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Artificial Intelligence Powered Pedagogy: Unveiling Higher Educators' Acceptance with Extended TAM

K. Kavitha[a], V. P Joshith[b]
[a]Central University of Kerala, India, [b]Central University of Kerala, India

Abstract

There is a growing prevalence of AI tools in the arena of higher education. The willingness and intentions of higher educators play a significant role in successfully incorporating these tools. This investigation extends the Technology Acceptance Model (TAM) to explore the multifaceted interplay among determinants shaping higher educators' intentions for employing AI tools in their professional and pedagogical domains. The data was gathered from 400 respondents, comprising educators holding positions ranging from assistant professors to professors within Indian HEIs. The investigation validated the TAM model's applicability using covariance-based systematic equation modeling (CB-SEM) and supported nine of the fifteen proposed hypotheses. Further, the investigation underscores the significance of fostering higher educators' competency and confidence in AI tools through focused training and support services. Additionally, it highlights the role of their inherent openness to be proficient in such novel technological advancements. This investigation advances the prevailing AI-strengthened pedagogical sphere of education.

Keywords: Artificial Intelligence, acceptance, Amos, CB-SEM, higher educators, TAM

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Introduction

Artificial Intelligence (AI) draws great global curiosity and attention since it profoundly brings astonishing features to our daily lives. The most recent and widely accepted definition of AI, as found in related literature, describes it as the ability of a computer or computer-controlled machine to comprehend, reason, and behave in a manner indistinguishable from human behaviour (Coombs et al., 2020; Enholm et al., 2022). With increased access to information and computational power, AI has become a transformative technology, fuelling innovation and revolutionising various sectors, from medical assistance in hospitals to robots in the automotive sector (Duan et al., 2019; Gursoy et al., 2019).

In recent decades, researchers have been exploring different ways of integrating AI technologies into the education environment (Cumming & Mcdougall, 2000; Lee & Yeo, 2022; K. Zhang & Aslan, 2021). This exploration has been reinforced by substantial investment, with global spending on AI-driven education reaching $1.047 trillion between 2008 and 2017 (Mou, 2019). The prominent investment reflects the expanding utilisation of AI technologies across educational domains, notably personalised academic support, constructive feedback, automatic assessment and grading systems, intelligent tutoring systems, and mental health support tools (Alqahtani et al., 2023; Martínez-Comesaña et al., 2023; Shvetcov et al., 2023; Spitzer & Moeller, 2023).

The latest advancements in educational AI, highlighted in the 2023 EDUCAUSE Horizon Report, spotlight the transformative impact of Generative AI (GenAI) and Predictive AI in higher education (Pelletier et al., 2023). Gen AI tools leverage cutting-edge algorithms to learn patterns and generate novel content, including texts, images, sounds, videos, and code, enhancing personalisation (Chan & Hu, 2023). For example, with ChatGPT, a form of GenAI and an AI chatbot specialised in generating text-to-text human-like conversations, students can accomplish high-quality tasks such as writing a 1000-word essay (Atlas, 2023), solving math problems, and composing music, all in under 30 seconds (Chiu, 2023). Another noteworthy GenAI tool, DALL-E, functions similarly to ChatGPT and produces digital photos as output (Open AI, 2023). Additionally, GenAI extends beyond student support, aiding in research tasks by generating and compiling knowledge, summarising a large quantity of text information, analysing data, and crafting manuscripts (Berg, 2023). In contrast, Predictive AI tools analyse learner data to identify at-risk students, devise personalised learning pathways for enhanced efficacy, and optimise the instructional design (Mozer et al., 2019; Nabizadeh et al., 2020; Ouyang et al., 2023; Taheri et al., 2021).

In the ever-evolving landscape of higher education, it is indispensable for educators to constantly keep up with novel technological integrations, which has become paramount (Mazman Akar, 2019). As AI tools are gaining prominence as a means of transforming this landscape (Crompton & Burke, 2023), understanding the motivations and intentions of higher educators in their adoption becomes crucial in navigating the challenges posed by the swiftly changing educational paradigm (Bearman et al., 2023). The rapid pace of technological change presents educators with opportunities and challenges as they strive to harness the potential of AI tools to optimise teaching, learning, and administrative processes. However, the complexity and diversity of AI tools require educators to navigate new terrain, necessitating a deep understanding of their motivations and intentions in adopting these technologies.

Moreover, gaining insights into higher educators' readiness supports the seamless integration of AI, directly impacting educational outcomes and nurturing learners for a technologically driven future. Within this realm, the Technology Acceptance Model (TAM) has long been a valuable framework (Dasgupta et al., 2002), focusing on factors such as perceived usefulness and perceived ease of use, particularly in the context of technology integration in teaching and learning (Salloum et al., 2019; Taha et al., 2022). However, AI tools' complex and diversified nature presents unique challenges and considerations that can only be partially captured with the traditional Technology Acceptance Model (TAM) framework within higher education settings. Unlike conventional technologies, AI tools often involve sophisticated algorithms and data-driven functionalities that require educators to possess specialised knowledge and skills for effective utilisation. Furthermore, AI tools offer a wide range of functionalities, from personalised learning experiences to data-driven insights and task automation, each with its own set of implications for teaching and learning in higher education settings (Celik et al., 2022; Maghsudi et al., 2021; Sghir et al., 2023). Therefore, expanding the TAM framework to incorporate five additional constructs, Personal Innovativeness (PI), AI Self Efficacy (AISE), Professional Excellence (PE), Perceived Privacy Concern (PPC), and Perceived Enjoyment (PE), is essential to comprehensively address the multifaceted nature of AI tool adoption in higher education. However, the successful incorporation of these tools depends on the willingness and intentions of higher educators to embrace this transformative technology, thereby informing the development of tailored strategies and interventions to support their effective integration into educational practice. The investigation is navigated through the subsequent research questions.

