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Research Article

Understanding artificial intelligence adoption in higher education: An SEM-based evaluation of readiness and relevance

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ABSTRACT

The advent of artificial intelligence (AI) has had a profound impact on the education sector, resulting in a transformative change in higher education worldwide. One such change is the usage of AI tools by teachers to enhance their teaching practices, including content creation, sharing, and personalized learning. Those certain obstacles persist for teachers while fully exploring the potential of AI and its adoption in teaching practices. An extensive review of the literature revealed a significant research gap in developing a comprehensive study to examine the influence of AI relevance and its readiness, performance expectancy (PE), and effort expectancy (EE) in shaping behavioral intention (BI) for AI adoption in teaching. Therefore, drawing cues from the unified theory of acceptance and use of technology a research framework was developed to examine these intricate relationships. We gathered data by administering a survey to higher education teachers across various educational organizations in India. Structural equation modeling (SEM) was employed to analyze the collected data and test the hypothesized relationships. The results uncovered a positive association between teacher's perceptions of AI's relevance and their readiness to adopt AI, with both factors positively influencing their BI. Furthermore, this study found that EE exhibited a significant positive effect on both BI and PE. This study discusses theoretical and practical implications, underscoring the importance of raising awareness about AI's relevance, and lays the groundwork for further exploration in this emerging area, intending to inform strategies and interventions to support successful AI adoption in educational organizations.

Keywords: artificial intelligence, AI adoption, relevance, readiness, SEM, higher education

INTRODUCTION

Technological innovation has a significant impact on many aspects of modern society, including education. The fifth generation is the Internet of things currently being implemented in education. There is a growing demand to include artificial intelligence (AI) applications in teaching and learning processes (Hwang & Tu, 2021; Pasupuleti & Thiyyagura, 2024). The attitudes of teachers toward new instructional strategies play an important role in their successful adoption. Despite execution, some teachers remain negative about using technology in the classroom (Wozney et al., 2006). This group prefers to use traditional teaching materials and approaches rather than technological applications. Teachers' efforts to incorporate technology into their educational practices may be affected by issues related to using emerging methods (Hébert et al., 2021). The teacher-focused approach aligns with studies recognizing their central role in successfully educating youth on emerging disciplines like AI (Jain & Raghuram, 2024; Trotsko et al., 2019). Considering the potential benefits, smart technologies are rarely used in K-12 schools (Pierce & Cleary, 2016). However, most K-12 AI education research in Africa focuses on learners rather than instructors, representing a gap that needs to be addressed (Aruleba et al., 2022). Overall, further investigation into teacher readiness to implement AI curricula is essential across diverse settings to promote global AI literacy.

There is growing interest in leveraging AI to enhance teaching and learning outcomes (D'Mello & Graesser, 2012). Bates et al. (2020) found that much of the applications and research in the educational application of AI did not offer the desired benefits and changes. Other researchers also found supportive results to these findings, including AI quality, user preferences, and ethical issues (König et al., 2023; Pasupuleti & Thiyyagura, 2024). One important aspect would be the emphasis placed in the educational sector on a techno-centric approach. This method emphasizes the significance of AI while disregarding the agency of educators, who play an important role in deciding what, when, and how AI technologies are used (Sanusi et al., 2024). Teachers are important players in the successful implementation of AI in schools because they serve as an interphase between student needs and school AI policy (Cingillioglu et al., 2024). Many teachers might still be unprepared for AI-enhanced instruction even though they are aware of the potential advantages of AI.

Teachers who are exceptionally ready for AI are generally considered to possess the knowledge and skills needed to reimagine their profession by investigating and adjusting to the opportunities presented by AI (Dahri et al., 2024; Shaikh et al., 2021). These innovative attempts may improve their work experience, leading to higher job satisfaction (Woodruff et al., 2023). Individuals with poor levels of AI readiness (RedAI) may feel threatened, express concerns about potential interruptions to their work, and hence alienate themselves from AI technology (Molefi et al., 2024; Ramadhani et al., 2022). While a high level of RedAI is regarded as critical for effective incorporation of AI into teaching (Cingillioglu et al., 2024), there is no empirical evidence on how RedAI affects instructors' work. Furthermore, little is known about whether and how RedAI differs among teachers from different demographic backgrounds, especially in the context of gender and socioeconomic status, which have frequently been linked to disparities in the use of traditional technologies (Chakraborty & Al Rashdi, 2018; Tarhini et al., 2024). The importance of AI has grown significantly, particularly since the closing of educational institutions caused by the COVID-19 epidemic. The many functions that AI plays in the teaching-learning process and its varied components indicate a significant and palpable impact on both current and future learners (Mahmoud, 2020). The key developments that have evolved because of this integration have made it easier for students and teachers to access information. As a result, including AI applications into curriculum design, teaching methods, and evaluations is critical for achieving successful learning outcomes (Eltabakh, 2019). Therefore, the present research focused on:

1. What are the direct and indirect relationships between AI relevance (RelAI), RedAI, performance expectancy (PE), effort expectancy (EE), and teachers' behavioral intention (BI) to use AI in higher education?
2. How do EE and PE mediate the relationship between RedAI and teachers' BI to adopt AI for academic purposes?
3. To what extent does the perceived RedAI influence teachers' BI to use AI, both directly and indirectly through RedAI?

