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Adoption of AI tools in Higher Education, Exploring the Role of AI Anxiety: A hybrid PLS-SEM & ANN Approach

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Abstract

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The use of AI tools for academic content creation and research in higher education is a complex process influenced by a range of personal and environmental factors. This is true, despite potential advantages. The purpose of this study is to identify the factors that influence behavioural intentions regarding the use and subsequent adoption among faculty in higher education. The UTAUT2 (Unified Theory of Acceptance and Use of Technology 2) served as the underlying theory in this research. Along with the variables proposed in the UTAUT2 framework, which include performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value and habit, AI anxiety was introduced as a novel predictor variable in the research framework. The sample consisted of 376 faculty members from higher education institutions across India. A hybrid PLS (partial least squares) structural equation modelling and ANN (artificial neural network) approach was utilised in this research. The results of this study posited that performance expectancy, hedonic motivation, facilitating conditions, and price value have a significant and positive effect on attitude towards the adoption of artificial intelligence tools among faculty in higher education. Furthermore, a positive attitude towards artificial intelligence tools significantly influences behavioural intention. Additionally, the hybrid assessment using PLS-SEM and ANN demonstrated similarity in predicting behavioural intentions through performance expectancy & facilitating conditions. This study contributes to the growing literature on AI, specifically in higher education and managerial practice.

***Keywords:** artificial intelligence tools, SEM, higher education, artificial neural network, AI anxiety.*

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1. Introduction

Despite being recognised in the early 1950s, Artificial intelligence has entered the mainstream only recently. Its application was in nascent stages and far from the academic field (Helmiatin et al., 2024). It was later realised that the transformative potential of artificial intelligence could disrupt and transform a number of industries, including education. The use of artificial intelligence in higher education can contribute to economic and societal growth (Sova et al., 2024). A lot has been spoken and written about artificial intelligence, especially after the launch of ChatGPT-3 by OpenAI in 2022 (Khlaif et al., 2024). which presents exciting possibilities for improving teaching and learning. AI has the capability to transform traditional teaching, learning and assessment systems. Learning management systems, lecture transcription, chatbot assistance, Intelligent tutoring systems, and automated grading systems are just a few examples of how AI can be used both inside and outside the classroom (Chaudhry et al., 2023). AI also has the potential to address scalability and accessibility challenges, eventually reaching a broader student audience and providing quality education worldwide (Alyoussef et al., 2025). Recently, Chat Generative Pre-Trained Transformer, or "ChatGPT," has attracted international interest as an AI-based technology, particularly in education (García-Peñalvo, 2023). Many academics have examined the benefits of ChatGPT, which, despite academic risks and unethical practices such as plagiarism, data manipulation, and conflicts of interest, remains popular among higher education faculty (Talan & Kalinkara, 2023). With millions of educators and students worldwide adopting ChatGPT, it is poised to surpass traditional teaching and learning methods (Sullivan et al., 2023). It is crucial to examine how faculty members perceive and behave when using ChatGPT, as its impact on research findings and educational outcomes continues to grow. Educational institutions around the world are moving towards massification. This trend has increased the faculty workload. As a solution to this problem, artificial intelligence tools can be utilised to address the workload problem (Andrea et al., 2015). Artificial intelligence, as a solution to the problem of massification and excessive workload, can yield results only if adopted by all stakeholders, including faculty, support staff, administrative staff, and students. The extant literature has shown that teachers' acceptance plays a vital role in the adoption of innovations (Sánchez-Prieto et al., 2017). Recent research on adoption of AI among faculties in Oman was conducted by Mughairi & Bhaskar (2014) in which they found that there are both positives and negatives in the adoption of AI, but as research in this area is still nascent (Mulaudzi & Hamilton, 2025), there is a need to further delve in this research area, especially in the higher education context of India (Agarwal, 2005). The adoption of artificial intelligence tools by professors in higher education remains a complex process influenced by a range of personal and environmental factors, despite their potential advantages (Ally & Prieto-Blázquez, 2014). It is crucial to look into how faculty members perceive and behave when using ChatGPT, as its impact on research findings and educational learning is only growing.

2. Review of Literature

2.1 (UTAUT2) Unified Theory of Acceptance and Use of Technology 2 framework

Venkatesh et al. (2012) developed a framework to elucidate the factors affecting the use and adoption intention of technology, namely the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). The UTAUT2 framework serves as a theoretical lens to investigate the complex dynamics underpinning technology adoption, including the addition of AI anxiety in the context of this study on faculty adoption of AI technologies in higher education (Venkatesh et al., 2012). The four primary constructs in the UTAUT2 framework are performance expectancy, effort expectancy, social influence, & facilitating conditions.

