Teachers' Adoption of ChatGPT in Higher Education: Integrating Technology Acceptance, Trust, and Perceived Risk

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ABSTRACT

In recent years, artificial intelligence (AI) technologies have become increasingly prominent in education, with ChatGPT emerging as a notable tool that enhances learning experiences. This study explores teachers' attitudes towards the adoption of ChatGPT as a learning technology, focusing on its potential benefits, limitations and implications for education. A quantitative approach was employed, involving an online survey targeting university educators. The survey assessed teachers' perceptions of ChatGPT in higher education and identified barriers to its implementation. The conceptual framework integrates elements from the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology and insights from risk perception theory. Data analysis was conducted using Partial Least Squares Structural Equation Modelling with SMART PLS software, ensuring reliability and discriminant validity. Findings indicate that most teachers view ChatGPT as an effective tool for enhancing student motivation, personalised learning and critical thinking. While teaching experience fosters positive perceptions and reduces perceived risks, it does not significantly influence challenges or trust in adoption decisions. Nonetheless, challenges persist, particularly regarding the reliability of information generated by ChatGPT. This study can assist policymakers, educators and technology developers in collaborating to implement practical and ethical AI-enabled tools like ChatGPT. Ultimately, while ChatGPT holds significant potential as an educational technology, its effectiveness hinges on addressing technical and pedagogical challenges.

Keywords: Artificial Intelligence, ChatGPT, Learning Technology, Teachers' Attitudes, Higher Education

INTRODUCTION

Teachers are increasingly integrating advanced technologies into their teaching practices to enhance student learning experiences [1] [2] [3]. The European Parliament defines artificial intelligence (AI) as 'a computer hardware or software system demonstrating intelligent behaviour based on gathering and processing information, analysing and interpreting the environment and acting with a degree of autonomy to achieve desired goals' [4]. Notably, several AI models can comprehend and engage in natural human language [5]. In February 2023, Google launched Bard, a large language model designed for dialogue applications [6]. Recently, ChatGPT has gained significant attention, highlighting the role of AI in various aspects of daily life [7]. However, there is a scarcity of empirical research on its potential applications in education, as teachers and students have only recently begun to utilise it. ChatGPT offers personalised learning that fosters critical and creative thinking, making it increasingly relevant [8]. It can serve as an individualised tutor tailored to each student's preferences, competencies and educational level [9]. Teachers can leverage ChatGPT for brainstorming ideas and curating appropriate course content, which can also enhance their critical thinking and exploration of diverse pedagogical approaches [10]. In the current digital age, universities should encourage the adoption of emerging technologies rather than resist them [3] [11] [12] [13]. Teachers could review their teaching practices and find new ways of integrating technology into the teaching and learning process to thrive in the digital age [11] [14]. Educators can reassess their teaching methods and discover innovative ways to incorporate technology into the learning process; these tools provide educational support and equitable access to resources for teachers across various geographic, social and cultural contexts [6]. Various studies have explored ChatGPT's potential impact on education, particularly in higher education (e.g. [6] [9] [15]).

Despite the rapid adoption of ChatGPT, teachers have expressed concerns. While it generates text that appears realistic, it is not a search engine and does not guarantee factual accuracy, posing a risk of disseminating misleading information [6]. Inappropriate content may arise from biases present in the training datasets [4]. Over-reliance on technology and generative tools like ChatGPT can impede knowledge acquisition and skill development [16]. The immediate availability of answers and the capacity to produce complete texts may diminish critical thinking and problem-solving skills, ultimately detracting from the learning experience [17]. Furthermore, ChatGPT raises concerns about academic integrity, particularly regarding written assignments, as it can paraphrase responses in a manner undetectable by plagiarism tools [18]. Another drawback is the potential for unfair learning assessments, where students using ChatGPT may achieve higher scores than those relying solely on their abilities, negatively affecting their educational experiences [6]. Additionally, ChatGPT and similar models collect and process personal data, raising privacy, security and misuse concerns [9]. Ethical issues also arise, especially for younger learners who may encounter age-inappropriate content [15]. Accessibility challenges are likely, including the lack of testing tools in developed countries due to government policies, censorship or other restrictions, alongside disparities in internet availability, cost and speed [12] [13] [3]. This study addresses a gap in the educational literature by exploring teachers' perceptions of ChatGPT as a learning tool and the implications of generative technology for teacher education.

This research is vital for several reasons:

- First, examining university teachers' acceptance and attitudes towards ChatGPT can yield valuable insights into the potential benefits and risks of integrating this technology into education.
- Second, it can inform decisions on effectively implementing ChatGPT in higher education, maximising its advantages while addressing associated challenges.
- Lastly, this study illuminates teachers' overall perceptions of ChatGPT as a teaching and learning tool, particularly relevant as AI-driven technologies become more prevalent in education.

The remainder of the paper is organised as follows: Section 2 reviews existing literature, Section 3 outlines the development of the theoretical framework, Section 4 details the methodology and Section 5 presents the results. Finally, Section 6 discusses the findings and implications, while Section 7 concludes with suggestions for future research.

LITERATURE REVIEW

integration of AI in education has garnered significant attention in recent years, with tools like ChatGPT emerging as transformative elements in teaching and learning. As researchers worldwide explore its potential, understanding teachers' perspectives is essential, particularly in culturally and contextually diverse settings. This literature review examines current research on AI tools in education, the experiences of teachers and students regarding technology adoption and the challenges associated with using ChatGPT in various learning environments.

Factors affecting ChatGPT adoption

Recent studies have drawn on established technology adoption models, such as the Technology Acceptance Model (TAM) [19], the Unified Theory of Acceptance and Use of Technology (UTAUT) [20], Social Cognitive Theory [21] the Theory of Planned Behaviour [22] to identify teachers' behavioural intentions towards adopting new tools and technologies. Many researchers have enhanced these conventional models by incorporating significant constructs and moderating variables to better align with their findings. For example, the adoption of digital library systems was examined through the lens of academic involvement [23], while the intention of teachers to adopt virtual reality technology was explored in relation to personal characteristics [1]. The acceptance of e-learning by users was assessed through individual cultural dimensions [2], and the influence of gender and age was considered in teachers' intentions to use educational video games [14]. There is a growing global interest in the use of ChatGPT in teaching and learning, yet research on teachers' perceptions of ChatGPT in educational settings remains limited. A few scholars have employed qualitative, quantitative and mixed method approaches to investigate this topic. Haque et al. [24] conducted a sentiment analysis to evaluate early adopters' attitudes towards ChatGPT, revealing predominantly positive sentiments. Conversely, Dwivedi et al.

[25] reported negative perceptions of ChatGPT. Iqbal et al. [16] applied the TAM to explore teachers' intentions to adopt ChatGPT, uncovering a negative inclination. Chocarro et al. [12] also utilised the TAM, emphasising the importance of perceived ease of use and perceived usefulness in shaping teachers' acceptance.

Global perspective of ChatGPT usage in learning and teaching

ElSayary [13] examined the perceptions of 41 teachers from various middle and high schools in the United Arab Emirates regarding ChatGPT. Teachers acknowledged the benefits of ChatGPT for lesson planning, teaching and learning, but found it less effective for assessment and feedback. Concerns were raised about bias, the accuracy of information provided and the lack of meaningful human interaction. Both students and teachers should critically evaluate and revise ChatGPT's outputs rather than accept them uncritically [6]. Human judgement remains crucial, as the model's reliance on natural language processing can introduce biases and discrimination. Furthermore, ChatGPT may lack creativity and critical thinking, produce inaccuracies or even lead to plagiarism, making its information not always reliable [12]. Bhaskar and Rana [15] investigated the motivating and inhibiting factors affecting teachers' willingness to adopt ChatGPT, based on insights from 48 teachers in India. Key barriers identified included technical challenges, limited functionality for educational and research purposes, tools that stifle innovation and creativity and concerns regarding the lack of personal interaction and ethical implications. Similarly, a case study by Bateman [10] indicated that while ChatGPT could save time and provide valuable resources for lecture preparation, teachers were apprehensive about potential misuse, such as facilitating plagiarism. In Sweden, teachers reported a lack of understanding regarding how to use ChatGPT in the classroom and felt unsupported by leadership and the Swedish National Agency for Education. However, the use of ChatGPT significantly increased students' confidence and conceptual understanding [8].