THEORETICAL FRAMEWORK

The current research presented the theoretical framework under two headings namely technology acceptance model (TAM) and unified theory of acceptance and use of technology (UTAUT).

Technology Acceptance Model

The TAM stands as a crucial theoretical framework for understanding how individuals adopt new technologies. Developed by Davis (1989), this model identifies two fundamental factors that shape technology acceptance: perceived ease of use and perceived usefulness. An individual's desire to accept new technology is directly determined by these characteristics. In the sphere of education, TAM has proven to be quite useful in studying how teachers approach and use new tools in their work (Scherer et al., 2019). What gives the model its enduring relevance is its adaptability and consistent ability to explain technological adoption behaviors in a range of circumstances. TAM provides an excellent foundation for analyzing faculty readiness and acceptability of these novel tools as AI becomes more common in education (Aburagaga et al., 2020). TAM has been shown to be effective in predicting instructors' intentions to use AI-based technology in a few studies. Ayanwale et al. (2022), for instance, employed TAM to look at the views of instructors regarding the applications of AI in higher education. The TAM was also applied by Nikou and Economides (2019) to look into what factors affect teachers' usage of mobile-based assessments in STEM education. Chocarro et al. (2021) studied about chatbots and found that formal language aspirations encourage using chatbots in education.

In addition, a number of studies have proved that TAM is a reliable indicator of teachers' adoption of other emerging technologies, including the metaverse, augmented reality, and e-learning platforms (Asiri & El Aasar, 2022; Aburbeian et al., 2022). Technology adoption among teachers was highly predicted by the combination of TAM components such PE, social influence, and EE (Lew et al., 2019). Teachers must have basic knowledge and understanding of AI adoption (AlKanaan, 2022). Targeted training facilitates incorporation into routine instruction and reduces related challenges (Cheok et al., 2017). Across different grades and disciplines, AI-assisted instruction has already demonstrated encouraging learning increases (Cukurova et al., 2021; Topal et al., 2021; Zhao et al., 2019). Teachers also favorably perceive their prospects in science education (Lin & Liu, 2024; Zhang et al., 2023). However, continuous teacher education and customized support remain essential considering most find AI concepts abstract currently (Shin & Shin, 2020).

Unified Theory of Acceptance and Use of Technology

The UTAUT, initially proposed by Parameswaran et al. (2015) and further refined in UTAUT2 (Singh et al., 2023), remains a cornerstone framework for understanding technology adoption across diverse contexts. This comprehensive model synthesizes eight acceptance theories, identifying four pivotal constructs: PE, EE, social influence, and facilitating conditions. In educational technology research, UTAUT has demonstrated robust predictive power, explaining up to 70% of the variance in adoption intentions (Birch & Irvine, 2009). UTAUT is continues to be relevant for assessing faculty adoption of cutting-edge teaching technologies, as indicated by recent studies that effectively applied it to developing technologies in education, such as AI tools and adaptive learning systems (Huang et al., 2023; Kim & Lee, 2022).

By extending the UTAUT, Wang et al. (2023) identified the factors that affect students' acceptance of mobile learning and BIs. To find out what factors affect the use of instructional technology at the school level, Mohamed and Hassan (2023) used UTAUT. Raffaghelli et al. (2022) evaluated responses beyond the phases of creation and testing to see how well students in a completely online university embraced an early warning system. This study employs a pre- and post-usage experimental design based on the UTAUT and structural equation modelling (SEM). The disconfirmation effect on the results showed differences in expectations before and after usage. The study offers insights into the integration of AI technology and emphasizes the importance of a nuanced approach in higher education virtual classrooms. Park and Lee's (2021) study evaluated the reliability of online education services and examined at how it impacted college students' admission intentions using the SERVQUAL technique. Using the UTAUT model, the study uncovers favorable connections between acceptance intentions and sub-factors related to the quality of online education services. Nalluri et al. (2023) set out to create a model based on the UTAUT and TAM in order to gain a better understanding of the decision-making process in higher education. In order to investigate their impact on learning management systems (LMS) use and student intention in the Saudi higher education system, Alshehri et al. (2020) combine UTAUT and usability measures. In the Saudi LMS context, the results validate the reliability and validity of UTAUT variables.