2.2 Performance expectancy and attitude towards adoption of AI tools

Performance expectancy describes educators' perceptions of the advantages and practicality of integrating AI into their teaching strategies. It covers their hopes for how AI will improve their ability to instruct and encourage learning outcomes

(Venkatesh et al., 2012). It pertains to the benefits and utility of employing AI in higher education for academic content creation and research. Shaikh et al. (2021) posit that performance expectancy has a direct effect on attitude and behavioural intentions. On the basis of the above argument, we hypothesise that:

H1 The effect of performance expectancy on attitude towards adoption of AI tools is positive and significant.

2.3 Effort expectancy and attitude towards the adoption of the AI tool

Effort expectancy reflects how teachers perceive the simplicity of use and the mental effort required to incorporate AI technologies into their lesson plans. It takes into account elements such as the perceived ease or difficulty of using AI, as well as any potential learning curve associated with the technology (Venkatesh et al., 2012). As per previous studies, it has been found that effort expectancy has a significant effect on attitude towards usage of a particular technology (Venkatesh et al., 2003; Venkatesh et al., 2012).

H2 The effect of effort expectancy on attitude towards adoption of AI tools is positive and significant.

2.4 Social influence and attitude towards the adoption of AI tools

Social influence examines how peers, managers, and coworkers influence instructors' adoption decisions. It includes how other people's beliefs, standards, and suggestions affect the adoption and use of AI technologies (Venkatesh et al., 2012). Gupta et al. (2024) posited that social influence affects attitudes towards technology, which in turn leads to behavioural intention. Similarly, Wijaya et al. (2022) reported findings similar to those of this study, in which social influence affected behavioural intention through the mediating role of attitude. On the basis of the same, we hypothesise as follows:

H3 The effect of social influence on attitude towards adoption of AI tools is positive and significant.

2.5 Hedonic motivation and attitude towards the adoption of AI tools

Hedonic motivation is defined as the pleasure or enjoyment a user derives from using a technology (Venkatesh et al., 2012). Prior studies have reported a positive relationship between hedonic motivation and behavioural intentions, mediated by a positive attitude towards a technology (Wijaya et al., 2022). This suggests that when a user enjoys using a technology, it fosters a positive attitude, which eventually drives adoption.

H4 The effect of hedonic motivation on attitude towards adoption of AI tools is positive and significant.

2.6 Price value and attitude towards adoption of AI tools.

Price-to-value refers to the cost associated with adopting AI tools. As noted by Venkatesh et al. (2012), pricing has a significant effect on technology adoption (Sarker et al., 2023). Ranaweera and Karjaluoto (2017) posit that a positive perception towards price leads to a positive attitude. In the case of AI tools, a value-driven price can positively influence attitudes towards their adoption.

H5 The effect of price value on attitude towards adoption of AI tools is positive and significant.

2.7 Habit and attitude towards the adoption of AI tools

Habit is defined as the tendency for people to perform behaviours automatically, as they have learned through prior experience with a particular technology (Venkatesh et al., 2012). Ngusie et al. (2024) posited that repeated use of a technology through positive experiences leads to a positive attitude towards technology.

H6 The effect of habit on attitude towards adoption of AI tools is positive and significant.

2.8 Facilitating conditions and attitude towards the adoption of AI tools

Facilitating conditions refer to the availability of the tools, infrastructure, and support that instructors need to embrace and incorporate AI technology into their pedagogical practices (Venkatesh et al., 2012). Prior studies have indicated a relationship between facilitating conditions and attitude towards a technology (Gupta et al., 2024). This signifies that the availability of support and tools enhances attitude towards a technology, eventually leading to adoption.

H7 The effect of facilitating conditions on attitude towards adoption of AI tools is positive and significant.

