World Journal of Educational Studies
Print ISSN: 2959-9989
Online ISSN: 2959-9997
DOI: https://doi.org/10.61784/wjes3193

EDUCATORS' ACCEPTANCE OF AI-ENABLED TEACHING METHODS IN CHINESE HIGHER EDUCATION: EXTENDING UTAUT WITH PERCEIVED RISK AND DEMOGRAPHIC MODERATORS

Tian Yuan[1], Yue Wang[2], BaoDong Cheng[3*]
[1]College of Applied Science and Technology, Beijing Union University, Beijing 100020, China.
[2]College of Applied Arts and Science, Beijing Union University, Beijing 100020, China.
[3]College of Economics and Management, Beijing Forestry University, Beijing 100083, China.
[*]Corresponding Author: BaoDong Cheng

Abstract: This study examines educators' behavioral intention to adopt AI-enabled teaching methods in China using an extended Unified Theory of Acceptance and Use of Technology (UTAUT) framework that incorporates perceived risk. Survey data were collected from 312 higher-education teachers and analyzed using confirmatory factor analysis and structural equation modeling, followed by multi-group comparisons across gender, age, educational background, and teaching experience. The results indicate that performance expectancy, effort expectancy, social influence, and facilitating conditions significantly and positively predict educators' intention to adopt AI-enabled teaching methods, whereas perceived risk exerts a significant negative effect. The proposed model explains 63.7% of the variance in behavioral intention. Multi-group analyses further suggest that age, educational background, and teaching experience moderate several relationships in the model, while gender does not show statistically significant moderation. These findings highlight the importance of demonstrating pedagogical value and reducing implementation barriers through institutional infrastructure, technical support, and targeted professional development, alongside transparent governance mechanisms for privacy, ethics, and data protection to mitigate risk perceptions. This study contributes to the AI-in-education adoption literature by validating an extended UTAUT model in a higher-education context and offers actionable implications for universities and policymakers aiming to promote responsible and scalable integration of AI into teaching practices.
Keywords: AI-enabled teaching methods; Educator adoption; Structural equation modeling

1 INTRODUCTION

Artificial intelligence (AI) is rapidly reshaping how knowledge is produced, delivered, and assessed in educational settings. In higher education, AI-enabled teaching methods—including AI-supported lesson planning, adaptive learning platforms, intelligent tutoring systems, automated assessment, and learning analytics—are increasingly positioned as practical solutions for improving instructional efficiency, enabling personalization, and strengthening feedback loops. Despite the growing availability of AI tools and the widely discussed potential benefits, the diffusion of AI-enabled teaching methods remains uneven across institutions and educators. In many cases, adoption decisions are not determined solely by the technical capabilities of AI systems but by educators' perceptions of value, usability, support conditions, and risk.

Understanding educators' acceptance is particularly important because teachers and instructors are not passive technology users. They are key agents who shape pedagogical design, classroom orchestration, and assessment practices, and their willingness to adopt AI-enabled teaching methods directly influences implementation quality and sustainability. Compared with student-focused adoption research, educator-focused evidence remains relatively limited, especially for AI-enabled teaching methods that may challenge traditional professional autonomy, ethical standards, and data governance expectations. As a result, there is a strong need for empirical research that explains what drives educators' intention to adopt AI-enabled teaching methods and what inhibits it.

Prior technology-adoption research in education has frequently relied on established models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). Among these, UTAUT provides an integrative framework with strong explanatory power by highlighting four core determinants of behavioral intention: performance expectancy, effort expectancy, social influence, and facilitating conditions. However, AI-enabled teaching methods differ from many conventional educational technologies in two respects. First, AI systems often operate through complex and partially opaque algorithms, which may affect educators' trust and perceived controllability. Second, AI use in teaching is closely tied to sensitive data, evaluation fairness, and accountability, making risk perceptions more salient than in many earlier educational technology contexts. Therefore, applying UTAUT in the AI-in-education domain can benefit from theoretically grounded extensions that incorporate risk-related concerns.

Perceived risk is a particularly relevant construct for AI-enabled teaching methods. Educators may worry about privacy and data security (e.g., student information processing), ethical and fairness issues (e.g., bias in AI outputs and automated assessment), reliability and pedagogical consequences (e.g., inaccurate feedback or over-standardized instruction), and potential threats to professional autonomy and role identity. These concerns can inhibit adoption even when educators acknowledge performance benefits. Without explicitly accounting for risk perceptions, adoption models may overestimate the influence of positive utility beliefs and underestimate the psychological and institutional barriers specific to AI-enabled teaching.

In addition, educator acceptance of AI-enabled teaching methods is unlikely to be homogeneous. UTAUT itself proposes that demographic characteristics may moderate the effects of core determinants on behavioral intention. In higher education, differences in age, educational background, and teaching experience can reflect variation in digital competence, pedagogical beliefs, risk tolerance, and openness to instructional change. For example, educators with stronger academic training or greater exposure to technology-mediated teaching may be more responsive to facilitating conditions and performance benefits, while those with longer teaching tenure may weigh autonomy and risk concerns more heavily. Examining such heterogeneity is essential for designing targeted interventions and support strategies that match the needs of different educator groups.