With an emphasis on academic achievement, Al-Rahmi et al. (2020) employed the UATUT to investigate social media use in higher education and its effects on students' lives. The UTAUT paradigm was expanded by Almaiah et al. (2019) to investigate the factors influencing 697 university students' adoption of mobile learning applications in higher education. Using the UTAUT paradigm, Lin et al. (2013) investigated the uptake of e-learning in businesses and academic institutions. In order to better understand the uptake of mobile learning in higher education systems in emerging nations, Thomas et al. (2013) examined extended versions of the UTAUT model. The study evaluates how much and in which direction BIs to adopt mobile learning are impacted by UTAUT features. Whereas UTAUT has repeatedly been able to predict the adoption of digital tools, AI apps are different in essential aspects warranting the inclusion of domain-specific constructs. For one, AI embeds an aspect of autonomy and opaqueness: teachers cannot really foresee outputs, and hence issues like accuracy, ethical use, and accountability set it apart from earlier EdTech like LMS. Two, AI adoption also assumes a threshold of readiness–connectivity to AI infrastructure, digital literacy, and organizational support. Without readiness, positive expectations cannot convert to adoption. Third, in AI applications, relevance comes into focus: teachers accept AI only when they perceive obvious pedagogical benefits and correspondence with instructional objectives. This is different from older technologies where usefulness was more inherent. Thus, the addition of RelAI and RedAI signifies not just an expansion but a theoretical need to encompass the distinctive logic of adoption in AI applications in education. Hence, The UTAUT model's constructs of PE, EE, and BI align well with the AI adoption context, justifying their inclusion alongside AI-specific constructs like the RelAI and RedAI. Integrating established technology acceptance factors with domain-specific AI factors can provide a comprehensive understanding of teachers' adoption of AI in higher education, leveraging UTAUT's proven applicability across educational settings.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Recent Developments of Artificial Intelligence in Education

Recent literature emphasize that AI is driving a paradigm shift in higher education globally (Anjali & Sreerekha, 2024). Research emphasizes that AI technologies are transforming fundamental practices in teaching, evaluation, and research while offering chances and ethical dilemmas for instructors and institutions (Yadav, 2024). Fuchs and Aguilos, (2023) points out that the successful integration of AI involves not only technological but also algorithmic literacy, along with systematic guidelines and teacher training. Excessive use of AI, nonetheless, threatens to dilute academic proficiency and teamwork, making balanced adoption measures more crucial (George & Wooden, 2023). Wu et al. (2025) integrates findings of 99 studies, which indicate general acceptance of AI across students and teachers, who appreciate its ability for individualized learning and instant feedback. However, serious concerns remain over data protection, bias in algorithms, and the potential to deepen digital inequities. Klimova et al. (2025) highlight the need for institutions to ensure human-centered pedagogy while benefitting from AI's potential for personalized and democratized learning. Policy-oriented scholarship recommends that universities are called to transition from reactive, integrity-based frameworks to proactive, comprehensive models that cover culture, regulation, access, familiarity, and trust the CRAFT model (Vartiainen & Tedre, 2023). This change guarantees that integration of AI promotes academic excellence, equity, and ethical strength, basically reshaping the delivery of higher education in an AI era.

Hypotheses Development

Several researchers have primarily focused on the direct association between literacy related to AI and readiness, rather than investigating the relationship between RedAI and relevance (AlGerafi et al., 2023; Essel et al., 2024). Notably, AI literacy has been discovered to be a strong predictor of students' readiness to learn (Singh and Singh, 2021), highlighting the significance of awareness or literacy in determining RedAI education. Davis (1989) stated that learners' openness to learning is influenced by the usefulness of information science and perceived relevance. Hence, we hypothesize as follows:

H1. Teachers' perceptions of the RelAI technologies in their teaching practices will positively influence their perceptions of RedAI.

Researchers have found that individuals' desire to learn is influenced by elements such as the expectation of positive outcomes, the attractiveness of the expected results, and the controllability of learning outcomes and behavioral processes (Dahri et al., 2024). The AI importance in determining BI is consistent with the first and second factors identified by Acquah et al. (2024). Dai et al. (2020) argued that learners cannot attach significance to AI unless they have sufficient knowledge about it and an awareness of what an AI-infused future entails. Hence, we hypothesize as follows:

H2. Teachers' perceptions of the RelAI technologies in their teaching practices will positively influence their BI.

The non-academic application of AI demonstrates how relevance influences preparedness to engage with AI tools, as evidenced in a study on online retailers who consider relevance when giving AI-based recommendation services to clients (Yoon & Lee, 2021). The question of whether the RelAI can predict teachers' readiness to use AI in educational establishments is worth addressing. This consistent optimism is expected to forecast BI toward AI (Mhina et al., 2019).

H3. Teachers' perceptions of their RedAI technologies will positively impact their BI.

