructure, resources, training, and other technical support can boost students' favourable attitudes and intentions to adopt AI technology.

Finally, attitude demonstrated a positive association with students' intention to adopt AI technology. NCA findings also revealed that attitude was an essential condition for predicting students' intentions. This is supported by the findings of (Emon et al. (2023) and Zhao et al. (2024). The bottleneck table results also indicated that there should be thresholds in which each predictor is required to meet the desired level of the outcome variable.

Implications

Theoretical implications

This study has significant theoretical implications by extending the UTAUT model to incorporate the additional variable of perceived trust within the context of AI technology in higher education institutions. This study broadens the UTAUT framework by showing how ease of use, usefulness, and tangible benefits promote technology acceptance. With the mediating role of attitude, this study further contributes to the existing area of research on technology adoption by providing a holistic model that underscores the relationship between drivers of AI adoption and students' behavioural intentions. This research also demonstrated a methodological contribution by integrating PLS-SEM and NCA techniques using UTAUT constructs to explore the dimensions of attitude and intention to adopt AI. The PLS SEM results established sufficient causal relationships to predict AI technology adoption. On the other hand, NCA highlighted the necessary conditions to define students' intention to adopt AI.

The study also highlighted the importance of various dimensions of AI technology adoption, suggesting that students' attitudes contribute significantly to forming positive intentions towards AI adoption. This extended framework contributes to the AI technology adoption literature and guides authorities in leveraging AI-enabled learning potential. Furthermore, the mediating effect of attitude extends the explanatory scope of the UTAUT model in the higher education context, which also provides a deeper understanding of students AI technology adoption.

.

Practical implications

This research offers actionable insights for both technology designers and higher education institutions to facilitate AI-enabled transformation. Higher education institutions can prioritise students' attitudes towards AI adoption, considering ease of use, perceived benefits, perceived beliefs, necessary facilities, and proper training. For this, institutions can conduct proper in-house practical training sessions on AI tools and their potential for learning. This could enhance students' attitude and adoption, ultimately resulting in more efficient educational outcomes. Moreover, the government can frame policies and practices to solve security and privacy concerns to build users trust in AI technology. Finally, technology designers should prioritise user-centric AI tools in learning and academic environments.

Limitations of the study and scope for future research

This study focuses only on arts and science college students in Kerala, and hence, limits the generalisability of the findings to a broader area. Future research could delve deeper into the nuances of AI adoption in varied educational contexts, including professional education, technical education, and distance learning. This research employs a cross-sectional design, and more research could provide greater insights into how additional dimensions of AI adoption and attitude offer students technology adoption using longitudinal research. Shaping attitudes towards AI could further illuminate factors that facilitate or hinder technology adoption. Additionally, the moderating effect of the category of colleges, course streams, gender, age, and academic level can explore group-wise differences in AI technology adoption and intention. Since the study is limited to a sample of students who are AI users, there is a gap in the literature on non-user adoption resistance.

REFERENCES

[1] Cao, G., Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2021). Understanding managers' attitudes and behavioral intentions towards using artificial intelligence for organizational decision-making. Technovation, 106, 102312.

[2] Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., ... & Wright, R. T. (2023). Opinion Paper:" So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. Int. J. Inf. Manag., 71(2), 102642.

[3] Emon, M. M. H., & Khan, T. (2025). The Mediating Role of Attitude Towards the Technology in Shaping Artificial Intelligence Usage Among Professionals. Telematics and Informatics Reports, 100188.

[4] Zhao, Y., Li, Y., Xiao, Y., Chang, H., & Liu, B. (2024). Factors Influencing the Acceptance of ChatGPT in High Education: An Integrated

Model With PLS-SEM and fsQCA Approach. SAGE Open, 14(4), 21582440241289835.

[5] Dul, J. (2016). Necessary condition analysis (NCA) logic and methodology of “necessary but not sufficient” causality. Organizational Research Methods, 19(1), 10-52.

[6] Dul, J., Van der Laan, E., & Kuik, R. (2020). A statistical significance test for necessary condition analysis. Organizational Research Methods, 23(2), 385-395.