Teachers' perspectives in Saudi Arabia

Few studies have examined teachers' attitudes and perceptions regarding the integration of ChatGPT into teaching practices in Saudi Arabia. According to Alharbi [9], is a significant gap between Saudi teachers' assessments of their students' AI proficiency and the actual state of AI integration. This discrepancy leads to inconsistencies in evaluating student understanding and the validity of assessments. Access to advanced AI technologies is not uniform across all students and educational institutions, potentially exacerbating educational inequalities. A study involving Saudi students and teachers indicated that AI tools enhanced creativity, learning experiences, time efficiency, productivity and independent learning, with 88.2% highlighting creativity as a key benefit. Teachers also recognised these advantages, particularly in improving the learning experience and providing academic support, albeit less frequently. However, they voiced concerns that over-reliance on ChatGPT could result in a homogenised writing style, ultimately diminishing students' autonomy and creativity in writing [26].

Furthermore, Wajid et al. [27] investigated the awareness and attitudes towards ChatGPT among researchers and academics at King Saud University in Riyadh. Participants largely agreed that large language models produce biased or discriminatory information, with 71.1% expressing concern that these tools generate less logical text. Similarly, Alammari [28] identified challenges within the Saudi context, including ethical implications, academic integrity, the risk of over-reliance on AI-generated content, uncertainty about students' ability to critically engage with AI tools, a lack of clear policies for responsible usage and insufficient training for teachers. It was suggested that while generative AI has the potential to transform education, successful implementation necessitates structured policies, ethical considerations and ongoing professional development.

Gaps in literature

The introduction and literature review indicate that while numerous studies have explored the benefits and limitations of ChatGPT, there is a lack of research on its adoption among teachers. There is a pressing need for literature focused on teachers' adoption of ChatGPT. Understanding teachers' experiences and expectations is crucial for developing effective strategies to integrate ChatGPT into the classroom. This research aims to fill this gap by contributing to the literature on ChatGPT adoption from the teachers' perspective. Additionally, it investigates the key factors that encourage or hinder teachers from integrating ChatGPT into educational settings. Understanding teachers' perspectives is particularly vital in Saudi Arabia, where the education system is undergoing significant transformation. Saudi Arabia's Vision 2030 strongly emphasises the need to modernise education and equip teachers with the digital literacy and critical thinking skills necessary for success in the twenty-first century [29]. Future studies on teachers' adoption of ChatGPT will benefit from the identified motivating and inhibiting factors, enriching the existing literature and conceptual models.

CONCEPTUAL FRAMEWORK

Researchers have been evaluating theoretical models to accurately predict user adoption of innovative technologies for many years [20]. In recent decades, various frameworks explaining technology acceptance have emerged in academic literature. However, do these models provide a more accurate representation than earlier ones? The original TAM was developed in the 1970s to understand how users adopt and utilise technology [30]. Several factors influence users' decisions on whether and how to employ new technologies [31]. Emerging structural equation modelling (SEM) techniques that incorporate non-linear relationships can yield different results compared to those derived from linear assumptions. One limitation of TAM is its reliance on user behaviour variables, which must be analysed through subjective criteria such as behavioural intention and interpersonal influence [32]. Furthermore, quantitative data may not adequately capture the underlying behaviours due to various subjective components, including societal values, individual characteristics and personality traits. Another framework related to technology adoption is the UTAUT, which has its own limitations, such as complexity, limited predictive power in specific contexts, lack of qualitative insights and potential cultural biases. Additionally, it may not fully account for evolving technological trends or individual differences in long-term technology adoption behaviours [33]. To address these limitations, we have combined constructs from previous frameworks to propose a new framework for this study. The proposed conceptual framework draws on elements from TAM, UTAUT and insights from risk perception theory. Perceived benefits (BEN) and adoption intention (ADO) are derived from TAM, while UTAUT expands on TAM by including additional constructs such as perceived challenges (CHLN). The inclusion of moderating variables, like teaching experience, aligns with UTAUT's recognition of factors related to adoption. Perceived risks (RISK), such as academic integrity and misinformation, are informed by risk perception theory. This combination of TAM/UTAUT with risk perception theory captures both the positive drivers (benefits, facilitating conditions) and barriers (risks, challenges) to adoption. Moderating variables like teaching experience allow for a nuanced analysis of how teacher-specific factors shape perceptions and intentions. The research framework is illustrated in Figure 1.

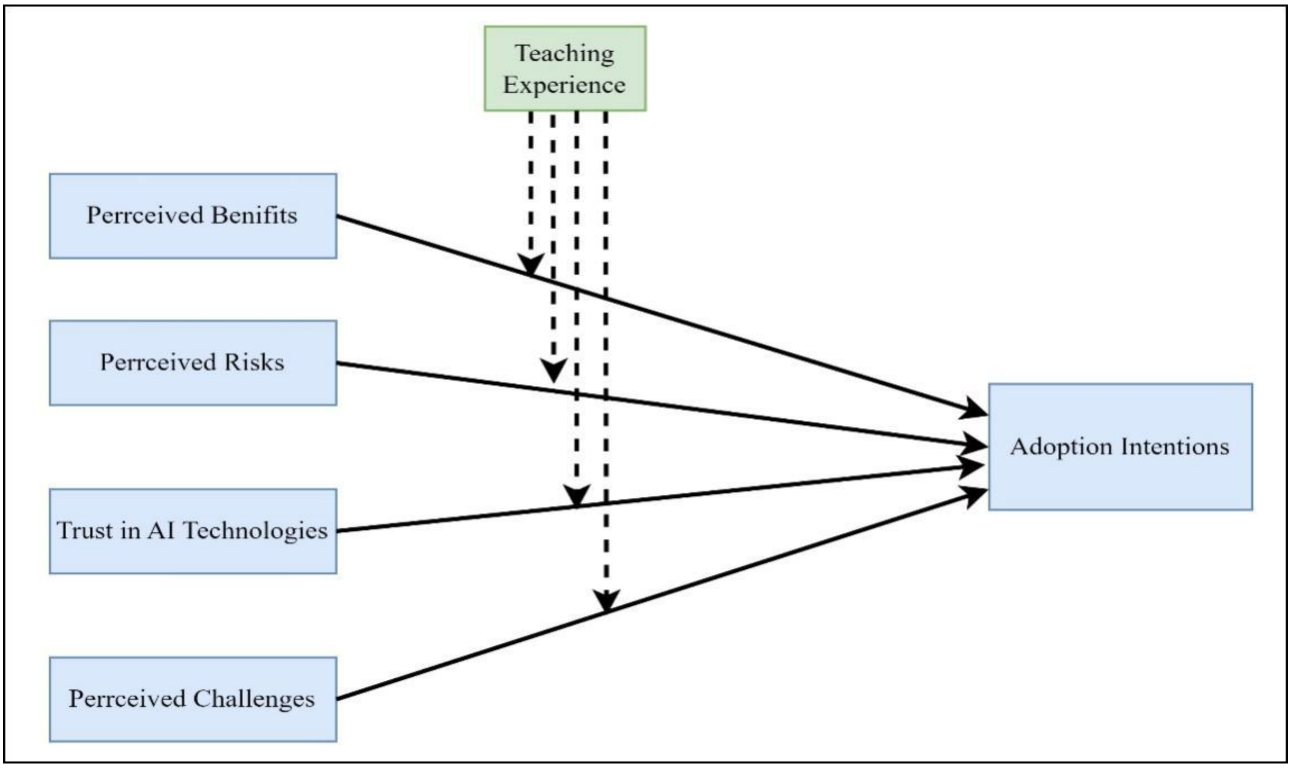

Figure 1: Our research framework

Perceived benefits

The BEN of ChatGPT as a learning tool are reflected in its perceived usefulness [19]. These benefits can be categorised into two main types: direct and indirect advantages [17]. Direct advantages refer to the immediate and tangible gains users experience from ChatGPT, while indirect advantages are less obvious and harder to quantify. Users' decisions to utilise ChatGPT for learning may not always be driven solely by these BEN, which are crucial for adopting new technology [1]. When considering whether to adopt new technologies, users often evaluate more than just the apparent benefits. The likelihood of adoption increases when the perceived advantages of a tool are seen to outweigh its costs [2]. In this study, the novelty of using ChatGPT contributes to its BEN. Therefore, we propose that BEN positively influence users' intention to adopt ChatGPT. Thus, we hypothesise that.