Researchers worldwide have recognized several stages in the learning process of students and teachers as they become acquainted with and confident in using information and communication technology (ICT) (Yee & Abdullah, 2022). Users are often encouraged to adopt new technology when they see it as beneficial in their daily lives (Appana et al., 2025; Gu et al., 2021). Users who have been exposed to past approaches and experiences in task execution over time have devised strategies to overcome current problems (Bervell & Umar, 2017). The impact of EE on the acceptability of new technology is particularly obvious in the early phases of its introduction (Al-Amri & Al-Abdullatif, 2024). De Smet (2024) developed a direct relationship between PE and EE. According to the concept, EE positively promotes PE, implying that when both potential and existing customers as simple to use and access, they have high expectations for the expected outcome. Zhou et al. (2010) expanded on this by combining the task-technology fit model with UTAUT to provide a model for m-banking user adoption, Utomo et al. (2021) proved this relationship in mobile health care applications. Their findings underscored that EE has a substantial influence on PE.

Educator attitudes regarding using technology in the educational process have a substantial influence on establishing meaningful usage of computer technology in education. While teachers' ICT views are not the only factors impacting their intention to use ICT for learning and teaching, they are influential (Prestridge, 2012; Semerci & Aydin, 2018). This reinforces the assumption that technology's EE of use adds to its BI and incorporation in educational settings.

H4. EE will have a significant positive effect on teachers' PE to adopt AI technologies in their teaching

H5. EE will have a significant positive effect on teachers' BI to adopt AI technologies in their teaching.

PE is a variable that measures users' expectations about how using a system would improve their work performance (Pardamean & Susanto, 2012; Yee & Abdullah, 2022). The integration of technology into education is well recognized for its ability to support high-quality teaching and learning outcomes. The greater the perceived benefit of using a specific technology, the more likely a potential user is to embrace and employ it (Pasupuleti & Seshadri, 2023). When course tutors utilize LMS for blended learning, they have a more positive attitude about LMS if they believe the LMS is effective (Bervell & Umar, 2017). As a result, the amount of PE relates favorably with the BI desire to adopt LMS technology.

H6. PE will have a significant positive effect on teachers' BI to adopt AI technologies in their teaching.

Figure 1 depicts the proposed research model.

DATA ANALYSIS AND RESULTS

The current research employed SPSS version 26 and AMOS version 21 software programs. This study utilized SEM, as described by Lin and Liu (2024), to assess the validity and reliability of the constructs, as well as to examine the proposed hypotheses and models.

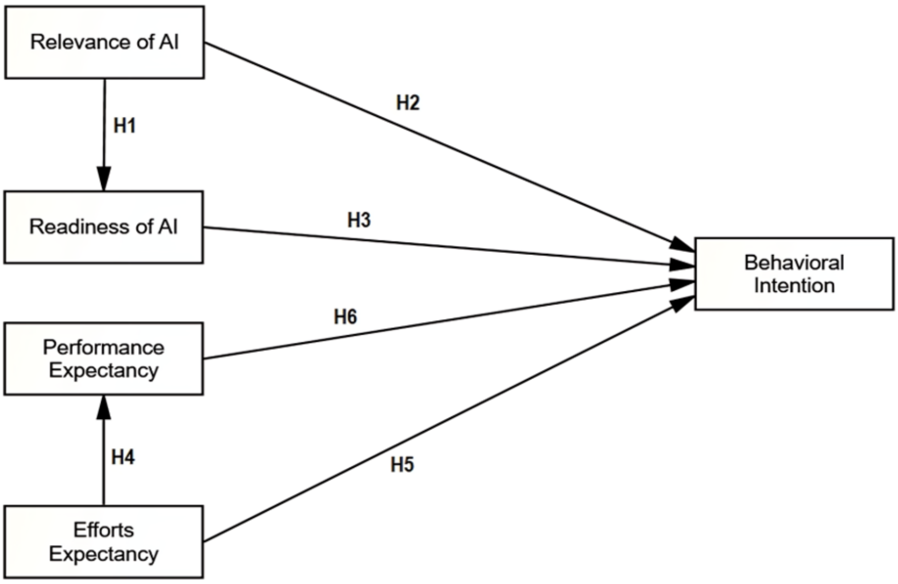

Figure 1. Proposed conceptual model developed by the authors

Table 1. Respondents' demographic characteristics

Measure	Item	Frequency (n)	Percentage (%)
Gender	Female	116	40.8
	Male	168	59.2
Age (in years)	Below 30	54	19.0
	30 to 39	121	42.6
	40 to 49	88	31.0
	50 and above	21	7.4
Educational qualification	Post-graduation	169	59.5
	PhD	107	37.7
	Post Doc	8	2.8
Department	Engineering (CSE, ECE, etc.)	117	41.2
	Basic sciences & humanities	55	19.4
	Under-graduation (BSc, BA, etc.)	94	33.1
	Post-graduation	18	6.3
Teaching experience (in years)	Below 5	25	8.8
	5 to 9	117	41.2
	10 to 19	90	31.7
	20 and above	52	18.3

Data Collection

In the prior research, the sample size depends on varies factors such as the number of latent indicators and variables, complexity of the model, desired statistical power, and effect sizes (Pasupuleti & Thiyyagura, 2024). Kline (2011) proposed that a minimum of 200 respondents should be recruited to take part in such studies. Kock and Hadaya (2018) also recommended 5:1 or 10:1 ratio for sample size to indicators, or sometimes 100 to 200 observations. For the present study 22 indicators are utilized hence a sample size of 220 observations is deemed necessary. The survey was conducted via an online Google Form and disseminated through emails, as well as shared on different online platforms, including WhatsApp and Facebook groups to the author's known higher education teachers where the authors are currently working. Participants were requested to respond to the survey and further circulate it among their respective networks. This survey was conducted in early February 2024 in India. Respondents were provided with informed consent and were informed of their option to discontinue the questionnaire at any time (**Appendix A**). The survey remained open until February 2024 and garnered 284 valid responses. **Table 1** presents respondents demographic information in this study.