Research questions:

- What factors influence higher educators' intentions to employ AI tools?
- How do these factors influence higher educators' intentions to employ AI tools
- How do higher educators perceive AI tools' usefulness and ease of use in their professional practices?

Despite the growing popularity of AI tools, there is a noticeable gap in the literature regarding higher educators' intentions to employ AI tools (Kim & Kim, 2022; Tang et al., 2023; Wang et al., 2023). Understanding their perspectives is significant for educational technology developers, institutions, and policymakers in designing effective strategies that facilitate AI tool adoption. By expanding TAM, this investigation not only advances theory but also holds implications for educational stakeholders seeking to utilise the benefits of AI in higher education. Additionally, the investigation endeavours to offer critical insights that could guide the productive integration of AI tools in higher education by thoroughly investigating the various aspects that impact higher educators' intentions in this regard. Though the study is being conducted within the framework of the Indian higher education system, the determinants influencing educators' intentions to employ AI tools are likely to have broader relevance across diverse educational settings globally. The Indian higher education system shares similarities with its international counterparts in its focus on providing quality, accessible education, fostering research and innovation, and adapting to technological advancements (Saini et al., 2023). Additionally, being a diverse country, the challenges and opportunities associated with AI integration in education are not unique to India but resonate with educational contexts worldwide (Agarwal & Vij, 2024). Therefore, while the study findings are rooted in the Indian higher education system, they can be generalised to inform discussions and initiatives to promote AI adoption and utilisation in various educational contexts internationally.

Literature Review and Hypotheses Development

In recent years, integrating AI-powered tools into higher education has substantially transformed instructional strategies and learning processes (Cardona et al., 2023; Zawacki-Richter et al., 2019). This integration spans various realms, such as student admissions, personalised learning, and assessment (Memarian & Doleck, 2023). For instructional content optimisation and automatic recommendation systems, multiple AI algorithms have been utilised within higher education, including Sequential Pattern Mining (SPM) (Romero et al., 2013), Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) (Christudas et al., 2018). For instance, Moseley and Mead (2008) successfully employed a machine-learning decision tree model to forecast enrollment declines in nursing institutions. Moreover, AI technology has been leveraged in specific educational applications, such as virtual reality (VR) for history learning, designed by Ijaz et al. (2017), significantly improving learners' engagement. Zhao et al. (2019) found that the practical implementation of AI-based instruction benefited learners' academic achievements. Additionally, Xiao et al. (2022) proposed an AI-assisted Multi-Objective Decision-Making model (AI-MODM) to forecast the performance of educators in higher education systems, achieving an impressive precision ratio of 97.9%. These significant AI-powered technological shifts have raised important questions about educators' intentions regarding incorporating AI tools into the pedagogical landscape.

Regarding technology adoption, the Technology Acceptance Model (TAM) is a widely recognised theoretical framework, offering a solid theoretical basis for comprehending users' acceptance of technology in an educational context (Granić & Marangunić, 2019). Rooted in the foundations of the Theory of Reasoned Action (Fishbein, 1980) and the Theory of Planned Behavior (Ajzen, 1991), the TAM examines the factors influencing people's intentions to adopt technology. The TAM is beneficial when outlining how educators employ various technologies in different contexts (Dele-Ajayi et al., 2017). As further criticism of TAM had contributed to the model's development in subsequent investigations, more external variables were added to it, including the TAM2 (Venkatesh & Davis, 2000), the Unified Theory of Acceptance and Use of Technology – UTAUT (Venkatesh et al., 2003) and the TAM3 (Venkatesh & Bala, 2008). Despite the spectrum of TAM versions, the key variables- perceived usefulness (PU) and perceived ease of use (PEOU) were found to be the prominent determinants affecting the uptake of technology (Davis et al., 1989; Zhang et al., 2023).

Multiple investigations involving educators have been carried out in recent years by utilising various versions of TAM to explore the factors influencing their perceptions of different technologies across diverse contexts (Dele-Ajayi et al., 2019; Hong et al., 2021; Scherer & Teo, 2019; Teo, 2019). For instance, Al Darayseh (2023) utilised the TAM framework to explore science educators' attitudes toward AI application use in education, revealing teachers' solid acceptance of AI. The study found no significant differences in educators' intentions to employ AI in science education based on gender, teaching experience, or qualifications. Furthermore, other studies have also showcased the applicability of TAM in determining educators' intentions to deploy chatbots, augmented reality applications, and mobile technology (Asiri & El, 2022; Chocarro et al., 2023; Walker et al., 2020).

TAM enables researchers to incorporate potential external constructs influencing the adoption of a particular technology, as external are identified to determine both PU and PEOU (Al-Adwan et al., 2023; Moon & Kim, 2001; Zhang et al., 2008). In this investigation, we extended TAM by including five additional external constructs: Personal Innovativeness (PI), AI Self Efficacy (AISE), Professional Excellence (WE), Perceived Privacy Concern (PPC), and Perceived Enjoyment (PE), which are anticipated to profoundly impact Higher educator's Behavioural Intention (BI) to employ AI tools into their pedagogical landscape.

Personal Innovativeness (PI)

In general innovation diffusion studies, it has long been acknowledged that highly innovative people actively seek new information and tend to be more positive towards accepting it (Dibra, 2015; Lu et al., 2005). PI, as recognised by Agarwal and Prasad (1998), signifies an individual’s willingness to experiment with information or technology. Given the inadequate state of AI training, educators frequently rely on their initiative and research-driven inventive traits to explore and integrate new technologies (Hsiao & Chang, 2023; Nguyen et al., 2021). It is widely recognised that educators' unique innovativeness has a considerable impact on how they explore, embrace, and integrate new technology and instructional strategies (Frei-Landau et al., 2022; Uzumcu & Acilmis, 2023). Previous studies have established a notable correlation between PI and BI, PU, PEOU and Self Efficacy (Chen, 2022; Joo et al., 2014). Therefore, incorporating PI as a construct in this study provides valuable insight into educators' readiness to adopt AI tools and their potential impact on AI acceptance and utilisation. Consequently, the subsequent hypotheses are proposed:

H1: Higher Educators' PI significantly influences their PU in employing AI tools.