H1: BEN significantly influence the intention to adopt ChatGPT.

Perceived risks

RISK, as defined by Ho et al. [34], are a person's subjective anticipation and belief regarding potential losses arising from specific events or combinations of events that affect decision-making [14]. Higher RISK can negatively impact a user's attitude, leading to more cautious behaviours. It is essential to recognise that teachers' subjective risk assessments may lead to resistance against new technologies in the classroom [31]. RISK is a critical factor influencing the intention to adopt AI technologies like ChatGPT, as indicated by recent research [35]. Current studies support various dimensions of RISK in technology adoption, including performance, time, financial, psychological, social and privacy risks [25]. Teachers often express concerns about the reliability, technological malfunctions, system failures, compatibility, security and privacy of educational technology systems [30]. Given that risk perceptions are closely linked to users' intentions to adopt new technologies [30, 33], measuring RISK is vital for ChatGPT adoption. Therefore, we propose the following hypothesis.

H2: RISK significantly influences the intention to adopt ChatGPT.

Perceived challenges

CHLN refer to the obstacles or barriers users anticipate or encounter when adopting and using new technology [25]. These barriers may include technical difficulties, usability issues, lack of knowledge and training, security and privacy concerns, compatibility problems and cost constraints. Such challenges can affect users' willingness to accept, adopt and effectively utilise technology [26]. We extend this assumption to ChatGPT in our study, leading to the following hypothesis.

H3: CHLN significantly influence the intention to adopt ChatGPT.

Perceived trust

Trust, as defined by Lee and See [36], is the belief or attitude that can help users achieve their goals in situations characterised by vulnerability and uncertainty. Trust is crucial for technology adoption, particularly when users interact with multiple technologies like ChatGPT [5]. User trust is a significant concern when sharing data with AI-powered technologies and services. Empirical evidence suggests that TRU is a key determinant of the intention to adopt AI technologies in educational services [5]. The implementation of ChatGPT underscores the importance of trust as a critical driver of users' willingness to engage with and rely on generative AI technology [37]. Based on these principles, we propose the following hypothesis.

H4: TRU significantly influences the intention to adopt ChatGPT.

Teaching experience

Teaching experience serves as a moderator in the implementation of ChatGPT, examining how it influences teachers' adoption and use of AI technology in learning. Experienced teachers are likely to leverage their pedagogical skills to effectively utilise ChatGPT for lesson planning, student motivation and personalised learning. This moderation captures how varying levels of teaching experience impact perceptions, self-efficacy and strategies for adopting AI, which in turn affects the effectiveness and adoption of tools within higher education. Therefore, we hypothesise that.

H5: Teaching experience significantly affects the intention to adopt ChatGPT.

H6: Teaching experience moderates the effect of RISK on the intention to adopt ChatGPT.

H7: Teaching experience moderates the effect of BEN on the intention to adopt ChatGPT.

H8: Teaching experience moderates the effect of TRU in AI on the intention to adopt ChatGPT.

H9: Teaching experience moderates the effect of CHLN on the intention to adopt ChatGPT.

The questions or statements concerning various constructs of the research framework are explained in Table 1.

Table 1: Various constructs of the research framework with statements.

Construct	Statements
Demographics	What is your age?
	How many years of teaching experience do you have?
	What is your primary subject area?
	Have you used AI tools like ChatGPT in your teaching before? (Yes/No)
Perceived Benefits	ChatGPT can help students better understand complex topics.
	Using ChatGPT increases students' engagement in the classroom.
	ChatGPT provides personalised learning experiences tailored to student needs.
	ChatGPT offers accessible resources for diverse learning levels and styles.
Perceived Risks	I am concerned that students might misuse ChatGPT for academic dishonesty (e.g. plagiarism).
	ChatGPT may provide inaccurate or misleading information to students.
	Students might become overly reliant on ChatGPT instead of developing independent thinking skills.
	The use of ChatGPT in education raises ethical concerns.
Perceived Challenges	Teachers need more training to use ChatGPT effectively.
	Integrating ChatGPT into the curriculum is challenging due to technical or logistical issues.
	There is insufficient institutional support for implementing AI tools in classrooms.
	ChatGPT's capabilities may not align well with standardised teaching objectives.
Trust in AI Technologies	I trust AI tools like ChatGPT to provide accurate and unbiased information.
	AI tools can complement traditional teaching methods effectively.
Adoption Intentions	I am willing to incorporate ChatGPT into my teaching practices.
	I believe ChatGPT could improve the overall quality of education in my classroom.
	I would recommend the use of ChatGPT to other teachers.

METHODOLOGY

Measurement development

The questions for the constructs in this study were adapted from existing literature. The conceptual framework draws on constructs from the TAM, the UTAUT and insights from risk perception theory. BEN and ADO are derived from TAM, while UTAUT expands on this by incorporating additional constructs, such as CHLN. The inclusion of moderators, specifically teaching experience, aligns with UTAUT's recognition of factors related to adoption. RISK is informed by risk perception theory. This combination of TAM/UTAUT with risk perception theory captures both the positive drivers (benefits, facilitating conditions) and barriers (risks, challenges) to adoption. Additionally, recommendations from two academics were sought to validate the questionnaire. The questionnaire, consisting of modified scale questions, was pilot tested with 10 participants from the university. Responses were measured using a Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

Data collection

This study employs a quantitative approach, using a questionnaire as the primary method for data collection. The questionnaire includes closed-ended questions to explore various constructs, including demographic data, to analyse teachers' perceptions. The online survey was distributed to teachers at Taif University in Saudi Arabia, using a database of their email addresses. Participation was entirely voluntary, and teachers were invited to complete the survey via email. The participants represented various departments, including science, engineering, medical sciences, technology and business. The survey comprised 21 questions designed to measure teachers' perceptions of ChatGPT as a learning tool. Sample items included: 'ChatGPT can help students better understand complex topics', 'ChatGPT may provide inaccurate or misleading information to students', and 'I am willing to incorporate ChatGPT into my teaching practices'. The survey contained 21 questions across six subsections: demographics (4 items), BEN (4 items), RISK (4 items), CHLN (4 items), TRU in AI technologies (2 items) and ADO (3 items). The teachers had diverse demographics and educational backgrounds. Before data collection commenced, participants were informed about the study's objectives and the definitions of all constructs. After addressing ethical concerns regarding consent, privacy and confidentiality, participants were granted access to the questionnaire via Google Forms. After one month, 230 participants completed and submitted the survey, of which 218 were valid. Responses with missing data were excluded from the analysis. Following the data collection phase, the online survey link was disabled to prevent further submissions.