Indicators for the RedAI construct were sourced from Woodruff et al. (2023), while those for constructs RelAI and BI were sourced from Mhina et al. (2019). UTAUT constructs EE and PE were adopted from

Table 2. Construct reliability and convergent validity

Construct	Indicator	Mean	Standard deviation	Factor loading	Composite reliability	Cronbach's alpha	AVE
RedAI	RE1	3.56	1.019	0.724	0.861	0.857	0.608
	RE2	3.58	0.896	0.789			
	RE3	3.50	0.938	0.791			
	RE4	3.46	0.945	0.812			
RelAI	RA1	3.73	0.981	0.793	0.824	0.775	0.61
	RA3	3.55	1.061	0.791			
	RA4	3.35	1.067	0.759			
PE	PE1	3.52	1.058	0.787	0.852	0.849	0.591
	PE2	3.83	0.980	0.657			
	PE3	3.88	1.115	0.799			
	PE4	3.90	1.028	0.821			
EE	EE1	3.74	1.018	0.783	0.851	0.85	0.588
	EE2	3.76	0.986	0.802			
	EE3	3.56	1.043	0.76			
	EE4	3.82	0.950	0.72			
BI	BI1	3.59	0.953	0.728	0.825	0.822	0.541
	BI2	3.58	0.876	0.744			
	BI3	3.66	0.861	0.776			
	BI5	3.52	0.895	0.692			

Venkatesh et al. (2003). Five-point Likert scale was utilized to rate respondents' disagreement or agreement, ranging as 5 (strongly agree) to 1 (strongly disagree). This scale strikes a balance between simplicity and depth offering respondents a manageable set of input.

Assessment of Common Method Bias

Common method bias (CMB) refers to the variance that arises from the measurement approach itself rather than the constructs being measured (Shin & Shin, 2020). Since the data for all the model aspects were collected from the same participants at the same time, and Certain of the proposed relationships in the structural model may have been impacted by CMB (Huang et al., 2022; Singh et al., 2023). To assess the potential impact of CMB, we employed the single-factor statistical control test (Lin & Liu, 2024). According to the findings, a one-factor solution could only explain 44.743% of the variation, which is less than the 50% criterion that is advised. This result implies that the results of the study were not likely to have been substantially impacted by common technique bias.

Confirmatory Factor Analysis

The data analysis followed a two-step procedure defined by Semerci and Aydin (2018). Initially, CFA was employed to examine the proposed model's the construct validity reliability, convergent validity, and discriminant validity. In the following phase, we evaluated and tested the assumptions using the structural model. We used numerous criteria to assess the measurement model's reliability, convergent validity, and discriminant validity (Hair et al., 2006). The constructions' internal reliability was assessed using Cronbach's alpha and composite reliability. As indicated in **Table 2**, the reliability coefficients exceeded the acceptable threshold of 0.70 (Chin, 1998) requirements. Factor loadings were used to assess the dependability of individual indicators. Convergent validity was evaluated using average variance extracted (AVE) values. AVE values have been employed to assess convergent validity. All of the variables in research had more than 0.50 (Fornell & Larcker, 1981). This suggests that the constructs correctly captured a significant amount of the variance in each indicator.

This study examined the heterotrait-monotrait (HTMT) ratio to determine discriminant validity as shown in **Table 3**. All of these ratios were less than 0.85, indicating that the constructs have discriminant validity under the Henseler et al. (2015) criterion. The detailed assessment of our measurement model revealed good internal reliability as well as discriminant and convergent validity, supporting the study instrument's statistical strength.

Hair et al. (1998) proposed that standard model fit indices should surpass or be at least comparable to established norms for assessing model fit. The following are the model fit indices determined by AMOS 21:

Table 3. Discriminant validity through HTMT ratio

	RelAI	RedAI	PE	EE	BI
RelAI	1				
RedAI	0.790	1			
PE	0.623	0.624	1		
EE	0.537	0.583	0.738	1	
BI	0.669	0.763	0.547	0.646	1

Table 4. Hypothesis test results

Hypotheses	Path	β	f^2	95% CI	p-value	Result
H1	RelAI → RedAI	0.215	0.631	[0.645, 0.773]	$p < 0.01$	Supported
H2	RelAI → BI	0.555	0.0717	[0.157, 0.404]	$p < 0.001$	Supported
H3	RedAI → BI	0.134	0.129	[0.193, 0.443]	$p < 0.05$	Supported
H4	EE → PE	0.737	0.657	[0.518, 0.713]	$p < 0.001$	Supported
H5	EE → BI	0.409	0.072	[0.102, 0.358]	$p < 0.001$	Supported
H6	PE → BI	-0.069	0.004	[-0.076, 0.162]	$p > 0.05$	Not supported

"Chi-square to degrees of freedom" (χ^2/df) value is 2.224, comparative fit index is 0.94, root mean square error of approximation is .066, and standardized root mean square residual is 0.045. Therefore, the proposed model demonstrates an acceptable level of fit, indicating that the model aligns well with the observed data.