2.9 Attitude on adoption of the AI tools

In psychology and related fields, it is evident that attitudes direct behaviour (Howe & Krosnick, 2017). Similarly, Bae and Chang (2021) posit that attitudes play a significant role in shaping behavioural intentions. People express their feelings to carry out a target behaviour, whether positive or negative. Attitude is covered in this (Fishbein & Ajzen, 1975). According to Davis et al. (1989), the TAM (Technology Acceptance Model) theory states that a person's attitude towards a system determines their behavioural intention (BI). Research supports the Theory of Planned Behaviour (TPB) in concluding that users' Behavioural Intentions (BI) are influenced by their Attitude (ATT) (Ajzen, 1991). Many previous studies have posited that attitude is a strong mediating variable in the relationship between determining factors and adoption (Aboelmaged, 2010; Cox, 2012). Numerous research papers support this study (Wang et al., 2009). Regarding each of these inputs and understanding the effect of the UTAUT2 framework and attitude in technology adoption, we hypothesise the following:

H8 The effect of attitude on the adoption of AI tools is positive and significant

2.10 AI Anxiety

Several factors, including AI anxiety, influence instructors' use and adoption of AI tools. In the words of Johnson & Verdicchio (2017), AI is a fear or agitation that people might have about AI. It has also been defined as the fear arising from the excessive use of AI in personal and social life (Kaya et al., 2024). As per Wang & Wang (2022), AI anxiety can be categorised into many dimensions that include anxiety related to job replacement, anxiety related to learning AI, sociotechnical blindness and AI configuration anxiety. In this study, we measure AI-related anxiety along two dimensions: job-replacement anxiety and AI-learning anxiety. Job replacement anxiety has been defined as the fear of the adverse effects of AI on business life. AI learning anxiety has been defined as the anxiety that arises out of the fear of learning AI technologies. Understanding the significance of AI fear in influencing teachers' adoption and use of AI becomes increasingly important as artificial intelligence becomes more common in educational settings. According to earlier studies, people's fear of technology can play a significant role in their behavioural intentions towards AI (Chau & Hu, 2002; Yi et al., 2006) . Similarly, instructors' AI-related concerns may play a significant role in determining whether they adopt or reject AI technology in higher education. Various components of the technology adoption process can be impacted by AI anxiety. For instance, it may affect how teachers view and feel about AI, as well as their readiness to integrate it into their teaching methods (Ayanwale et al., 2022). Higher levels of AI anxiety may cause resistance or reluctance to adopt AI because teachers may worry about how AI will affect their role as educators, how well AI will help them achieve their pedagogical goals, or what difficulties they may encounter when using AI technologies (Kim & Kim, 2022). For educational institutions seeking to support the effective integration of artificial intelligence in higher education, understanding the impact of AI fear is essential. It is possible to develop effective techniques and interventions to encourage the adoption and effective use of AI in educational settings by identifying and addressing teachers' fears and apprehensions about AI. Overall, teachers' judgements and attitudes about the use of AI technology in higher education may be influenced by their level of AI concern. Educational institutions may create a welcoming climate that encourages teachers to embrace AI and leverage its potential to improve teaching and learning outcomes by addressing these concerns.

Based on the above arguments, we hypothesise the following:

H9 AI Job replacement anxiety affects the attitude towards the adoption of AI tools

H10 AI Learning anxiety influences attitude towards adoption of AI tools.

3. Research Objectives

The purpose of this study is to identify the factors that influence behavioural intentions in the usage and subsequent adoption among higher education faculties.

4. Research Questions

1. What are the antecedents influencing the attitude of faculties of higher education institutions towards behavioural intentions towards adopting AI tools?
2. Whether AI Anxiety affects the attitude of faculties towards intention to adopt AI tools?
3. Whether attitude towards AI tools affects the behavioural intention towards adoption in higher education?

5. Methodology

A descriptive cross-sectional survey approach was used in this study as recommended by Bryman and Cramer (2012). This method is used to collect data on a specific social phenomenon at a given time. Non-Probability convenience sampling was used to draw a sample of 100 faculty members for the pilot study. On the basis of the results of the pilot study, a larger sample of 675 faculties from across Business Schools across India were approached for this study. To collect data, a Google Form was created and shared across broadcast WhatsApp groups comprising faculty from across India. 397 filled forms were received out of which 376 were considered for data analysis. A 5-point Likert Scale was utilised for denoting the responses. UTAUT 2 scale as given by Venkatesh (2012) was used for measuring Performance Expectancy, Effort Expectancy, Facilitating Conditions, Social Influence, Habit, Hedonic Motivation and Price Value. Attitude was measured using 5 statements adopted from Chatterjee & Bhattacharya (2020). AI Anxiety was measured using a scale adapted from Yang and Yang (2022). For data collection, a Google Form was created, and a link was shared with faculty members at higher education institutions via personal references of the authors, through broadcast WhatsApp groups comprising faculty members from various business schools across India. 397 filled forms were received, of which 376 were included in the final data analysis. After omitting erroneous and incomplete questionnaires, the data were analysed using SPSS version 26. The data analysis used a two-stage analytical technique (PLS-SEM-ANN) to assess the research hypotheses and validate the research model. To begin with, the reliability and validity of the constructs and indicators were assessed using Partial Least Squares structural equation modelling (PLS-SEM), the most widely used technique in research (Hair et al., 2021). Measurement model assessment was done by checking the correlations between constructs and their indicators. After validating the measurement model, the structural model was assessed. Structural model assessment involved testing the relationships among constructs (the inner model) and validating the hypotheses. As a novelty, predictor variables influencing the use of AI tools were assessed using an ANN. As per many recent studies (Al-Sharafi et al., 2022, 2023), the artificial neural network (ANN) method yields predictions with higher accuracy than the various regression techniques currently employed. Furthermore, it has been observed that the ANN approach is highly effective at discovering both linear and nonlinear correlations, compared with statistical methods such as multiple regression, logistic regression, and SEM (Al-Sharafi et al., 2022). This study is based on past research (Lee et al., 2020) that supports the applicability of ANN in this field.