Data analysis

Descriptive statistics for all measurements were calculated initially. The routing model was analysed using Partial Least Squares SEM (PLS-SEM) with SMART PLS software, which included assessments of reliability and discriminant validity. PLS-SEM, a composite-based approach to SEM, aims to maximise the explained variance of the dependent constructs in the routing model [38]. This method is particularly useful for researchers investigating competitive advantages and success factors. Unlike traditional SEM approaches, PLS-SEM allows for the estimation of complex models with numerous constructs and moderating variables [39]. Additionally, it offers high flexibility regarding data requirements and enables the estimation of both reflective and formative constructs. As a nonparametric approach, PLS-SEM focuses on explaining variance through latent variables that are not directly observable [40]. Smart PLS-SEM is less stringent regarding assumptions about residual distribution, measurement scales and sample size, making it a robust and flexible analytical tool [38]. Discriminant validity tests were conducted first on the outer model of the proposed research framework, followed by an evaluation of the inner model to test the hypotheses.

RESULTS

Table 2 presents the demographic information of the survey respondents. It shows that the majority of respondents belong to the age group 31–40 (43.1%), followed by those over 41 (50.5%) and the age group 18–30 (6.4%). Most respondents were over 30 years old, indicating a higher participation rate from a relatively older population. As shown in Table 2, the male respondents (47.2%) were slightly fewer than the female respondents (52.8%). In terms of teaching experience, the largest cohort had 11–15 years of experience (47.2%), followed by those with 6–10 years (22.9%). Lastly, regarding ChatGPT usage, 54.9% of participants reported having experience with it, while 45.4% had no prior experience.

Table 2: Demographics statistics

Feature	Category	Frequency	Per cent
Gender	Male	103	47.2
	Female	115	52.8
Age (years)	18–30	14	6.4

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	31–40	94	43.1
	>41	110	50.5
Teaching experience (years)	1–5	23	10.6
	6–10	50	22.9
	11–15	103	47.2
	>16	42	19.3
ChatGPT usage	Yes	119	54.6
	No	99	45.4

Model specification

Model specification involves defining the expected relationships between observed and latent variables. This step is crucial, as any relationships not explicitly specified are assumed to be absent (zero) [38]. Before conducting the analysis in SEM, researchers must establish hypothesised relationships among the variables. Three types of parameters can be specified: directional effects, variances and covariances. Directional effects indicate the associations between indicators and latent variables (known as factor loadings) and between latent variables themselves (referred to as path coefficients) [41].

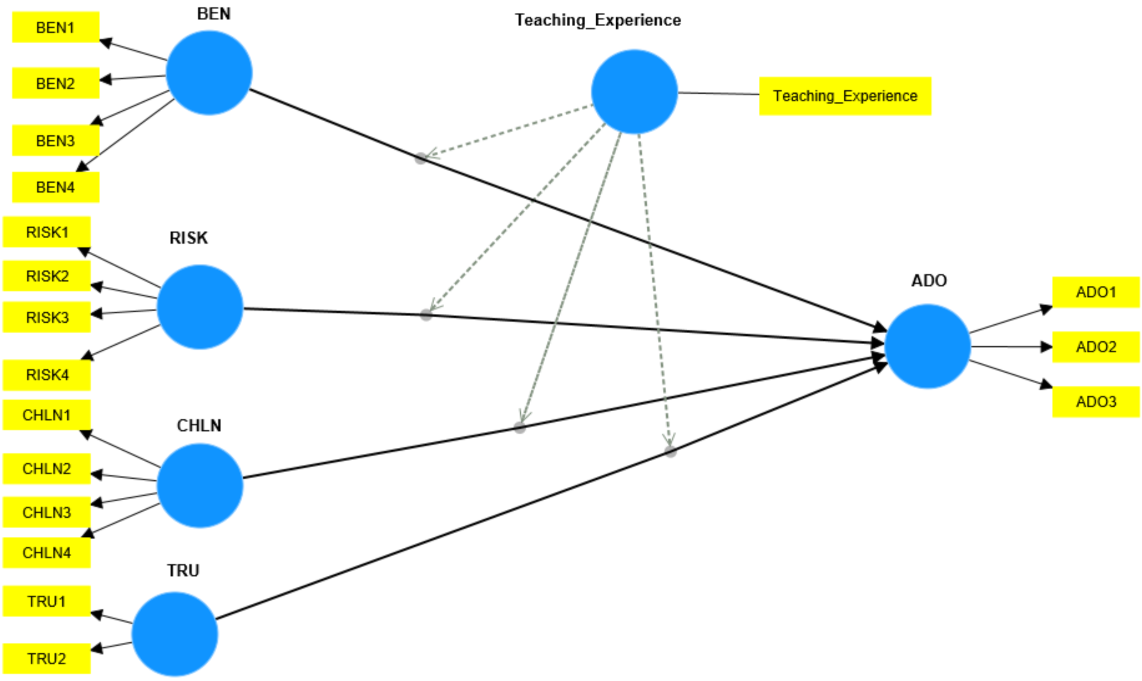

Figure 2: The models for measurement and structure

One of the advantages of SEM over other methods is its capacity to manage variance estimates (note that processes like regression require variables to be measured without error) [39]. Researchers can model the error of dependent observable and latent variables in two ways. One approach is to set the loadings of error variables on the dependent variables to 1.0 while estimating the variance of each error term. This results in parameters that quantify error variance. Alternatively, researchers can estimate the loadings and set the error variances to 1.0 [40]. The second option calculates parameters that represent factor loadings while standardising the error term. The primary goal of model specification is to define both the inner (structural) and outer (measurement) models. The inner model illustrates the relationships between constructs, while the outer model specifies how indicators relate to constructs [38]. Hair et al. [41] emphasise that the first step in PLS-SEM is to create a path model that establishes connections between variables and constructs. Figure 2 visually represents the inner and outer models used in this study.

Measurement model evaluation

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The structural model is validated based on its explanatory and predictive capabilities, as well as the interpretation and significance of the path coefficients [42]. This research employed two tests to validate the measurement model: reliability and validity. Validity refers to the extent to which a study measures what it intends to measure, free from the influence of extraneous variables or bias. Reliability, indicates the degree to which research outcomes are consistent and stable over time and across different samples, techniques and evaluators [43]. Hair et al. [41] utilise Cronbach's alpha (CA) and composite reliability (CR) to assess the reliability of the measurement model. CA coefficient quantifies a survey's internal consistency or reliability [42]. A high CA indicates strong consistency in participants' responses across constructs, suggesting that the measurements are reliable and likely assess the same characteristic [44]. Conversely, a low CA suggests poor reliability, indicating that the items may not effectively measure the same construct. The assessment of a construct's internal consistency and reliability is referred to as CR [45]. The CA method has been widely used in previous studies to estimate a construct's reliability [9] [15]. This method is the simplest reliability test for any research undertaking [45]. However, Hair et al. [46] note that CA assumes all items are equally reliable and have equal outer loading on the construct. CR scores range from 0 to 1, with scores of 0.60 to 0.70 considered acceptable. Internal consistency and reliability are deemed low when CR scores fall below 0.60 [46].

Table 4 shows that the CR values for all latent variables exceed the established threshold of 0.7. All constructs have a CA above 0.7, indicating good internal consistency. The construct BEN (0.907) demonstrates the highest reliability, reflecting strong internal consistency among its items. TRU (0.800) and RISK (0.807) have the lowest but still acceptable reliability. All constructs have ρc values above 0.8, confirming strong construct reliability. BEN (0.935) and ADO (0.910) exhibit the highest CR, indicating they are highly reliable measures. RISK (0.873) and TRU (0.909) also meet the recommended threshold (>0.7), signifying acceptable reliability. The constructs show high reliability, meaning the indicators within each construct are internally consistent, as illustrated in Table 3.