Structural Equation Model

The SEM approach was applied to assess the path coefficients, which allowed for determining the strength and direction of the proposed relationships among aspects and explanatory power of the endogenous constructs. This analysis aligns with the strategy recommended by Hair et al. (2013). As shown in **Table 4**, In **H1**, RelAI had a significant and positive influence on RedAI ($\beta = 0.215$, $f^2 = 0.631$, $p < 0.01$), whose 95% confidence interval (CI) [0.645, 0.773] remained fully above zero, supporting strongly. In **H2**, RelAI had a strong impact on BI ($\beta = 0.555$, $f^2 = 0.072$, $p < 0.001$), and the 95% CI [0.157, 0.404] verified significance. **H3** was also supported, as RedAI had a significant prediction of BI ($\beta = 0.134$, $f^2 = 0.129$, $p < 0.05$), with the 95% CI [0.193, 0.443] not including zero, though to a lesser extent than RelAI. For EE-related hypotheses, H4 showed a robust positive path from EE to PE ($\beta = 0.737$, $f^2 = 0.657$, $p < 0.001$), with the 95% CI [0.518, 0.713], which supported the robustness of this relation. In H5, EE also had a direct effect on BI ($\beta = 0.409$, $f^2 = 0.072$, $p < 0.001$), with the 95% CI [0.102, 0.358] greater than zero, although the effect size was small. In contrast, H6 was not supported since PE did not significantly correlate with BI ($\beta = -0.069$, $f^2 = 0.004$, $p > 0.05$), and its CI [-0.076,0.162] cut through zero, indicating no significant effect.

Regarding explanatory power, the R^2 values also reflect the goodness of the model. BI had an R^2 of 0.591 (adjusted $R^2 = 0.586$), implying 59.1% of the variance in BI is explained by RelAI, RedAI, EE, and PE. PE had a moderate explanatory power with $R^2 = 0.396$ (adjusted $R^2 = 0.394$), which was mainly contributed by EE. RedAI evidenced high explanatory variance, with $R^2 = 0.508$ (adjusted $R^2 = 0.506$), which indicates the strong explanatory contribution of RelAI. The results show that the model explains a significant proportion of variance in the essential constructs, with BI evidencing strong predictability in particular. Together, the findings show that BI is largely influenced by RelAI and EE, with second-level influence from RedAI. Although EE significantly influences PE, there is no support for the expected direct relationship between PE and BI. R^2 values also show that the hypothesized model is successful in predicting variance in BI, PE, and RedAI, with BI showing the greatest explanatory power of the endogenous variables. **Figure 2** shows the result of structural model.

DISCUSSION

The findings of this study deliver key insights into understanding the teachers' BIs to use AI in their teaching practices. The association of RelAI and RedAI is emphasized by Kline's (2011) and Nikou and Economides (2019) and suggesting that instructors are likely to adopt and embrace technologies like AI because its adoption resonates with their teaching methods and enhances their learning procedures increasing teachers' sense of preparedness. Kline's (2011) study confirms that the adoption of AI increases if teachers acknowledge