6. Results

6.1 Common Method Bias

Data were collected using an online survey instrument, which introduces the risk of respondent bias; this needs to be addressed to avoid collinearity issues. Common method bias can occur when a single factor explains a significant portion of the variance (Harman, 1976). To eliminate potential common-method bias, this study employs two approaches. First, as suggested by Podsakoff et al. (2003), VIF values for items can be assessed to detect CMB. Chin at al. (2012) suggest VIF values of below 0.5 to ascertain any possible case of CMB. The VIF values, as shown in Table No. 3, are below the threshold of 0.5. Secondly, Harman's single-factor test was conducted to examine whether the majority of the dataset's variance is explained by a single factor. EFA was performed by constraining the selected factors to 1. It was found that a single factor accounted for only 33.58%, indicating the absence of CMB.

6.2 Model Assessment

Model assessment was conducted using a two-step approach, including measurement and structural model evaluation, as suggested by Hair et al. (2017). At the initial stage, the measurement model analysis (outer model) included evaluating outer loadings, composite reliability scores, AVE (average variance extracted), Cronbach's alpha, discriminant validity, and VIF for multicollinearity. After the measurement model, structural model assessment was done using path coefficients (Beta Values), p-values, F-squared, t-values and the R2 coefficient of determination.

6.3 Assessment of Measurement Model

For the measurement model analysis, assessments of internal consistency reliability, convergent validity, and discriminant validity were conducted using factor loadings, composite reliability, Cronbach's alpha, and average variance extracted, as suggested by Hair et al. (2021). Discriminant validity of the model was assessed using the HTMT ratio. All these figures are displayed in the table.1

Table 1

Reliability and Validity Scores

Constructs	Items	Loadings	Cronbach's alpha	CR (rho_a)	CR (rho_c)	AVE
PE	**PE1**	0.822	0.860	0.866	0.905	0.705
	PE2	0.857				
	PE3	0.892				
	PE4	0.784				
EE	**EE1**	0.807	0.878	0.904	0.915	0.730
	EE2	0.876				
	EE3	0.916				
	EE4	0.815				
SI	**SI1**	0.923	0.899	0.980	0.933	0.824
	SI2	0.944				
	SI3	0.854				
HM	**HM1**	0.918	0.918	0.938	0.948	0.857
	HM2	0.927				
	HM3	0.932				
PV	**PV1**	0.864	0.847	0.859	0.907	0.765
	PV2	0.864				
	PV3	0.895				
HB	**HB1**	0.874	0.902	0.908	0.931	0.772
	HB2	0.904				
	HB3	0.851				
	HB4	0.884				
FC	**FC1**	0.774	0.796	0.815	0.864	0.615
	FC2	0.817				

	FC3	0.809				
	FC4	0.734				
ATT	**ATT1**	0.662	0.810	0.824	0.867	0.568
	ATT2	0.817				
	ATT3	0.777				
	ATT4	0.737				
	ATT5	0.764				
BI	**BI1**	0.868	0.865	0.873	0.917	0.786
	BI2	0.890				
	BI3	0.902				
AIJ	**AIJ1**	0.766	0.851	0.829	0.873	0.538
	AIJ2	0.587				
	AIJ3	0.805				
	AIJ4	0.816				
	AIJ5	0.628				
	AIJ6	0.765				
AIL	**AIL1**	0.835	0.950	0.966	0.957	0.738
	AIL2	0.924				
	AIL3	0.923				
	AIL4	0.899				
	AIL5	0.867				
	AIL6	0.762				
	AIL7	0.845				
	AIL8	0.807				