Table 3: Reliability and validity tests with average variance extracted

	Cronbach's alpha	**Composite reliability (CR) (ρ_a)**	**CR (ρ_c)**	**Average variance extracted**
ADO	0.852	0.854	0.910	0.772
BEN	0.907	0.910	0.935	0.782
CHLN	0.849	0.853	0.898	0.687
RISK	0.807	0.823	0.873	0.631
TRU	0.800	0.800	0.909	0.833

The validity of the measurement model is assessed by examining both convergent and discriminant validity. Discriminant validity determines whether a construct is distinct from other constructs within the model [43]. According to the Fornell-Larcker criterion, the square root of the average variance extracted (AVE) (shown as diagonal values in bold) must exceed the correlations between constructs (off-diagonal values). If a model lacks discriminant validity, the conclusions drawn from it may be questionable, as it becomes unclear whether the results are genuinely supported by the data or influenced by the repeated use of a construct [44]. The square roots of the AVEs for each latent variable are highlighted in Table 4. By comparing these square roots with other values column-wise, it is evident that the square roots of all AVE latent variables are greater than the correlations for each latent variable. The findings indicate that the discriminant validity of all latent variables is adequate [43].

Table 4 also presents the confirmatory factor analysis measurement loadings for all latent variables used in this study. ADO (Adoption Intention) shows strong positive correlations with BEN (0.713) and TRU (0.661), suggesting that higher BEN and TRU in AI technologies enhance adoption intention. RISK exhibits negative correlations with all constructs, particularly ADO (−0.541) and TRU (−0.496), indicating that increased RISK diminishes both ADO and TRU. The correlation between BEN and TRU is the highest at 0.681, signifying a close relationship between BEN and TRU in AI technologies. CHLN is positively correlated with ADO (0.649), though this correlation is weaker than that of BEN (0.713), indicating that while perceived challenges do influence adoption intention, they do so less strongly than BEN.

Table 4: The evaluation of discriminant validity through the Fornell-Larcker criterion

	ADO	BEN	CHLN	RISK	TRU
ADO	**0.879**				
BEN	0.713	**0.884**			
CHLN	0.649	0.654	**0.829**		
RISK	−0.541	−0.431	−0.463	**0.795**	
TRU	0.661	0.681	0.587	−0.496	**0.913**

Structure model evaluation

Once the validity and reliability of the measurement model have been established, the structural model is examined. This section outlines the necessary steps for reviewing the structural model. The size and coefficient of determination are calculated to assess the structural model [47]. The coefficient of determination (R^2) is a crucial statistical measure in regression analysis that indicates the proportion of variance in the dependent variable explained by the independent variable [48]. It evaluates the model's goodness of fit, demonstrating how well the data aligns with the regression model. R^2 values range from 0 to 1, with values closer to 1 indicating that the model accounts for a larger share of the variance, reflecting greater explanatory power [47]. The R^2 value for ADO is 0.674, suggesting that the four independent variables explain 67.4% of the variance in ADO. Overall, BEN, TRU in AI and CHLN positively influence ADO, while RISK has a negative effect.

Table 5 displays the path coefficients and p-values for the proposed hypotheses. The path coefficient indicates the significance of the hypothesised relationships between the constructs. Path coefficients reflect the strength and direction of the relationships between independent and dependent variables, while p-values indicate statistical significance. A p-value of less than 0.05 signifies a statistically significant relationship. BEN has the most substantial positive influence on ADO (0.331). TRU in AI (0.163) and CHLN (0.181) also positively contribute to ADO. Conversely, RISK (−0.143) negatively impacts ADO, indicating that a higher perception of risk reduces the likelihood of adoption. Teaching Experience does not directly affect ADO ($p = 0.915$). When evaluating measurement loadings, all indicator loadings should be 0.50 or higher on their intended component [46] and must be statistically significant ($p < 0.05$). Table 6 presents the measurement loadings from the confirmatory factor analysis for all latent variables in this study.

Table 5: Hypotheses' path coefficients along with their p-values.

Hypothesis	P-Value	Path coefficient	Decision
H1: BEN → ADO	0.000	0.331	Significant
H2: CHLN → ADO	0.022	0.181	Significant
H3: RISK → ADO	0.014	−0.143	Significant
H4: TRU → ADO	0.031	0.163	Significant
H5: Teaching Experience → ADO	0.005	0.915	Not Significant

Teaching experience and ADO

Teaching experience can influence the adoption of ChatGPT (ADO) in several ways. Experienced teachers may be more reluctant to adopt ChatGPT due to established teaching practices, scepticism about the effectiveness of AI or concerns regarding academic integrity. However, teaching experience enhances the positive impact of perceived benefits (BEN) on ADO (0.174, $p = 0.031$), indicating that experienced teachers place greater value on the benefits of AI adoption. Additionally, teaching experience mitigates the negative impact of perceived risk (RISK) on ADO (−0.110, $p = 0.019$), suggesting that experienced teachers are less influenced by risk concerns when considering AI adoption. While teaching experience positively moderates the relationship between BEN and ADO (BEN → ADO: 0.174, $p = 0.031$), significantly enhancing it, it does not significantly affect the influence of TRU and CHLN on ADO. Specifically, teaching experience does not significantly alter the relationship between CHLN and ADO (CHLN → ADO: −0.069, $p = 0.314$). Overall, while teaching experience

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plays a crucial role in shaping perceptions of benefits and risks, it does not significantly impact all aspects of AI adoption.

Table 6: Measurement model's outer loadings

	ADO1	ADO2	ADO3	BEN1	BEN2	BEN3	BEN4	CHLN1	CHLN2	CHLN3	CHLN4	RISK1	RISK2	RISK3	RISK4	TRU1	TRU2	Teaching Experience
ADO1	1.000	−0.477	−0.553	0.015	−0.062	0.001	0.040	0.117	−0.014	−0.045	−0.054	0.008	−0.091	−0.015	0.092	0.101	−0.101	−0.050
ADO2	−0.477	1.000	−0.469	−0.086	−0.055	0.101	0.063	−0.027	0.170	−0.057	−0.114	0.005	0.006	−0.041	0.034	−0.011	0.011	0.107
ADO3	−0.553	−0.469	1.000	0.067	0.115	−0.097	−0.100	−0.092	−0.147	0.099	0.163	−0.013	0.085	0.054	−0.125	−0.091	0.091	−0.052
BEN1	0.015	−0.086	0.067	1.000	−0.121	−0.514	−0.628	−0.150	−0.045	0.040	0.162	0.016	0.016	0.081	−0.119	0.153	−0.153	−0.015
BEN2	−0.062	−0.055	0.115	−0.121	1.000	−0.463	−0.365	0.027	−0.092	−0.008	0.088	−0.152	0.041	0.090	0.005	−0.089	0.089	0.092
BEN3	0.001	0.101	−0.097	−0.514	−0.463	1.000	0.126	0.001	0.094	−0.049	−0.060	0.052	−0.002	−0.074	0.035	0.049	−0.049	−0.116
BEN4	0.040	0.063	−0.100	−0.628	−0.365	0.126	1.000	0.158	0.054	0.005	−0.226	0.076	−0.057	−0.115	0.108	−0.150	0.150	0.040
CHLN1	0.117	−0.027	−0.092	−0.150	0.027	0.001	0.158	1.000	−0.299	−0.360	−0.281	−0.079	0.001	−0.064	0.141	0.035	−0.035	0.041
CHLN2	−0.014	0.170	−0.147	−0.045	−0.092	0.094	0.054	−0.299	1.000	−0.410	−0.455	0.002	0.094	−0.166	0.093	0.073	−0.073	−0.082
CHLN3	−0.045	−0.057	0.099	0.040	−0.008	−0.049	0.005	−0.360	−0.410	1.000	−0.182	−0.012	−0.097	0.136	−0.048	−0.162	0.162	−0.007
CHLN4	−0.054	−0.114	0.163	0.162	0.088	−0.060	−0.226	−0.281	−0.455	−0.182	1.000	0.088	−0.012	0.119	−0.201	0.045	−0.045	0.062
RISK1	0.008	0.005	−0.013	0.016	−0.152	0.052	0.076	−0.079	0.002	−0.012	0.088	1.000	−0.117	−0.451	−0.325	−0.004	0.004	0.078
RISK2	−0.091	0.006	0.085	0.016	0.041	−0.002	−0.057	0.001	0.094	−0.097	−0.012	−0.117	1.000	−0.391	−0.384	0.056	−0.056	−0.033
RISK3	−0.015	−0.041	0.054	0.081	0.090	−0.074	−0.115	−0.064	−0.166	0.136	0.119	−0.451	−0.391	1.000	−0.317	−0.105	0.105	−0.029
RISK4	0.092	0.034	−0.125	−0.119	0.005	0.035	0.108	0.141	0.093	−0.048	−0.201	−0.325	−0.384	−0.317	1.000	0.066	−0.066	−0.011
TRU1	0.101	−0.011	−0.091	0.153	−0.089	0.049	−0.150	0.035	0.073	−0.162	0.045	−0.004	0.056	−0.105	0.066	1.000	−1.000	−0.137
TRU2	−0.101	0.011	0.091	−0.153	0.089	−0.049	0.150	−0.035	−0.073	0.162	−0.045	0.004	−0.056	0.105	−0.066	−1.000	1.000	0.137
Teaching Experience	−0.050	0.107	−0.052	−0.015	0.092	−0.116	0.040	0.041	−0.082	−0.007	0.062	0.078	−0.033	−0.029	−0.011	−0.137	0.137	1.000