H2: Higher Educators' PI significantly influences their PEOU in employing AI tools.

H3: Higher Educators' PI significantly influences their BI in employing AI tools.

H4: Higher Educators' PI significantly influences their AISE in employing AI tools.

AI Self Efficacy (AISE)

Self-efficacy is often defined as one's perception of their level of competence (Bandura, 1977). AI Self-Efficacy (AISE) extends the concept of self-efficacy to the realm of AI technologies, representing individuals' judgments of their ability to effectively utilise AI tools (Wang et al., 2023). Given the significant impact of self-efficacy on constructs such as Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) in previous studies (Alharbi & Drew, 2019), the inclusion of AISE is crucial for understanding educators' readiness to adopt AI tools. Bandura and Locke (2003) assert that self-efficacy is positively correlated with personal behavioural actions and results, such as overcoming obstacles, striving for success, and eventually excelling in different domains of life. Considering the potential benefits of AI for educators in both learning and teaching, AISE plays a vital role in shaping educators' attitudes and behaviours towards adopting AI tools. Consequently, the subsequent hypotheses are proposed:

H5: Higher Educators' AISE significantly influences their PU in employing AI tools.

H6: Higher Educators' AISE significantly influences their PEOU in employing AI tools.

H7: Higher Educators' AISE significantly influences their PEx in employing AI tools.

Professional Excellence (PEx)

To achieve professional excellence in the context of adopting AI in academia, educators must possess the requisite knowledge, skills, and technology efficacy (Azad, 2017). AI can catalyse educators' professional excellence by offering tailored instructional resources to learners, automating administrative tasks, and supplying data-driven insights for optimising outcomes (Ghamrawi et al., 2023). Introducing the new construct, PE emphasises the importance of educators' competency and technology efficacy in effectively adopting and utilising AI tools in academic settings. Consequently, the subsequent hypotheses are proposed:

H8: Higher Educators' PEx significantly influences their BI in employing AI tools.

Perceived Privacy Concern (PPC)

In general, privacy concerns include worries about losing one's privacy and the necessity for protection against the misuse of personal information (Smith et al., 1996). Dinev and Hart (2005) found a negative impact of privacy concerns on the intention to use internet-based technology, indicating their significant influence on technology acceptance. This influence extends to AI technologies, where privacy concerns have been shown to affect perceived usefulness and acceptance (Dhagarra et al., 2020; Komatsu, 2013; Schomakers et al., 2022). AI's capability to collect, analyse, and retain vast amounts of personal data raises substantial privacy concerns, posing a critical obstacle to adoption (Walsh, 2023). Therefore, incorporating PPC as a construct in this study provides valuable insights into educators' perceptions and concerns regarding the privacy implications of AI adoption, which are essential considerations in their decision-making process. Consequently, the subsequent hypotheses are proposed:

H9: Higher Educators' PPC significantly influences their PU in employing AI tools.

H10: Higher Educators' PPC significantly influences their BI in employing AI tools.

Perceived Usefulness (PU)

The extent to which people believe using a particular technology enhances their performance is termed PU (Davis, 1989). This study outlines PU as the extent to which higher educators anticipate that deploying AI tools will enhance their professional and pedagogical expertise. Previous studies indicate that PU is the strongest predictor of the intention to use a potential technology (Rafique et al., 2020) in education (Adwan et al., 2018; Sprenger & Schwaninger, 2021). Consequently, the subsequent hypotheses are proposed:

H11: Higher Educators' PU significantly influences their BI in employing AI tools

Perceived Ease of Use (PEOU)

PEOU is the extent to which people perceive the technology as effortless to use, and it is supposed to have a beneficial impact on people's intentions about the technology's usefulness (Davis, 1989; Venkatesh & Davis, 2000). PEOU and PU are critical indicators of future technology adoption in various sectors, including education (Dhingra & Mudgal, 2019). This indicates that when educators perceive that a particular technology is beneficial in making teaching and learning more accessible and practical, they are more inclined to adopt it (Teo, 2011). Previous studies have also proved the significant influence of PEOU on PU and BI in the acceptance of technology in education (Chang et al., 2012; Rienties et al., 2016; Sánchez-Mena et al., 2017). Furthermore, when technology is easy and convenient, individuals seem to find it more enjoyable. Previous studies have found a significant correlation between PEOU and perceived enjoyment (Akdim et al., 2022; Davis et al., 1992; Wang et al., 2022). Consequently, the subsequent hypotheses are proposed:

H12: Higher Educators' PEOU significantly influences their PU in employing AI tools.

H13: Higher Educators' PEOU significantly influences their PE in employing AI tools.

H14: Higher Educators' PEOU significantly influences their BI in employing AI tools.

Perceived Enjoyment (PE)