[7] Richter, N. F., Schubring, S., Hauff, S., Ringle, C. M., & Sarstedt, M. (2020). When predictors of outcomes are necessary: Guidelines for the combined use of PLS-SEM and NCA. Industrial management & data systems, 120(12), 2243-2267.

[8] Basco, R., Hair Jr, J. F., Ringle, C. M., & Sarstedt, M. (2022). Advancing family business research through modeling nonlinear relationships: Comparing PLS-SEM and multiple regression. Journal of Family Business Strategy, 13(3), 100457.

[9] Teare, M. D., Dimairo, M., Shephard, N., Hayman, A., Whitehead, A., & Walters, S. J. (2014). Sample size requirements to estimate key design parameters from external pilot randomised controlled trials: a simulation study. Trials, 15, 1-13.

[10] Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. American journal of theoretical and applied statistics, 5(1), 1-4.

[11] Helmiatin, Hidayat, A., & Kahar, M. R. (2024). Investigating the adoption of AI in higher education: a study of public universities in Indonesia. Cogent Education, 11(1), 2380175.

[12] Rahiman, H. U., & Kodikal, R. (2024). Revolutionizing education: Artificial intelligence empowered learning in higher education. Cogent Education, 11(1), 2293431.

[13] Kwak, Y., Seo, Y. H., & Ahn, J. W. (2022). Nursing students' intent to use AI-based healthcare technology: Path analysis using the unified theory of acceptance and use of technology. Nurse Education Today, 119, 105541.

[14] Foroughi, B., Senali, M. G., Iranmanesh, M., Khanfar, A., Ghobakhloo, M., Annamalai, N., & Naghmeh-Abbaspour, B. (2024). Determinants of intention to use ChatGPT for educational purposes: Findings from PLS-SEM and fsQCA. International Journal of Human–Computer Interaction, 40(17), 4501-4520.

[15] Fang, W., Na, M., & Alam, S. S. (2025). Usage Intention of AI Among Academic Librarians in China: Extension of UTAUT Model. Sustainability, 17(7), 2833.

[16] Andrews, J. E., Ward, H., & Yoon, J. (2021). UTAUT as a model for understanding intention to adopt AI and related technologies among librarians. The Journal of Academic Librarianship, 47(6), 102437.

[17] Ho, J. C., Wu, C. G., Lee, C. S., & Pham, T. T. T. (2020). Factors affecting the behavioral intention to adopt mobile banking: An international comparison. Technology in Society, 63, 101360.

[18] Emon, M. M. H., Khan, T., Rahman, M. A., & Siam, S. A. J. (2024, September). Factors influencing the usage of artificial intelligence among Bangladeshi professionals: Mediating role of attitude towards the technology. In 2024 IEEE International Conference on Computing, Applications and Systems (COMPAS) (pp. 1-7). IEEE.

[19] Biswas, A., Jaiswal, D. andKant, R. (2021), “Augmenting bank service quality dimensions: moderation of perceived trust and perceived risk”, International Journal of Productivity and Performance Management,doi: 10.1108/IJPPM-04-2021-0196

[20] Choung, H., David, P., & Ross, A. (2023). Trust in AI and its role in the acceptance of AI technologies. International Journal of Human–Computer Interaction, 39(9), 1727-1739.

[21] Beldad, A. D., & Hegner, S. M. (2018). Expanding the technology acceptance model with the inclusion of trust, social influence, and health valuation to determine the predictors of German users’ willingness to continue using a fitness app: A structural equation modeling approach. International Journal of Human–Computer Interaction, 34(9), 882-893.

[22] Pesonen, J. A. (2021, July). ‘Are you ok?’Students’ trust in a Chatbot providing support opportunities. In International conference on human-computer interaction (pp. 199-215). Cham: Springer International Publishing.

[23] Hamidi, H., & Chavoshi, A. (2018). Analysis of the essential factors for the adoption of mobile

learning in higher education: A case study of students of the University of Technology. Telematics and Informatics, 35(4), 1053-1070.

[24] Aslam, W., Ahmed Siddiqui, D., Arif, I., & Farhat, K. (2023). Chatbots in the frontline: drivers of acceptance. Kybernetes, 52(9), 3781-3810.