Furthermore, trust in AI technologies (TRU) affects adoption intention (ADO) independently of teaching experience (TRU → ADO: 0.034, $p = 0.636$). In summary, while teaching experience enhances positive perceptions and reduces perceived risks, it does not significantly influence challenges or trust in adoption decisions. Table 7 displays the path coefficients and p-values for the proposed hypotheses.

Table 7: Hypotheses' path coefficients along with their p-values.

Hypothesis	P-Value	Path coefficient	Decision
H6: Teaching Experience x RISK → ADO	0.019	−0.110	Significant
H7: Teaching Experience x BEN → ADO	0.031	0.174	Significant
H8: Teaching Experience x TRU → ADO	0.636	0.034	Not Significant
H9: Teaching Experience x CHLN → ADO	0.314	−0.069	Not Significant

Moderation effect on perceived benefits

At all levels of teaching experience, the slope is positive, indicating that higher perceived benefits (BEN) lead to greater adoption intention (ADO). This reinforces the direct positive effect of BEN on ADO. Teachers with greater teaching experience (+1 SD) exhibit a stronger relationship between BEN and ADO, suggesting that experienced teachers are more influenced by perceived benefits when adopting AI technologies. Conversely, teachers with lower teaching experience (−1 SD) demonstrate a weaker relationship between BEN and ADO, indicating that less experienced teachers are less impacted by perceived benefits in their consideration of AI adoption. experience positively moderates the relationship between BEN and ADO, with more experienced teachers being more likely to adopt AI when they perceive significant benefits. In contrast, less experienced teachers may not respond as strongly to BEN, potentially due to limited exposure or confidence in using AI tools. The interaction effect is significant ($p = 0.031$), confirming that teaching experience enhances the positive impact of BEN on AI adoption intention. The moderation effect of teaching experience on BEN is illustrated in Figure 3.

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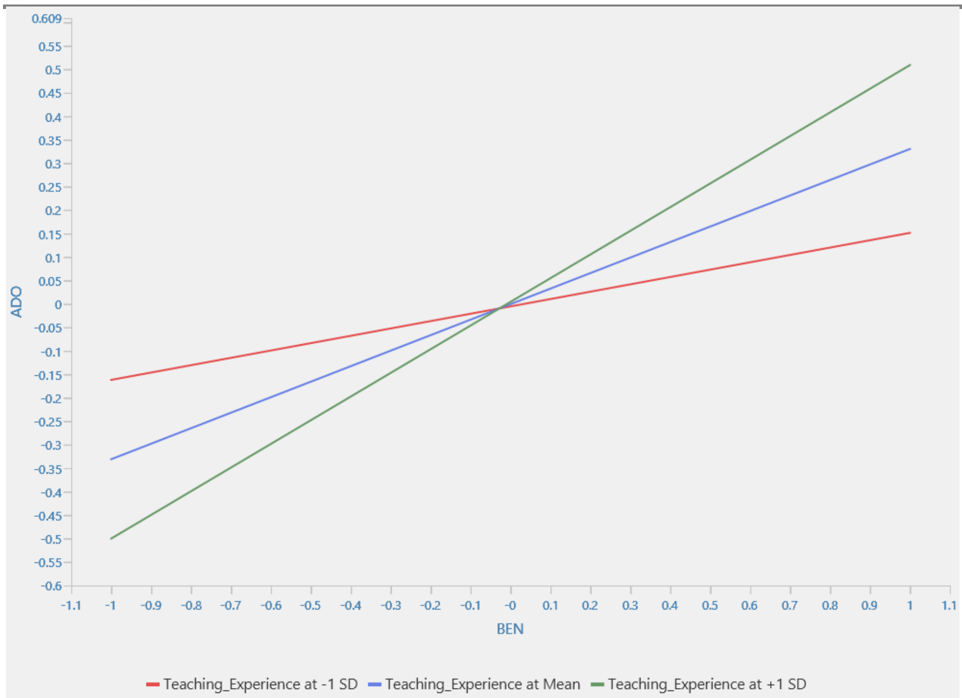

Figure 3: The moderation effect of teaching experience on perceived benefits

Moderation effect on perceived risks

The slopes are negative across all levels of teaching experience, indicating that adoption intention (ADO) decreases as perceived risk (RISK) increases. This confirms that a higher perception of risk acts as a barrier to AI adoption. Teachers with greater teaching experience (+1 SD) are more significantly affected by risk perceptions, meaning that when experienced teachers perceive high risks associated with AI, their likelihood of adoption declines markedly. Conversely, RISK also influences teachers with lower teaching experience (−1 SD), suggesting that less experienced teachers may be more open to adopting AI, even if they perceive some risks. Teaching experience moderates the relationship between RISK and ADO, with experienced teachers being more negatively impacted by risk perceptions than their less experienced counterparts. New teachers appear less sensitive to risk when deciding to adopt AI. As teaching experience increases, the negative impact of RISK on ADO diminishes. The moderation effect of teaching experience on RISK is illustrated in Figure 4.

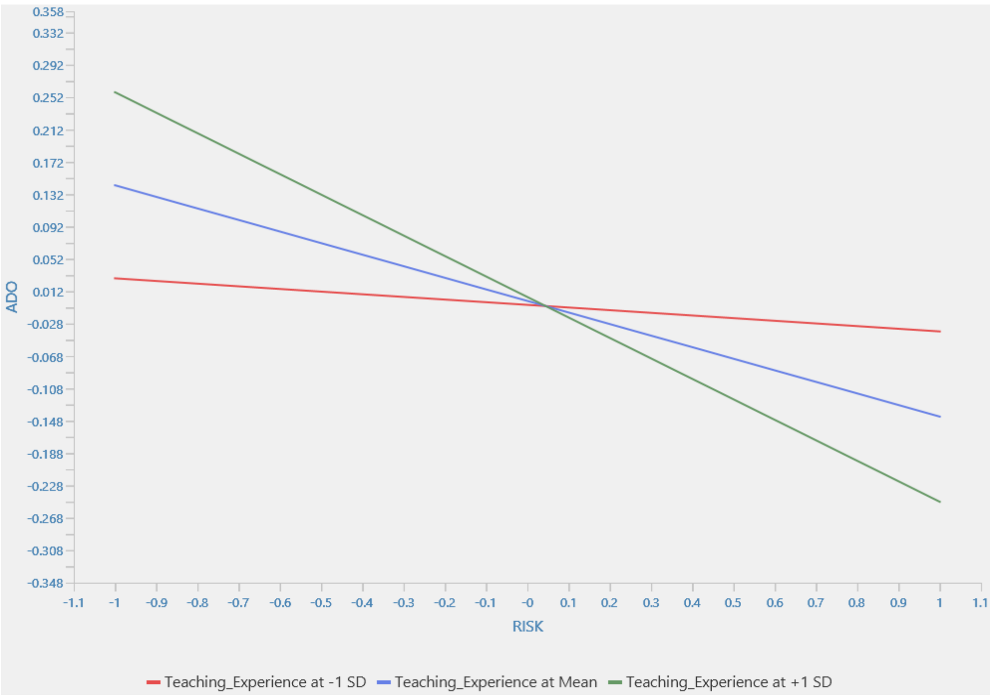

Figure 4: The moderation effect of teaching experience on perceived risks

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Moderation effect on challenges