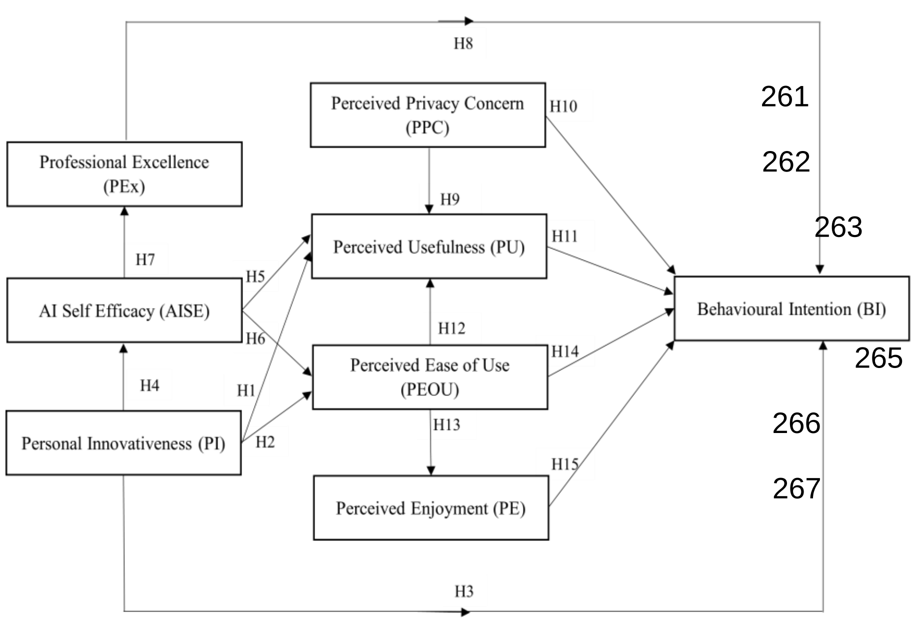
PE is integral in understanding individuals' intentions towards technology adoption, as it measures the degree of pleasure and fun an individual receives from a specific technology (Venkatesh, 2000). Research has shown that PE significantly influences individuals' technology adoption intentions, particularly regarding hedonic systems that offer pleasure or joy (Koufaris, 2002; Venkatesh et al., 2002). In the context of AI adoption in higher education, educators who perceive AI tools as enjoyable and capable of delivering thrilling outcomes are more inclined to dedicate effort towards their adoption (Bagdi & Bulsara, 2023; Humida et al., 2022; TURAN et al., 2022). Consequently, the subsequent hypotheses are proposed:

H15: Higher Educators' PE significantly influences their BI in employing AI tools.

The proposed research model for the investigation is displayed in Figure 1.

Figure 1

Proposed Research Model



Methodology

Research Approach

This investigation employed a quantitative research approach using a cross-sectional survey design. It selected covariance-based structural equation modeling (CB-SEM) to evaluate interconnected unobserved relationships among the study's constructs (Dash & Paul, 2021). This method was fitting because it assessed untested and tested constructs within the well-established TAM theoretical framework (Fussell & Truong, 2022).

Data Collection and Sampling

Following expert validation, refining phrases, and eliminating non-matching items, the final survey questionnaire was distributed during the last quarter of 2023 through in-person interactions and online via a Google form. Respondents were provided with detailed information about the purpose and objectives of the research and the procedures involved through a consent letter included at the beginning of the survey questionnaire. This ensured their voluntary participation and understanding of the research aims and procedures. The respondents comprised educators holding positions ranging from assistant professors to professors within Indian higher educational institutions. The data collection process followed strict ethical guidelines established by the Institutional Human Ethics Committee (IHEC), prioritising minimal collection of personal data beyond essential demographic information (Table 1).

Table 1

Respondents' profile summary (n=400)

	Category	***n***	**%**
Gender	Female	115	28.75
	Male	285	71.25
Academic Rank	Assistant Professor	220	55
	Associate Professor	126	31.5
	Professor	54	13.5
Stream of Specialization	STEM	156	39
	Arts/Humanities	72	18
	Social Science	110	27.5
	Management/Commerce	62	15.5

Experience with AI Tools	Limited	41	10.25
	Moderate	287	71.75
	Advanced	72	18
Frequency of employing AI tools in professional landscape	Not often	38	9.5
	Occasionally	295	73.75
	Regularly	67	16.75
	Always	-	-

The study's sample size was determined using Daniel Soper’s (2023) online sample size calculator, drawing from Cohen's (1988) and Westland's (2010) methodologies. The *a priori sample method for structural equation modeling* was employed to establish the minimum required sample size. Considering an estimated effect size of .3, a desired statistical power level of .8, 8 exogenous constructs, and 28 items at a .05 significance level, a minimum sample size of 177 was recommended. The study gathered data from 400 respondents employing the technique of convenience sampling, surpassing the required sample threshold. Hence, for evaluating a proposed theoretical model, a non-probability sample is often found to be appropriate (Hulland et al., 2018).

Survey Instrument

The survey instrument comprised an initial section presenting the study's purpose and seeking consent, followed by the first section dedicated to gathering demographic data. The next part contained 28 measurement items to analyse the model's factors. These constructs were evaluated through three to four indicator variables, following content validation by experts (Table 2), utilising a 5-point Likert scale extending from "strongly disagree" (1) to "strongly agree" (5).

Table 2

Research Constructs and Items

Constructs	Items	Questions
Professional Excellence	PEx1	AI tools are highly beneficial for enhancing my work and productivity
	PEx2	AI tools enable me to achieve high professional proficiency.
	PEx3	AI tools can potentially benefit the quality of my work.
	PEx4	By utilising AI tools, I can effectively and precisely complete my tasks.

AI Self Efficacy	AISE1	I have the resources and support to employ AI tools effectively.
	AISE2	I have the fundamental understanding and expertise to employ AI tools efficiently.
	AISE3	AI tools seamlessly integrate with the other technologies I employ
Personal Innovativeness	PI1	I enjoy consistently experimenting with new AI Technologies and Tools
	PI2	When I hear about a new AI tool, I try and improve it differently.
	PI3	I invest time and effort to keep myself updated with developments of the latest AI tools.
	PI4	I discuss and share ideas with my colleagues about the possibilities of AI Tools.
Perceived Privacy Concern	PPC1	I have worries about the potential misuse of my data when using AI tools.
	PPC2	I have concerns about my digital privacy while using AI tools.
	PPC3	I am sceptical about sharing my sensitive information with AI-powered tools.
Perceived Usefulness	PU1	Using AI tools significantly enhances my productivity and work efficiency.
	PU2	AI tools can offer helpful knowledge and suggestions for the tasks I undertake.
	PU3	I find AI tools to be an excellent asset in achieving my goals and objectives.
	PU4	AI tools enable me to complete tasks more quickly and effectively.