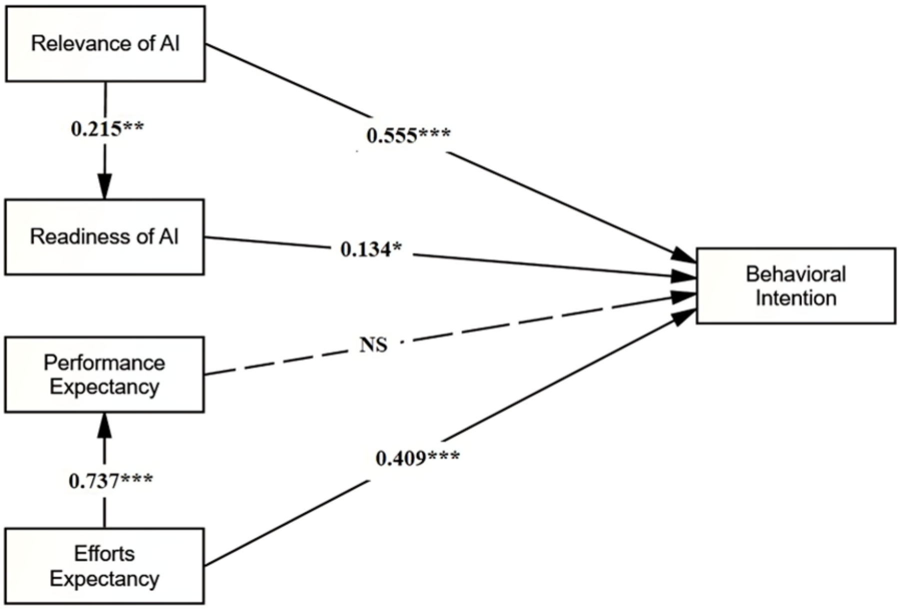

Figure 2. Result of structural model (*p < 0.05, **p < 0.01, ***p < 0.001) (Prepared by the authors)

its relevance with their course content and readiness to include it in their teaching methods. Interestingly, RedAI is a greater influencer on BI than RelAI, revealing that teachers' willingness to use AI is the key determinant in shaping BI positively. Consequently, the study recommends the requisite training and support programs for teachers to embrace AI tools in the classroom with the necessary abilities and expertise. Further, Nikou and Economides (2019) study has shown a stronger positive correlation between RelAI and RedAI, suggesting that instructors show a greater readiness and are prepared to adopt AI technology believing its applicability in their teaching practices. Therefore, these associations emphasize that teacher's preparedness and RedAI technology positively shape BI. Along the same line, the present study's findings also prove a stronger association between the factors RelAI and RedAI, and both can predict teachers' BI. While comparing RelAI was found to be a stronger predictor of teachers' BI than RedAI. Providing a new perspective that the relevance of AI with course content, teaching methods, and practices has a greater impact on determining BI. Furthermore, RelAI also positively influences RedAI indicating that teachers' readiness to adopt majorly contributed to realizing the relevance of AI.

The present study further extends in examining the association of EE, PE, and BI and found a meaningful correlation between them, and these findings are consistent with Tummalapenta et al. (2024), Mohamed and Hassan (2023), Seshadri and Pasupuleti (2023), and Hebert et al. (2021). These studies determine that teachers anticipate higher productivity in their role and enhance teaching practices when they feel at ease and effortless in using AI technologies. This association is consistent with a well-established theory of technology acceptance, which states that users are likely to develop positive intentions and adopt technological interfaces that are useful and easy to use with minimum effort. Thus, while examining EE's role in predicting BI, teachers tend to embrace AI technology in enhancing learning and teaching practices when they perceive less effort while adopting AI technology.

One of the most striking findings of the present study was the limited influence of PE on BI. Even this result is in line with Shaik et al. (2021), historically, PE has been the most potent adoption driver in TAM and UTAUT research. Our finding contradicts this common wisdom and suggests that expected performance advantages by themselves do not instigate intentions for adoption in the field of AI in education. A number of distinctive factors might be responsible for this decoupling. Educators can see the value of AI but refrain based on issues of fairness, bias, or transparency (König et al., 2023). Teachers might fear AI taking over conventional pedagogy jobs, suppressing their enthusiasm to embrace in spite of realizing advantages. Although teachers perceive potential advantages, they also face structural obstacles (missing policies and ambiguous responsibility), rendering performance improvement less compelling. This counterintuitive finding makes a new theoretical contribution: in the adoption of AI, readiness, trust, and relevance are more important than

PE. This implies that established TAMs need to be adapted to situations where socio-professional and ethical stakes are high.

Overall, the results of this study reveal the perceived favorability of teachers in adopting AI technology due to its relevance in teaching procedures. Further, teachers express their readiness to adopt AI for its value in addition to their teaching methods. Moreover, teachers' intention to utilize AI technology can be enhanced by improving their familiarity with AI tools by undergoing training and practice leading to less effort in quick adoption. On the other hand, the results revealed a disassociation of PE and BI, which suggests further research to determine the underlying factors.

Implications

The results of the research have various ramifications for technology developers, educational organizations, and governments. First, the positive relationship between perceived RelAI and RedAI underscores the importance of raising awareness and demonstrating practical AI uses in educational settings. Educational institutions can help teachers feel more relevant and prepared by showcasing how AI can improve teaching and learning processes. Workshops, case studies, and hands-on training sessions can help to demonstrate the potential AI benefits and applications in a variety of educational fields. Second, the significance of thorough professional development programs is underscored by RedAI's significant influence on BI's adoption of AI. Institutions of higher learning should fund programs that provide educators with the abilities, know-how, and self-assurance they need to successfully incorporate AI tools into their lesson plans. Peer learning opportunities, practical instruction, and continuing assistance from instructional designers or technology specialists could all be a part of these programs. Thirdly, the beneficial relationship between EE and PE emphasizes how important intuitive and user-friendly AI technologies. The creation of AI technologies that are simple to use and demand little work from educators should be a top priority for technology developers. Iterative feedback and teacher testing are two examples of user-centered design techniques that can assist guarantee AI products fit instructors' requirements, preferences, and current workflows. Additionally, given EE's strong influence on BI, teachers' intents to use AI technologies may be greatly increased if the perceived effort required to do so is decreased. To reduce the perceived effort and enable the smooth integration of AI technology into teaching methods, educational institutions should offer sufficient technical assistance, resources, and training.