At all levels of teaching experience, the slopes are positive, indicating that as perceived challenges (CHLN) increase, ADO also rises. This suggests that teachers who recognise challenges remain motivated to adopt AI technologies, possibly because they see potential solutions or strategies to overcome these obstacles. Teachers with lower teaching experience (−1 SD) are more influenced by challenges, meaning their likelihood of adopting AI increases more steeply when they perceive additional challenges. This may indicate that less experienced teachers are more adaptable and view challenges as opportunities for growth rather than barriers. In contrast, teachers with higher teaching experience (+1 SD) exhibit a weaker positive relationship between CHLN and ADO, suggesting that they may already have strategies to manage challenges, resulting in less drastic changes in their adoption intention. Teaching experience moderates the relationship between CHLN and ADO, with less experienced teachers responding more positively to challenges, thereby increasing their intention to adopt AI. While challenges still influence experienced teachers, the effect is less pronounced. The moderation effect of teaching experience on CHLN is shown in Figure 5.

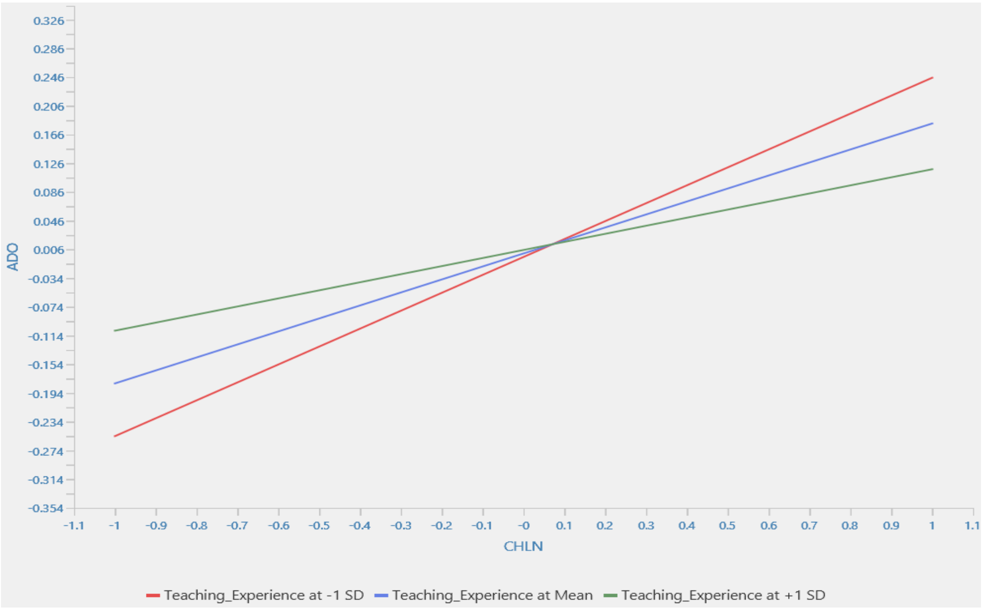

Figure 5: The moderation effect of teaching experience on perceived challenges

Moderation effect of perceived trust

Across all levels of teaching experience, the slopes are positive, indicating that higher TRU in AI leads to greater ADO. This confirms that TRU is a crucial factor influencing teachers' willingness to adopt AI technologies. The slopes for low, medium and high teaching experience levels are nearly identical, suggesting that teaching experience does not significantly alter the impact of TRU on ADO. Since the lines do not diverge or converge, the moderation effect is likely non-significant ($p = 0.636$). TRU in AI has a strong positive impact on ADO, regardless of teaching experience. Thus, teaching experience does not significantly moderate this relationship. Teachers with higher TRU in AI are more likely to adopt AI technologies, irrespective of their teaching experience. The moderation effect of teaching experience on TRU is illustrated in Figure 6. Figure 7 presents the final structural model along with the results of the path coefficients.

DISCUSSION

The integration of AI tools in education has gained attention in recent years, with ChatGPT serving as a prime example of how AI can enhance learning outcomes. This study explored teachers' perceptions of using ChatGPT as a learning tool in Saudi Arabia, focusing on its advantages, challenges and implications for educational settings. The findings reveal a nuanced understanding among teachers, who express both optimism and concerns about implementing ChatGPT in higher education. The discussion synthesises key findings, situates them within the broader literature and offers insights into theoretical and practical implications.

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Teachers' perceptions of ChatGPT's potential

The study found that most teachers view ChatGPT as a valuable learning tool. They noted its ability to provide immediate feedback, generate personalised learning materials and encourage students to develop critical thinking and problem-solving skills. This aligns with previous research highlighting the necessity of AI in facilitating adaptive and personalised learning environments [8]. For example, teachers indicated that ChatGPT's real-time responses to student queries could reduce their workload, allowing them to focus on higher-level teaching activities. This supports the assertion made by Alharbi [9], who argued that AI tools can complement teachers' skills by handling low-level tasks and fostering more interactive engagement with students.