Perceived Ease of Use	PEOU1	Learning to use AI tools has been effortless for me
	PEOU2	I have access to the necessary resources for using AI tools.
	PEOU3	I have confidence in my skills and expertise to use AI tools efficiently.
	PEOU4	AI tools are relatively easy to use and do not require much effort.
Perceived Enjoyment	PE1	The experience of employing AI technologies never fails to captivate me.
	PE2	Using AI Tools adds an element of excitement to my profession.
	PE3	Accomplishing my tasks with the assistance of AI Tools is very satisfying.
Behavioural Intention	BI1	I plan on incorporating AI tools into my daily tasks more often.
	BI2	I am going to increase the usage of AI tools.
	BI3	I will be utilising AI tools in the future.

Data Analysis

The present investigation employed a two-step process (Anderson & Gerbing, 1988) to verify the proposed model framework. The model's reliability, validity, and fit are assessed in the first stage, followed by testing the hypotheses in the second stage using IBM SPSS 25 and Amos 22.

Results

Measurement Model – Reliability, Validity, and Model Fit Analysis

The data was initially examined through IBM SPSS Statistics 25 for missing information, uncommitted replies, and outliers. Following this, the normality assumptions of the data were confirmed using the Skewness and Kurtosis measures before continuing to the further estimates analysis of the measurement model (Kline, 2016) displayed in Figure 2. The measured skewness and kurtosis values were between the desirable ranges, ± 3 and ± 10 (Brown, 2006).

The measures of Cronbach's alpha (α) and Construct Reliability (CR) were used to assess the construct's reliability. The values of both the measures for each construct were found to be above the pre-determined limit of 0.7 (Hair et al., 2009; Lance et al., 2006), given in Table 3. Further, convergent and divergent validity measures were used to evaluate the validity of the constructs. Standardised factor loadings and Average Variance Extracted (AVE) values were measured to evaluate the constructs' convergent validity (Table 3). As Hair et al. (2009) outlined, the standardised factor loadings exceeded the pre-determined limit of 0.50. Similarly, as Fornell and Larcker (1981) outlined, the AVE measures exceeded the pre-determined limit of 0.5, ranging from 0.650 for PPC to 0.542 for PEOU.