CONCLUSION

This study gives important insights into the elements that influence teachers' BIs to include AI in their teaching techniques. This study underlined the critical roles of perceived RelAI, preparedness to adopt AI technology, effort expectation, and PE. Educational organizations can improve instructors' readiness and intentions to integrate AI into their classrooms by promoting a better knowledge of its importance, providing thorough professional development programs, and building user-friendly AI technologies. In addition, this study contributes to the body of existing knowledge, it also emphasizes the need for future research to investigate new variables, use mixed methodologies approaches, and perform longitudinal and cross-cultural studies. Addressing the constraints and pursuing the proposed future research topics can help us gain a better understanding of this phenomenon and inform the creation of effective strategies for successful AI deployment in educational environments, eventually benefiting both teachers and students. While this study contains some interesting findings, it is critical to recognize its limitations. Initially, the study was based on instructors' self-reported data, which could have been influenced by biases and social desirability considerations. Next, the study concentrated on a specific context and sample, which may restrict the generalizability of the findings. This cross-sectional study method provides insight into instructors' thoughts and aims at a specific period. Longitudinal study may shed further light on the evolution of these attitudes and intents as teachers gain experience with AI technologies over time.

Coming to this study limitation, many possibilities for further research might be proposed: firstly, qualitative research, such as interviews or focus group discussions, may provide more detailed insights into the unique concerns, challenges, and motives that impact instructors' attitudes and intentions regarding AI adoption. Another limitation is our sampling strategy. Data were gathered through convenience sampling from WhatsApp and Facebook educator groups. This method probably reached already technology-forward faculty members, resulting in possible selection bias with reduced generalizability. Although our SEM analysis shows internal validity, the external validity of this research is limited. Future research should utilize institution-level probabilistic sampling or mixed-method designs involving less technology-savvy populations to gain more representative findings. Future studies should look into potential moderating and mediating variables that could alter the interactions between the constructs examined in this model. For example, institutional support, teacher self-efficacy, and perceived risk of AI could all be investigated as potential moderators or mediators. Combining qualitative and quantitative approaches in a mixed-methods design would offers a more complete knowledge of the phenomenon. Conducting cross-cultural or cross-national studies could provide useful insights into how environmental and cultural factors influence teachers' intentions and perceptions to adopt AI. Future research could look into teacher attitudes and intentions toward specific AI applications or tools, such as automated grading systems, intelligent tutoring systems, and personalized learning platforms. This would provide more specific data and may identify distinct aspects driving the adoption of certain AI technologies. Academics can contribute to a better understanding of the factors influencing teachers' adoption of AI technologies by resolving these inadequacies and studying the indicated future research directions.

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Ethics declaration: This study involved the collection of voluntary, anonymous survey responses from teachers working in higher education institutions. The study did not include any experimental manipulation, clinical procedures, or collection of sensitive personal data. According to the institutional research guidelines of Tirumala Engineering College, affiliated with JNTU Kakinada University, studies that involve minimal-risk, anonymous survey responses from adult participants are exempt from formal ethics committee review. Therefore, ethics committee approval, approval date, and protocol/document number are not applicable for this research. All participating teachers were informed about the purpose of the study, assured of confidentiality, and provided voluntary consent before completing the survey. No personally identifying information was collected, and participation involved no anticipated risks.

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APPENDIX A

Table A1. Questionnaire

Construct	Indicator	Source
RedAI	RE1. I have the relevant knowledge to use AI. RE2. I have access to appropriate hardware to use AI RE3. I have access to appropriate software to use AI. RE4. I have access to relevant content to use AI.	Woodruff et al. (2023)
RelAI	RA1. Learning AI for teaching will be useful. RA2. AI content will be related to things I have seen, done or thought about in my own life. RA3. It is clear to me how the content of AI is related to my lifestyle. RA4. The content of AI will be useful to me in terms of learning the concept effectively.	Mhina et al. (2019)
PE	PE1. If I use AI, I will increase my chances of achieving better performance. PE2. I would find AI is useful. PE3. Using AI increases my productivity. PE4. Using AI enables me to accomplish tasks more quickly.	Venkatesh et al. (2003)
EE	EE1. It would be easy for me to become skillful at using AI. EE2. I would find AI easy to use. EE3. My interaction with AI would be clear and understandable. EE4. Learning to operate AI is easy for me.	Venkatesh et al. (2003)
BI	BI1. I will continue to learn about AI knowledge. BI2. I will keep myself updated with the latest AI applications. BI3. I plan to spend time in learning AI technology in the future. BI5. I intend to use AI to assist my teaching.	Mhina et al. (2019)