As shown in Table 1, the factor loadings for each construct were greater than 0.5, the minimum required cutoff; this indicated that each item measured each construct precisely. Furthermore, for all the constructs, the values of Cronbach's alpha were higher than 0.7, which was the minimum required threshold value as indicated by Hair et al. (2021), Sijtsma (2009), and Cronbach and Shavelson (2004). The composite reliability values, which exceed the cutoff of 0.7. The CR values, which are preferred over Cronbach's alpha, further supported the dependability of all construct elements (Hair et al., 2016, 2017). As suggested by Hair et al. (2017) and Kline (2015), the average variance extracted (AVE) the criterion for checking internal consistency, should be greater than or equal to 0.5, this criterion was met as all the AVE values were above 0.5 The AVE values in Table 1 meet the requirements for convergent validity because they are between 0.613 and 0.813.

Table 2

Discriminant Validity using HTMT

	AIJ	AIL	ATT	BI	EE	FI	HB	HM	PE	PV
AIJ										
AIL	0.529									
ATT	0.215	0.262								
BI	0.192	0.276	0.65							

EE	0.143	0.181	0.390	0.291						
FI	0.182	0.112	0.659	0.333	0.56					
HB	0.174	0.575	0.307	0.571	0.328	0.175				
HM	0.084	0.213	0.525	0.579	0.255	0.368	0.443			
PE	0.224	0.384	0.626	0.657	0.272	0.44	0.45	0.422		
PV	0.25	0.362	0.657	0.493	0.242	0.576	0.425	0.451	0.545	
SI	0.261	0.377	0.206	0.413	0.096	0.124	0.462	0.214	0.289	0.319

The Heterotrait-Monotrait ratio of correlations (HTMT) as suggested by Henseler et al. (2015) is a popular technique for assessing discriminant validity in partial least squares structural equation modelling. A threshold value of 0.90 is recommended for constructs that might appear to be similar and 0.85 for constructs that are dissimilar. All HTMT values were above the threshold, as shown in Table No. 2, thereby demonstrating strong discriminant validity among the constructs.

Table 3

VIF Values (Inner and Outer Model for collinearity check)

		(VIF)	
Sr.No	**Variables**	**Inner Model**	**Outer Model**
1	Performance Expectancy	1.535	1.729-2.658
2	Effort Expectancy	1.399	1.869-2.673
3	Social Influence	1.278	2.451-4.165
4	Hedonic Motivation	1.401	3.078-3.539
5	Price Value	1.724	1.899-2.148
6	Habit	1.854	2.251- 3.217
7	Facilitating Conditions	1.846	1.396-2.150
8	Attitude	1	1.360-1.935
9	AI Job Replacement Anxiety	1.397	1.660-2.688
10	AI Learning Anxiety	1.968	2.586-4.838

6.4 Structural Model Assessment

The hypothesised paths in the research model were assessed during the structural model assessment. A bootstrapping procedure with 5000 resamples was undertaken in the structural model assessment. Figure 1 and Table 4 show the results of this procedure. Results of the structural model assessment showed that AI learning anxiety and AI job replacement anxiety failed to have a significant impact on attitude. Attitude positively and significantly affected behavioural intentions ($\beta = 0.572$, $t = 7.187$, $p < .05$). A positive path coefficient indicates that a positive attitude towards AI will increase behavioural intention to use AI by 572 units. Among the other significant factors affecting attitude towards AI were facilitating conditions ($\beta = 0.254$, $t= 2.612$, $p<.05$), hedonic motivation ($\beta = 0.215$, $t= 2.834$, $p<.05$), performance expectancy ($\beta = 0.262$, $t= 2.903$, $p<.05$), and price value ($\beta = 0.212$, $t= 2.272$, $p<.05$). Factors that did not have a significant effect on attitude towards AI included effort expectancy, habit and social influence. The model's predictive ability was assessed using the coefficient of determination (R2). The coefficient of determination indicated that performance expectancy, effort expectancy, Social Influence, habit, price value and facilitating conditions accounted for 52 per cent variance in the attitude towards AI.