[25] Bilquise, G., Ibrahim, S., & Salhieh, S. E. M. (2024). Investigating student acceptance of an academic advising chatbot in higher education institutions. Education and Information Technologies, 29(5), 6357-6382.

[26] Ruiz-Real, J. L., Uribe-Toril, J., Arriaza Torres, J. A., & de Pablo Valenciano, J. (2021). Artificial intelligence in business and economics research: Trends and future. Business Economics and Management (JBEM), 22(1), 98-117.

[27] Wang, Y., Liu, C., & Tu, Y. F. (2021). Factors affecting the adoption of AI-based applications in higher education. Educational Technology & Society, 24(3), 116-129.

[28] Chatterjee, S., & Bhattacharjee, K. K. (2020). Adoption of artificial intelligence in higher education: A quantitative analysis using structural equation modelling. Education and Information Technologies, 25, 3443-3463.

[29] Emon, M. M. H., Khan, T., Rahman, M. A., & Siam, S. A. J. (2024, September). Factors influencing the usage of artificial intelligence among Bangladeshi professionals: Mediating role of attitude towards the technology. In 2024 IEEE International Conference on Computing, Applications and Systems (COMPAS) (pp. 1-7). IEEE.

[30] Helmiatin, Hidayat, A., & Kahar, M. R. (2024). Investigating the adoption of AI in higher education: a study of public universities in Indonesia. Cogent Education, 11(1), 2380175.

[31] Camilleri, M. A. (2024). Factors affecting performance expectancy and intentions to use ChatGPT: Using SmartPLS to advance an information technology acceptance framework. Technological Forecasting and Social Change, 201, 123247.

[32] Wu, W., Zhang, B., Li, S., & Liu, H. (2022). Exploring factors of the willingness to accept AI-assisted learning environments: an empirical investigation based on the UTAUT model and perceived risk theory. Frontiers in Psychology, 13, 870777.

[33] Shen, S., Xu, K., Sotiriadis, M., & Wang, Y. (2022). Exploring the factors influencing the adoption and usage of Augmented Reality and Virtual Reality applications in tourism education within the context of COVID-19 pandemic. Journal of hospitality, leisure, sport & tourism education, 30, 100373.

[34] Wang, T., Lund, B. D., Marengo, A., Pagano, A., Mannuru, N. R., Teel, Z. A., & Pange, J. (2023). Exploring the potential impact of artificial intelligence (AI) on international students in higher education: Generative AI, chatbots, analytics, and international student success. Applied Sciences, 13(11), 6716.

[35] Khalil, M., & Er, E. (2023, June). Will chatgpt g et you caught? rethinking of plagiarism detection. In International conference on human-computer interaction (pp. 475-487). Cham: Springer Nature Switzerland.

[36] Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., ... & Wright, R. (2023). Opinion Paper:"So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. International journal of information management, 71, 102642.

[37] Khademi, A. (2023). Can ChatGPT and Bard generate aligned assessment items? A reliability analysis against human performance. arXiv preprint arXiv:2304.05372.

[38] Wang, Y., & Zhang, W. (2023). Factors Influencing the Adoption of Generative AI for Art Designing among Chinese Generation Z: A structural equation modeling approach. IEEE Access, 11, 143272-143284.

[39] Yang, F., Ren, L., & Gu, C. (2022). A study of college students' intention to use metaverse technology for basketball learning based on UTAUT2. Heliyon, 8(9).

[40] Osei, H. V., Kwateng, K. O., & Boateng, K. A. (2022). Integration of personality trait, motivation and UTAUT 2 to understand e-learning adoption in the era of COVID-19 pandemic. Education and Information Technologies, 27(8), 10705-10730.

[41] Chatterjee, S., & Bhattacharjee, K. K. (2020). Adoption of artificial intelligence in higher education: A quantitative analysis using structural

equation modelling. Education and Information Technologies, 25, 3443-3463.