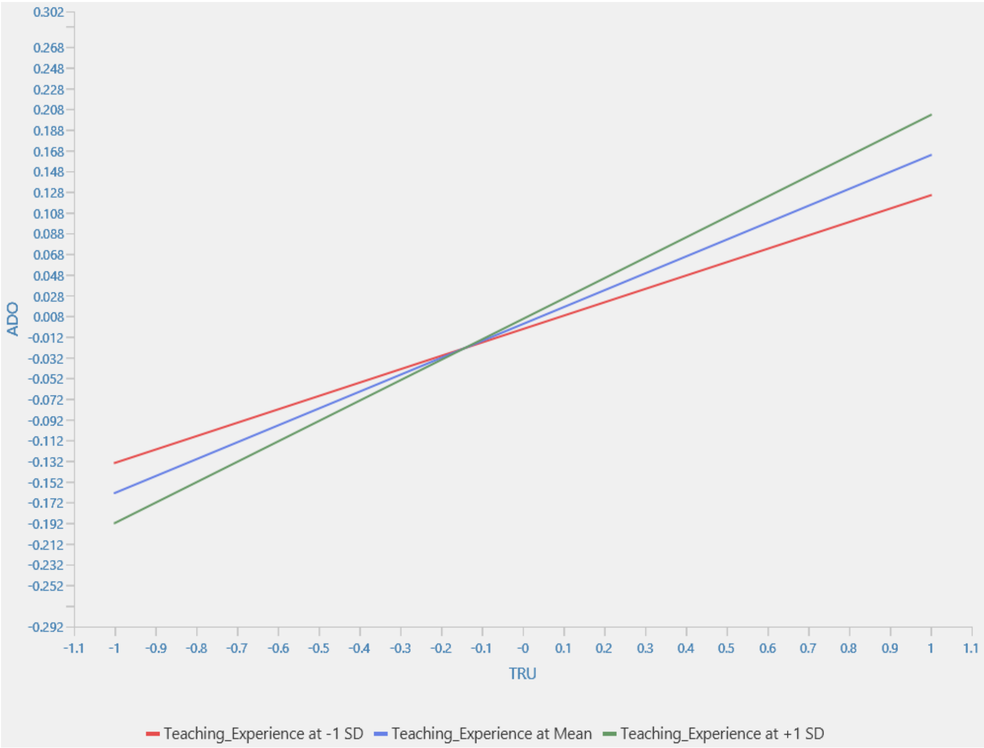

Figure 6: The moderation effect of teaching experience on trust

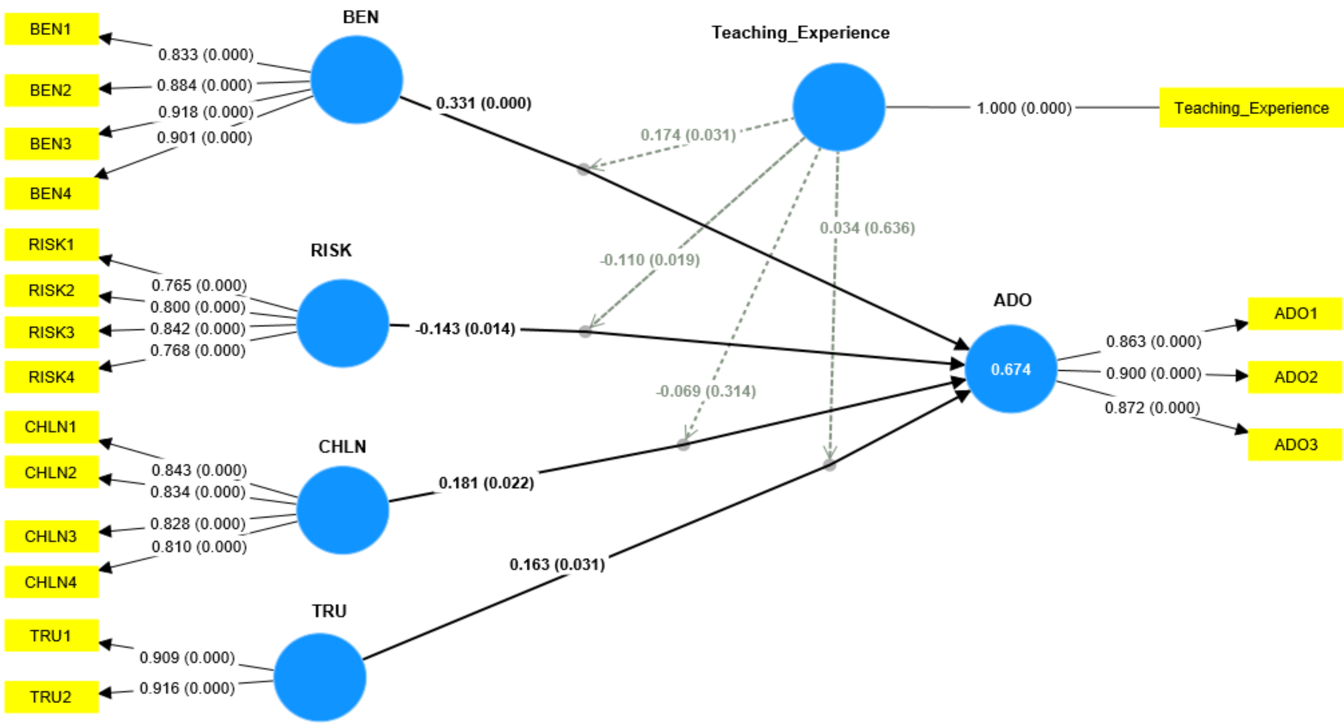

Figure 7: The final structure model with path coefficient values.

Teachers also expressed enthusiasm about ChatGPT's potential to address educational access inequities, particularly in remote or disadvantaged areas. This is particularly relevant in the Saudi context, where disparities in education quality and geography remain significant challenges [28]. The findings suggest that more experienced teachers are more likely to use ChatGPT than their less experienced counterparts. This is consistent with previous studies indicating that experienced teachers are more inclined to adopt new technologies in their teaching, as they understand pedagogical practices and can adapt to new tools [8] [27]. For experienced teachers, ChatGPT can be seen as an extension of their existing expertise, enhancing student learning and engagement. This aligns with the TAM, which posits that perceived ease of use and perceived usefulness are critical predictors of technology acceptance [19].

Challenges and concerns

Despite the noted advantages, the study also identified significant concerns among teachers regarding the use of ChatGPT in learning. A primary concern was the risk of over-reliance on AI, which could undermine students' critical thinking and self-learning abilities. Many teachers worried that students might use ChatGPT as a shortcut to complete assignments without fully understanding the material. This concern is supported by research indicating that dependency on AI tools can lead to superficial learning and poor comprehension [15].

Another major concern was the trustworthiness and accuracy of the responses generated by ChatGPT. This is particularly critical in academic settings, where factual accuracy is paramount. Previous studies have also highlighted the limitations of AI-based language models in providing accurate information [13] [12]. Additionally, the cultural and institutional context in Saudi Arabia plays a role in ChatGPT adoption. The country's Vision 2030 aims to leverage technology in education to foster innovation and economic development [29]. Such a policy framework could support the adoption of ChatGPT, but institutional backing—such as training and resources—is essential for successful implementation. Teachers who reported receiving adequate training on ChatGPT were more likely to adopt the tool, regardless of their experience level. This underscores the importance of professional development programmes in bridging the gap between experienced and novice teachers [9] [15].

Theoretical implications

Theoretically, this research contributes to existing models of educational technology adoption, such as TAM and UTAUT, by incorporating the influence of teachers' experience on AI adoption. It adds to the literature on ChatGPT's utility as an educational technology within the Saudi Arabian context. This study paves the way for developing a universal model of teachers' readiness to utilise AI-enabled tools. It also provides a valuable cross-cultural perspective by clarifying the unique challenges and viewpoints of Saudi teachers when employing ChatGPT in their teaching environments. Furthermore, it enriches the global discourse on AI in education by examining the factors influencing adoption in a non-Western educational context. The research supports constructivist and individualised learning theories by recognising ChatGPT's potential to enhance student-centred learning. AI-powered tools can facilitate adaptive learning and manage cognitive load, making education more personalised.

Practical implications

Practically, the study has implications for professional development and teacher training. Given that teachers with varying levels of experience respond differently to AI implementation, policymakers can use these findings to design tailored professional development programmes. Experience-based workshops and AI literacy training can help teachers transition to using ChatGPT effectively. The research also has policy and curriculum implications, identifying key challenges and opportunities related to AI adoption. It can guide higher education institutions and policymakers in developing systematic approaches to ensure the professional and ethical acceptance of ChatGPT in higher education. Additionally, the study highlights ChatGPT's potential to enhance student motivation and learning outcomes. AI-enabled interactions can provide personalised feedback, automate assessments and differentiate instruction, allowing universities and teachers to create more interactive and engaging classroom environments.

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Limitations and future work

While this study sheds light on teachers' attitudes towards ChatGPT, it has some limitations. First, the survey was conducted with a relatively small population of teachers, which may limit the generalisability of the findings. Future research should involve a larger, more representative sample to better reflect the broader population. Moreover, the study focused solely on teachers' perspectives, neglecting the views of students, parents and other stakeholders. Their insights are essential for providing a comprehensive understanding of the implications of using ChatGPT in education.

CONCLUSION

Exploring teachers' perspectives on using ChatGPT as a learning tool in Saudi Arabia reveals a nuanced understanding of its potential and challenges. Teachers believe that ChatGPT can significantly enhance student engagement and individualise learning. Its ability to provide instant feedback, adapt to diverse learning needs and support critical thinking aligns with Saudi Arabia's Vision 2030, which emphasises innovation and technology in education. However, the study also highlights important concerns that must be addressed to ensure the ethical and effective use of ChatGPT in higher education. Policymakers, educators and technologists must collaborate to develop new ethical frameworks. This study contributes to the growing body of literature on AI in education while considering the specific educational and cultural context of Saudi Arabia. The findings underscore several critical areas for future research and practical initiatives aimed at optimising the use of ChatGPT and similar AI tools in education, particularly within Saudi Arabia. A key direction for future work is to expand the research scope to include a more extensive and diverse participant sample, covering various educational levels, regions and disciplines. Additionally, future studies should investigate students' experiences and perceptions of using ChatGPT as a learning tool.

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