Figure 1

Structural Model

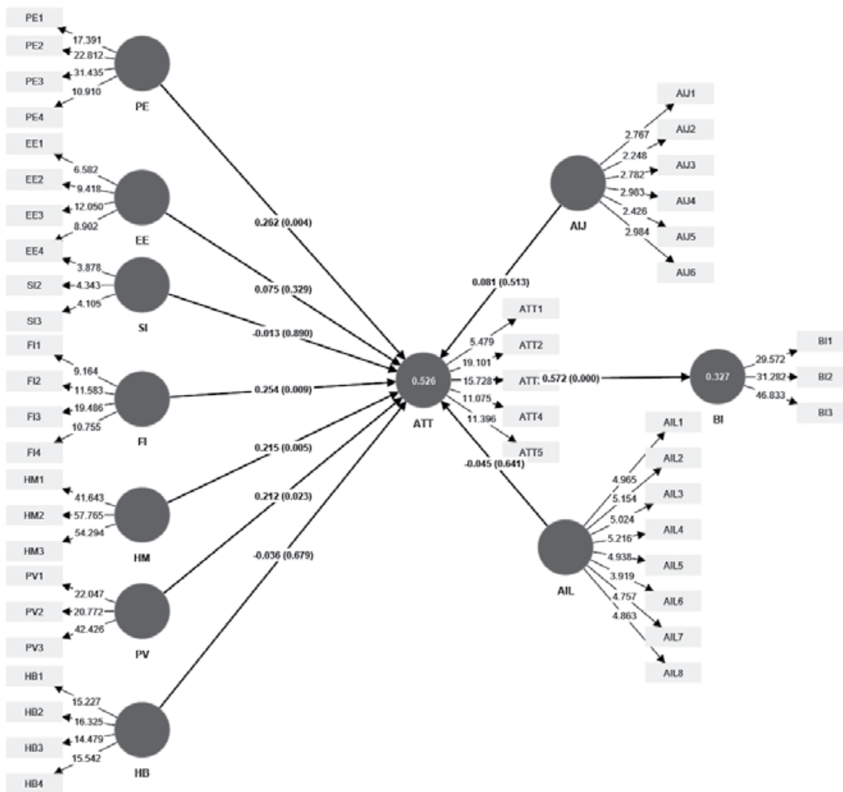

Table No.4

Path Analysis Results

Hypothesis	Structural Path	B	T Value	P values	F	R	2.5 LLCI	97.5 ULCI	Empirical Evidence
H1	PE -> ATT	0.262	2.903	0.004	0.094	0.526	0.096	0.447	S
H2	EE -> ATT	0.075	0.976	0.329	0.009	0.526	-0.067	0.24	NS
H3	SI -> ATT	-0.013	0.138	0.890	0	0.526	-0.251	0.136	NS
H4	HM -> ATT	0.215	2.834	0.005	0.07	0.526	0.068	0.365	S
H5	PV -> ATT	0.212	2.272	0.023	0.055	0.526	0.039	0.407	S
H6	HB -> ATT	-0.036	0.414	0.679	0.001	0.526	-0.21	0.13	NS
H7	FC -> ATT	0.254	2.612	0.009	0.074	0.526	0.064	0.445	S
H8	ATT -> BI	0.572	7.187	0	0.486	0.327	0.387	0.704	S
H9	AIJ -> ATT	0.081	0.654	0.513	0.01	0.526	-0.263	0.248	NS
H10	AIL -> ATT	-0.045	0.467	0.641	0.002	0.526	-0.262	0.127	NS

6.5 ANN Results

As previously mentioned, this study was conducted in two stages: to begin with, partial least squares structural equation modelling was done to analyse the path relationships among constructs and ascertain the factors that influence the faculties in the usage of AI tools; this was followed by ANN, whereby the factors identified through partial least squares structural equation modelling were ranked. As mentioned previously, Al-Sharafi et al. (2022) demonstrated in their study that ANN is a stronger technique for validating both linear and nonlinear relationships than other statistical techniques such as SEM and regression. An important indicator of an ANN model's predictive accuracy is the R-Squared value. The R-Squared value for the artificial neural network (ANN) model was calculated using a method as suggested by Hew and Kadir (2016). R^2= 1- RMSE/ S^2. According to this formula, the R2 for our ANN model was 1 - 0.455/1.868 = 1 - .243 = 0.757. This value indicates that the ANN model predicted attitude towards AI with an accuracy of 75%.