Figure 2

The Measurement Model

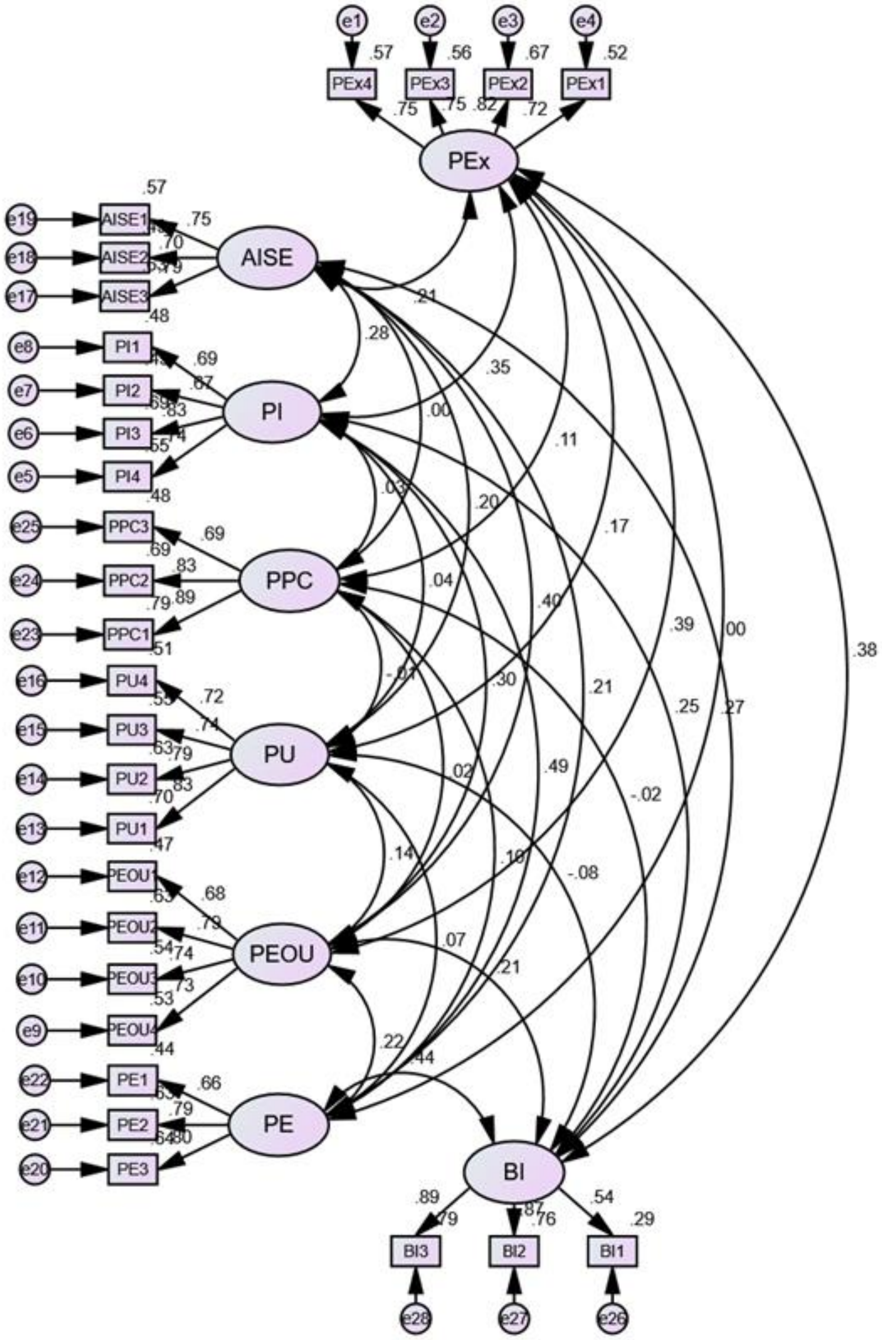


Table 3

Constructs	Items	Standardised Factor Loadings
Professional Excellence (PEx)	PEx1	0.724
(α= .845, CR=.846, AVE=0.578)	PEx2	0.817
	PEx3	0.748
	PEx4	0.753
AI Self Efficacy (AISE)	AISE1	0.755
(α= .789, CR=.794, AVE=0.563)	AISE2	0.700
	AISE3	0.793
Personal Innovativeness (PI)	PI1	0.695
(α= .821, CR=.825, AVE=0.543)	PI2	0.669
	PI3	0.830
	PI4	0.744
Perceived Privacy Concerns (PPC)	PPC1	0.887
(α= .841, CR=.845, AVE=0.650)	PPC2	0.831
	PPC3	0.689
Perceived Usefulness (PU)	PU1	0.835
(α= .848, CR=.854, AVE=0.595)	PU2	0.791
	PU3	0.739
	PU4	0.716
Perceived Ease of Use (PEOU)	PEOU1	0.682
(α= .823, CR=.825, AVE=0.542)	PEOU2	0.793
	PEOU3	0.736

	PEOU4	0.731
Perceived Enjoyment (PE) **(α= .791, CR=.796, AVE=0.567)**	PE1	0.661
	PE2	0.791
	PE3	0.799
Behavioural Intention (BI) **(α= .786, CR=.820, AVE=0.614)**	BI1	0.536
	BI2	0.874
	BI3	0.889

The construct's discriminant validity was evaluated using the Fornell and Larcker criterion (Fornell & Larcker, 1981) and the Heterotrait-Monotrait (HTMT) ratio (Kuppelwieser et al., 2019). As given in Table 4, all of the constructs adequately fulfilled the Fornell and Larcker criterion since each construct's square root of the AVE is higher than its correlation with other constructs. Additionally, as given in Table 5, all of the constructs confirmed the discriminant validity since the HTMT ratios were below the pre-determined limit of 0.85, as outlined by Henseler et al. (2015).

Table 4

Measurement Model - Discriminant Validity: Fornell - Larcker Criterion

Construct	PEx	AISE	PI	PPC	PU	PEOU	PE	BI
PEx	**0.760**							
AISE	0.207	**0.750**						
PI	0.351	0.283	**0.736**					
PPC	0.110	0.003	0.033	**0.806**				
PU	0.175	0.198	0.035	-0.090	**0.771**			
PEOU	0.387	0.402	0.303	0.016	0.137	**0.736**		
PE	0.272	0.212	0.494	0.097	0.066	0.317	**0.753**	
BI	0.381	0.038	0.247	-0.022	0.177	0.215	0.443	**0.783**

Note. Bold digits represent the square root of AVE

Table 5

Measurement Model - Discriminant Validity: Heterotrait - Monotrait Ratio

Construct	PEx	AISE	PI	PPC	PU	PEOU	PE
AISE	0.207						
PI	0.361	0.309					
PPC	0.088	0.037	0.032				
PU	0.185	0.208	0.059	0.041			
PEOU	0.390	0.409	0.330	0.055	0.153		
PE	0.264	0.218	0.511	0.074	0.273	0.312	
BI	0.381	0.023	0.288	0.189	0.385	0.210	0.431

In summary, the above-reported findings establish the constructs' reliability and validity. Further, the convergent validity results confirm the internal consistency of the indicators in measuring their respective constructs (Bagozzi, 1981), and discriminant validity results ensure that each construct in the study distinctly differs from other constructs (Ab Hamid et al., 2017).

The following fit indices: χ^2 divided by degree of freedom (CMIN/DF), root mean square error of approximation (RMSEA), comparative fit index (CFI), and parsimonious normed fit index (PNFI) were employed to evaluate the model fit using Amos. Further, the above-fit indices were categorised into three distinct groups as per the Hooper et al. (2008) classifications: absolute fit (CMIN/DF, RMSEA), incremental fit (CFI), and parsimonious fit (PNFI). The results reported in Table 6 confirm the model's fitness, implying that the exogenous constructs included in the proposed model could account for their influence on the endogenous constructs in determining higher educators' intentions for successfully integrating AI tools.

Table 6

Model's Fit Indices

Fit indices	Model fit indices	Recommended values	Sources
Absolute Fit Indices			
CMIN/DF	2.104	≤ 3	
RMSEA	0.051	≤ .05	(Cangur & Ercan, 2015; Hu & Bentler, 1999; Lin & Yu, 2023)
Incremental Fit Index			
CFI	0.931	≥ .90	

Parsimony Fit Index		
PNFI	0.746	≥ .50

Structural Model – Analysis and Hypothesis Testing

The structural model displayed in Figure 3 was further evaluated before proceeding with the hypothesis testing. Initially, by using the following fit indices: CMIN/DF = 2.151, RMSEA= 0.049, CFI=0.956, and PNFI = 0.753, the structural model was found to have an appropriate fit as per the recommended values from the sources given in Table 6.

In the subsequent step, the hypothesised structural relationships were tested using the standardised path coefficients (β) (Jang et al., 2021; Mueller & Hancock, 2018), as reported in Table 7. Nine of the fifteen hypotheses tested were supported and had standardised path coefficients ranging from 0.159 to 0.386. The hypotheses H2, H4, H6, H7, H8, H13 and H15 were supported at 0.001 significance level, and H5 and H11 were supported at 0.01 significance level. The path within PU to BI had the lowest standardised path coefficient (β = 0.159), whereas the path within PE to BI had the highest significant path coefficient (β = 0.386). Moreover, the following hypotheses, H1, H3, H9, H10, H12 and H14, were not supported since they were not significant either at 0.001 or 0.01 levels of significance.