[42] Lund, B. D., Wang, T., Mannuru, N. R., Nie, B., Shimray, S., & Wang, Z. (2023). ChatGPT and a new academic reality: Artificial Intelligence-written research papers and the ethics of the large language models in scholarly publishing. Journal of the Association for Information Science and Technology, 74(5), 570-581.

[43] Lim, M. S., Ho, S. B., & Chai, I. (2021). Design and functionality of a university academic advisor chatbot as an early intervention to improve students' academic performance. In Computational Science and Technology: 7th ICCST 2020, Pattaya, Thailand, 29–30 August, 2020 (pp. 167-178). Singapore: Springer Singapore.

[44] Smolansky, A., Cram, A., Raduescu, C., Zeivots, S., Huber, E., & Kizilcec, R. F. (2023, July). Educator and student perspectives on the impact of generative AI on assessments in higher education. In Proceedings of the tenth ACM conference on Learning@ Scale (pp. 378-382).

[45] Gill, S. S., Xu, M., Patros, P., Wu, H., Kaur, R., Kaur, K., ... & Buyya, R. (2024). Transformative effects of ChatGPT on modern education: Emerging Era of AI Chatbots. Internet of Things and Cyber-Physical Systems, 4, 19-23.

[46] Hwang, G. J., & Chang, C. Y. (2023). A review of opportunities and challenges of chatbots in education. Interactive Learning Environments, 31(7), 4099-4112.

[47] Hoi, S. C. (2023, February). Responsible AI for trusted AI-powered enterprise platforms. In Proceedings of the sixteenth ACM international conference on web search and data mining (pp. 1277-1278).

[48] Kamalov, F., Santandreu Calonge, D., & Gurrib, I. (2023). New era of artificial intelligence in education: Towards a sustainable multifaceted revolution. Sustainability, 15(16), 12451.

[49] Mogavi, R. H., Deng, C., Kim, J. J., Zhou, P., Kwon, Y. D., Metwally, A. H. S., ... & Hui, P. (2023). Exploring user perspectives on chatgpt: Applications, perceptions, and implications for ai-integrated education. arXiv preprint arXiv:2305.13114.

[50] Hwang, G. J., & Chang, C. Y. (2023). A review of opportunities and challenges of chatbots in education. Interactive Learning Environments, 31(7), 4099-4112.

[51] Saihi, A., Ben-Daya, M., Hariga, M., & As' ad, R. (2024). A Structural equation modeling analysis of generative AI chatbots adoption among students and educators in higher education. Computers and Education: Artificial Intelligence, 7, 100274.

[52] Ivanov, S., Soliman, M., Tuomi, A., Alkathiri, N. A., & Al-Alawi, A. N. (2024). Drivers of generative AI adoption in higher education through the lens of the Theory of Planned Behaviour. Technology in Society, 77, 102521.

[53] Hasan, M. R., Chowdhury, N. I., Rahman, M. H., Syed, M. A. B., & Ryu, J. (2024). Understanding AI Chatbot adoption in education: PLS-SEM analysis of user behavior factors. Computers in Human Behavior: Artificial Humans, 2(2), 100098.

[54] Hair Jr, J. F., Howard, M. C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. Journal of business research, 109, 101-110.

[55] Hair, J. F., Astrachan, C. B., Moisescu, O. I., Radomir, L., Sarstedt, M., Vaithilingam, S., & Ringle, C. M. (2021). Executing and interpreting applications of PLS-SEM: Updates for family business researchers. Journal of Family Business Strategy, 12(3), 100392.

[56] Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2017). A primer on partial least squares structural equation modeling (PLS-SEM) (p. 165). Sage.

[57] Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European business review, 31(1), 2-24.

[58] Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the academy of marketing science, 43, 115-135.

[59] Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the academy of marketing science, 43, 115-135.

[60] Henseler, J., Ringle, C. M., & Sarstedt, M. (2016). Testing measurement invariance of composites

using partial least squares. International marketing review, 33(3), 405-431.

[61] Lee, J. C., & Chen, X. (2022). Exploring users' adoption intentions in the evolution of artificial intelligence mobile banking applications: the intelligent and anthropomorphic perspectives. International Journal of Bank Marketing, 40(4), 631-658.