ANN Model: ATT= f(PE,EE,SI,FC,SI,AIJ,AIL,HM,PV)

Figure 2

ANN Input Output Diagram

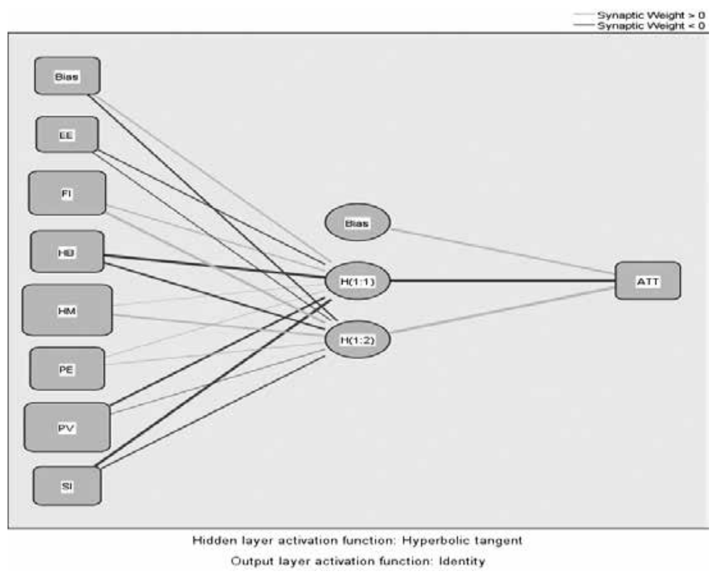

Table 5

Number of Sample, SSE, RMSE Values during the training and testing stages for ANN Model

	Training			Testing			
Neural Networks	N	SSE	RMSE	N	SSE	RMSE	Total Sample
One	326	27.697	0.484400	50	3.131	0.373958	376
Two	339	17.539	0.471470	37	2.428	0.499281	376
Three	334	25.294	0.556807	42	1.723	0.453554	376
Four	330	23.454	0.466354	46	1.007	0.374382	376
Five	327	24.851	0.435666	49	2.607	0.307446	376
Six	326	21.392	0.613632	50	1.428	0.498165	376
Seven	338	20.593	0.326049	38	0.803	0.461483	376
Eight	330	23.777	0.555718	46	1.754	0.631697	376
Nine	330	26.387	0.530881	46	1.654	0.413977	376
Ten	323	18.778	0.393620	53	2.144	0.539401	376
Mean		22.976	0.483	Mean	1.868	0.455	
SD		3.318	0.085	SD	0.721	0.094	

6.6 PLS-SEM & ANN Results (Comparison)

As described by Yidana et al. (2023), a comparison was made between the results of path coefficients generated from partial least squares structural equation modelling and normalized relative importance from ANN. Results from this comparison are shown in Table No.6. Among the various indicators, it was found that performance expectancy and facilitating conditions were significant and ranked alike in both Artificial Neural network (ANN) as well as partial least squares structural equation modelling (PLS-SEM).

Table 6

PLS-SEM & ANN Results (Comparison)

Construct	Path Coefficient	R Square	PLS-SEM Ranking	ANN-Normalized Relative Performance	R Square	ANN Ranking	Matching PLS SEM with ANN
ANN Model 1 ATT=f(PE,EE,FC,HM,PV,SI,HB)							
PE	0.262	0.526	1	79%	0.812	1	Match
FC	0.254		2	78%		2	Match
HM	0.215		3	64%		4	Do not Match
PV	0.212		4	77%		3	Do not Match

7. Discussion

The study utilised UTAUT2 and added AI anxiety with two dimensions, namely AI job replacement anxiety and AI Learning anxiety as novel constructs. The study combined the PLS-SEM-ANN approach to comprehensively examine the factors that affect faculty attitudes and behavioural intentions toward adopting AI tools to aid teaching and research. Results demonstrated that attitude towards AI was positively and significantly impacted by performance expectancy (H1) and facilitating conditions (H7). This aligned with previous studies (Emon et al., 2023; Kelly et al., 2023). These findings indicate that faculties who find AI to be contributing positively to their teaching and research will develop a positive attitude towards AI and may adopt AI tools, thereby enhancing their teaching and research. Facilitating conditions with regard to AI also contribute positively towards the attitude towards AI among faculties, indicating that technical and organisational support play a vital role in the adoption of AI among faculties. Further, hedonic motivation (H4) also plays a significant role in fostering a positive attitude towards AI. This aligns with findings from earlier studies (Chi et al., 2022; Lin et al., 2020). This indicated that the enjoyment derived from AI use also plays a vital role in shaping a positive attitude towards AI. Additionally, it was found that price value (H5) plays a positive and significant role in shaping attitudes towards AI, which resonates with earlier research (Gansser & Reich, 2021). Another important and significant finding was the influence of attitude on behavioural intentions (H8) towards AI. These finding sheds light on the important role a positive attitude towards AI plays in faculty intentions to adopt AI tools for teaching and research. This aligns with the findings of Hasan et al. (2024). Results of this study indicated that AI Learning Anxiety did not predict attitude towards AI (H10) which was in contradiction the results of a study by Salifu et al. (2024) where they found AI Learning anxiety to affect attitude towards AI, this contradiction in finding might be due to sample distribution and the context of India which is separate from other studies in literature. This finding also throws light on the technology readiness of Indian users who are comfortable in learning new technologies. Also, AI Job Replacement Anxiety (H9) was found to be insignificant in influencing attitude towards AI, this finding is consistent with findings from Salifu et al. (2024). Other factors that were found insignificant in affecting attitude towards AI were effort expectancy (H2), this was in contradiction to findings of Gursoy et al. (2019) habit (H6) was also insignificant in influencing attitude; and social influence (H3) was also insignificant, this is in line with earlier findings of Kim and Lee (2024). We argue that cultural differences, methodological differences, sample size, and technological factors may explain differences in the study's results compared to those of earlier studies.