Figure 3

The Structural Model

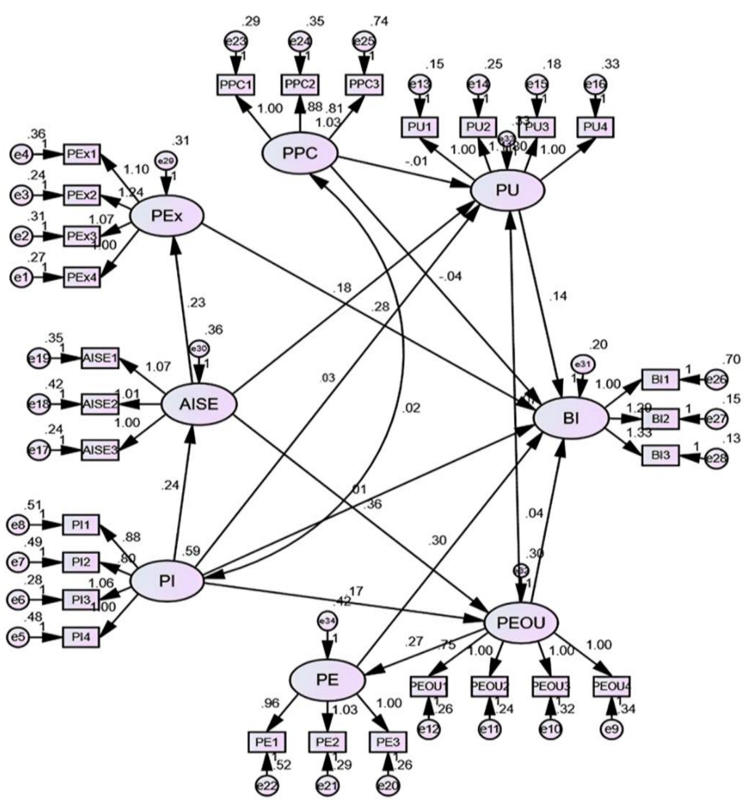


Table 7

Results of Hypothesis Testing

Hypothesis	β	95% CI	*p*-Values	Decision
H1: PI → PU	0.045	(-.201 - .108)	0.458	Not Supported
H2: PI → PEOU	0.210	(.069 - .337)	***	**Supported**
H3: PI → BI	0.014	(-.140 - .118)	0.797	Not Supported
H4: PI → AISE	0.298	(.179 - .434)	***	**Supported**
H5: AISE → PU	0.194	(.053 - .336)	0.004**	**Supported**
H6: AISE → PEOU	0.362	(.217 - .512)	***	**Supported**
H7: AISE → PEx	0.250	(.105 - .388)	***	**Supported**
H8: PEx → BI	0.313	(.199 - .411)	***	**Supported**
H9: PPC → PU	-0.010	(-.114 - .097)	0.856	Not Supported
H10: PPC → BI	-0.084	(-.188 - .007)	0.090	Not Supported
H11: PU → BI	0.159	(.072 - .279)	0.002**	**Supported**
H12: PEOU → PU	0.070	(-.111 - .268)	0.292	Not Supported
H13: PEOU → PE	0.247	(.088 - .404)	***	**Supported**
H14: PEOU → BI	0.042	(-.096 - .184)	0.459	Not Supported
H15: PE → BI	0.386	(.251 - .506)	***	**Supported**

Discussion

The present investigation examines multiple determinants influencing higher educators' intentions to employ AI tools in their pedagogical and professional domains. Expanding upon TAM, this study performed CB-SEM analysis with fifteen hypotheses to validate the proposed pertinent determinants in the model. The analysis showed a significant influence of PI on higher educators' PEOU and AISE in employing AI tools. This finding implies that educators' attitudes and personal traits, particularly their inherent openness to new technological advancements, significantly impact their perception and self-efficacy regarding AI tools (Gökçearslan et al., 2022;

Vidergor, 2023). Further, the AISE of higher educators was a significant determinant of PU, PEOU and PEx in employing AI tools. This highlights the role of competence and confidence of educators in shaping their perception of the usefulness and ease of utilising AI tools, along with enhancing their professional performance (Kulviwat et al., 2014; Sharma & Saini, 2022). Moreover, it underscores the need to foster educators' self-efficacy by providing appropriate training, support, and opportunities to develop the essential skills and confidence to employ AI tools effectively. Additionally, PEx and PE significantly affected higher educators BI in employing AI tools. Besides the practical advantages, the results emphasise the importance of enjoyable experiences with AI tools in driving educators to employ them in their professional and pedagogical domains.

In line with earlier studies (Georgiou et al., 2023; Koutromanos et al., 2023), the present investigation has demonstrated the significant role of PU in determining higher educators' BI in employing AI tools. However, in contrast to other studies (Nikou & Economides, 2019; Rafique et al., 2023), PEOU had an insignificant influence on PU and BI (Utami et al., 2022). This can be explained by prioritising the practical merits of AI tools over their ease of use. This preference may also arise from higher educators' limited familiarity with AI tools, causing them to focus more on the advantages offered by this advancing technology rather than considering how user-friendly it is, especially during this early stage of development and exposure. Even though ease of use does not directly influence their choices about usefulness or intention to employ AI tools, it does play a substantial role in their overall satisfaction or enjoyment in employing them, as indicated by the notable effect of PEOU on PE.

The negligible effect of both PI and PPC on PU and BI conforms with educators' preference for practical benefits in deciding their intentions to use AI tools. Additionally, educators may prioritise noticeable benefits above privacy concerns or individual innovativeness while evaluating the use of AI tools during this early exposure and advancement period. These findings underscore the need for additional studies to give further information regarding these insignificant relationships.