8. Conclusions and Implications

The study employed UTAUT2 theory, incorporating AI anxiety and attitude, to predict faculty behavioural intention to adopt AI tools for teaching and research. A hybrid PLS (partial least squares) structural equation modelling and ANN (artificial neural network) approach was utilised to analyse data collected from 376 faculties. The results of the study indicated that attitudes towards artificial intelligence tools and behavioural intentions to adopt were positively and significantly affected by performance expectancy, facilitating conditions, price value, and hedonic motivation. The predictor constructs identified as common across PLS-SEM and ANN results were performance expectancy and facilitating conditions, indicating that functional performance and requisite infrastructure play a vital role in the adoption of AI tools. The results of this study highlight the importance of attitude, performance expectancy, and facilitating conditions as key drivers of AI tool adoption. Since AI tools are becoming an integral part of teaching and research within the academic community, the results of this study provide crucial insights to aid adoption.

9. Theoretical Implications

This study adopts the UTAUT2 model to identify the factors influencing faculty members' attitudes towards AI tools in higher education. The results partially support the influence of UTAUT2 variables on attitude towards artificial intelligence tools. The study supports the influence of performance expectancy, price value, hedonic motivation, and facilitating conditions on the attitude towards AI tools. The UTAUT2 theory explains the role of factors such as performance expectancy, effort expectancy, facilitating conditions, price value, hedonic motivation, and habit in predicting behavioural intentions to adopt technology. This study adds and successfully validates attitude towards AI tools as an antecedent of behavioural intentions towards AI tools, thereby contributing to the theory of AI tool adoption. Furthermore, this study adds two novel variables in the existing UTAUT2 predictors, i.e. Job replacement anxiety and AI learning anxiety. Furthermore, this study examines the effects of these two novel variables on attitudes towards AI tools.

10. Managerial Implications

The results of this study provide useful insights to academicians, administrators and higher education faculty. This study found that facilitating conditions play an important role in the adoption of AI tools. This finding will aid administrators at higher education institutions in providing the infrastructure, tools, and training to faculty to effectively utilise AI tools for teaching and research. Furthermore, performance expectancy also plays an important role in the adoption of AI tools. This finding has implications for developers of AI tools, to make the tools as accurate as possible in light of perceptions regarding the authenticity of data generated by AI tools. If the accuracy of AI tools improves, it can lead to faster, broader adoption in the interests of faculty and students at higher education institutions.

11. Limitation and Future Research

There are several limitations in this study. First is with respect to the sample size. The first study included only 376 participants; a larger sample would improve the validity and generalizability of the results. A cross-country sample selection can enable cross-country comparisons. Secondly, this research has used a purely quantitative approach; future research in this area can consider utilising mixed-methods research to draw more meaningful insights into the adoption of AI tools in higher education. Since research on AI applications is at a very nascent stage, future studies can examine possible mediators such as attitude towards AI, trust in AI, and teaching self-efficacy. Moderators such as digital literacy, institutional support, and various demographic variables (e.g., age, qualification, gender) can be used to strengthen relationships among the proposed variables. Furthermore, UTAUT2 was used as an underlying theory in this study; further studies can introduce other technology adoption theories like the theory of planned behaviour (TPB), the technology-organisation-environment framework (TOE), the technology acceptance model (TAM), the innovation diffusion theory (IDT), or any possible combinations of the same.

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