Implications, Limitations and Direction for Future Research

The present investigation has unveiled significant insights into the determinants impacting higher educators' intentions to employ AI tools, offering substantial implications. Based on the findings, prioritising faculty development initiatives becomes pivotal, focusing on enhancing higher educators' receptiveness towards current technological advancements and boosting their confidence in effectively utilising AI tools (Rott et al., 2022). Additionally, recognising the significant role of educators' competence and confidence (AISE) in shaping their perspectives on the usefulness, ease of use, and professional excellence associated with AI tools, targeted support and skill development programs should be developed both at the national and institutional level to foster educators' self-efficacy (Seufert et al., 2021). Furthermore, to address the inclination of educators to prioritise the practical benefits of AI tools over their ease of use, it is crucial to devise additional collaborative strategies that emphasise the practical advantages and effectiveness of such tools, aligning with educators' preferences and decision-making processes (Nikiforos et al., 2020; Prieto et al., 2018). Moreover, investments in refining and developing easy-to-use user interfaces are essential to ensure user-friendly experiences (Meske & Bunde, 2022; Stige et al., 2023), ultimately enhancing educators' overall satisfaction with AI tools. The study also signifies the need for a national-level policy to establish and ensure robust privacy protocols and inclusivity in AI integration within the education domains (Chan, 2023; Kazim & Koshiyama, 2021) despite the observed negligible impact of PPC on BI and PU. Furthermore, the research findings underscore the importance of fostering a culture of innovation and collaboration within academic institutions, encouraging the sharing of best-responsible practices and facilitating the integration of AI technologies into teaching and learning practices.

Even though this investigation provides valuable information about the determinants impacting higher educators' employment of AI tools in their professional and pedagogical domains, additional research is still needed to acknowledge the limitations and enhance the applicability of these findings. Instead of the present cross-sectional design, a longitudinal investigation can potentially be undertaken to offer a thorough understanding of the way the attitudes and intentions of higher educators change over time with AI. Furthermore, the effects of diverse mediating factors, including gender, can be explored in future investigations. Hence, the sole basis of the present investigation was the higher educators' prior experience in employing AI tools. Subsequent experimental and comparative investigations can explore the potential role of specific AI tools in higher educators' professional and pedagogical domains. Building on the significance of Professional Excellence (PEx) and Perceived Enjoyment (PE) uncovered in this study, future research should consider these constructs when examining AI tool adoption across different educational levels, including teacher education. Additionally, investigations can be made into specific AI tools' roles in educators' professional and pedagogical domains, which could provide valuable insights. Furthermore, exploring the impact of institutional contexts, such as organisational culture and leadership support, can significantly promote AI integration. By incorporating these recommendations into future research endeavours, we can deepen our understanding of AI integration in education and contribute to informed decision-making and practice in the field.

Conclusion

The growing prevalence of AI in education marks a paradigm shift in instructional approaches and pupil engagement (Gill et al., 2024). However, the successful integration of this groundbreaking technology heavily relies on the willingness and intentions of higher educators to embrace this transformative technology in their professional and pedagogical spheres. Expanding upon TAM, this investigation provides insightful information on the multifaceted interplay among determinants shaping higher educators' intentions for employing AI tools in their pedagogical and professional domains. The significant influence of PI on PEOU and AISE, underscored in the investigation, highlights the importance of higher educators' inherent openness to be proficient in new technological advancements. Notably, the emergence of educators' AI self-efficacy as a key determinant in influencing their perceptions of usefulness, ease of use, and professional excellence underlines the significance of fostering educators' competency and confidence in AI tools through focused training and support services. Further, the notable path from PEx and PE to BI emphasises the importance of enjoyable experiences with AI tools in driving higher educators to employ them. Additionally, the investigation found the substantial influence of PU over PEOU on the BI of higher educators in employing AI tools. Moreover, the negligible effect of both PI and PPC on PU and BI underscores the need for future studies to explore additional factors regarding these insignificant relationships.

With the more technologically proficient evolving generations, Gen Z and Gen Alpha (Chan & Lee, 2023; Jukic & Skojo, 2021), it has become a crucial need for higher educators to get acquainted with the upcoming technological advancements, including AI. In this context, this investigation contributes to the existing TAM literature by evaluating the model's suitability in exploring the multifaceted interplay among determinants shaping higher educators' intentions for employing AI tools. Meanwhile, the implications of these findings reach policymakers, higher educational bodies, institutions, and policymakers, signifying the need to balance privacy concerns, practical benefits, and higher educators' perceptions to facilitate effective implementation and utilisation of AI tools in educational settings.

Further, as the integration of AI in education becomes increasingly prevalent across various educational levels, including K-12, vocational training and teacher education (Akgun & Greenhow, 2022; Hui, 2020; Schmidt-Crawford et al., 2023), the insights gained from this investigation can inform strategies for AI adoption and utilisation in these settings. While the study specifically focuses on higher educators' intentions to employ AI tools, the underlying determinants identified, such as perceived usefulness, ease of use, and professional excellence, may also apply to educators in other contexts. Additionally, the significance of factors like personal innovativeness and perceived enjoyment suggests broader implications for understanding technology adoption among educators across different educational levels. By considering the transferability of these findings, policymakers, educational institutions, and stakeholders can adapt strategies and interventions to effectively integrate AI tools into diverse educational contexts, ultimately enhancing teaching and learning outcomes on a broader scale.

Conflict of Interest

The author(s) disclose that they have no actual or perceived conflicts of interest. The authors disclose that they have not received any funding for this manuscript beyond resourcing for academic time at their respective university. Except for grammar correction, citations, and references handled with Grammarly and Mendeley software, the author did not use any other AI technologies in the ideation, design, or writing of this research, as per Crawford et al. (2023). The authors list the following CRediT contributions: K. Kavitha: Conceptualization, Methodology, Data curation, Writing- Original draft preparation, Software, V. P Joshith: Supervision, Software, Validation, Reviewing and Editing

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