Against this background, this study investigates educators' behavioral intention to adopt AI-enabled teaching methods in the context of Chinese higher education by developing and testing an extended UTAUT framework that incorporates perceived risk. Specifically, we address the following research questions:

RQ1: To what extent do performance expectancy, effort expectancy, social influence, and facilitating conditions explain educators' behavioral intention to adopt AI-enabled teaching methods?

RQ2: How does perceived risk influence educators' behavioral intention to adopt AI-enabled teaching methods when considered alongside the core UTAUT determinants?

RQ3: Do demographic characteristics (gender, age, educational background, and teaching experience) moderate the relationships between the determinants and educators' adoption intention?

To answer these questions, we collect survey data from higher-education educators in China and employ confirmatory factor analysis and structural equation modeling to test the measurement model and the hypothesized structural relationships. We further use multi-group comparisons to explore potential moderation patterns across key demographic groups.

This study makes three contributions. First, it contributes to the AI-in-education adoption literature by offering educator-centered empirical evidence on AI-enabled teaching methods, a domain where acceptance dynamics can differ from both student adoption and traditional educational technology adoption. Second, it extends UTAUT by integrating perceived risk into the model, providing a more comprehensive explanation that captures both enabling mechanisms (expected benefits, ease of use, social influence, and support conditions) and inhibiting mechanisms (risk perceptions) relevant to AI-enabled teaching. Third, by examining demographic moderators, the study provides nuanced insights into adoption heterogeneity, offering practical guidance for higher-education institutions and policymakers to design differentiated support systems, professional development programs, and risk-governance measures that facilitate responsible AI integration into teaching.

The remainder of the paper is organized as follows. Section 2 reviews relevant literature and develops hypotheses. Section 3 describes the research design, sample, measures, and analytical procedures. Section 4 reports the empirical results. Section 5 discusses theoretical and practical implications, and Section 6 concludes with limitations and directions for future research.

2 LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 AI-Enabled Teaching Methods: Definition and Relevance

Artificial Intelligence (AI)-enabled teaching methods encompass a broad range of digital technologies designed to replicate or enhance human cognitive functions within educational contexts. These technologies include adaptive learning systems, intelligent tutoring systems, automated grading platforms, natural language processing (NLP)-based assistants, and personalized learning analytics [1]. Such innovative approaches aim to enhance the efficiency, effectiveness, and personalization of education by dynamically adapting to students' learning styles, preferences, and performance levels.

Adaptive learning systems, a cornerstone of AI-enhanced education, leverage sophisticated algorithms to continuously analyze learner performance data, tailoring instructional content and pacing to individual students. These systems demonstrate substantial improvements in learning outcomes by enabling personalized instruction that addresses individual strengths and weaknesses more precisely than traditional methods [2].

Intelligent tutoring systems (ITS), another key AI-driven approach, emulate the personalized tutoring interactions traditionally provided by human instructors. These systems utilize cognitive science principles and data-driven insights to deliver targeted feedback, adaptive problem-solving assistance, and customized learning pathways, thereby significantly enhancing students' engagement and retention rates [3-4].

Automated grading and assessment tools powered by AI have also become increasingly prevalent. These systems reduce educators' workload substantially by providing rapid, consistent, and objective evaluations of student performance, particularly beneficial in large-scale or online learning environments [5-6]. Recent studies demonstrate that educators who adopt automated grading tools can redirect their efforts toward more complex instructional tasks, fostering deeper student-teacher interactions and enhancing overall educational quality [7].

Natural language processing (NLP)-based teaching assistants and chatbots represent another critical category of AI-enabled educational tools. Such AI assistants offer real-time guidance, answer frequent student queries, and provide immediate feedback on tasks, significantly improving learner support and accessibility outside traditional classroom settings [8-9]. NLP-based tools also facilitate more interactive, engaging learning experiences by providing learners with immediate and context-sensitive responses, fostering greater learner autonomy and reducing response delays.

Furthermore, personalized learning analytics driven by AI support educators in identifying at-risk students, monitoring learning progress, and adapting teaching strategies proactively. By leveraging data analytics and predictive modeling, educators can make informed decisions, enhance student outcomes, and address learning barriers promptly and effectively [10].

Despite these clear benefits, educators face multiple challenges in integrating AI-driven methods into teaching practice, including concerns related to technological complexity, data security, ethical implications, and the perceived threat of job replacement by technology [1]. Recent empirical evidence emphasizes that the successful integration of AI-enabled teaching methods largely depends on educators' acceptance, their perceived ease of use, perceived benefits, perceived risks, and the availability of robust institutional support mechanisms [11].

Therefore, to facilitate the widespread adoption of AI-enabled teaching methods, it is essential to comprehensively understand educators’ perceptions and attitudes, as their acceptance significantly influences the effectiveness and sustainability of technology integration efforts within educational institutions.

2.2 Theoretical Foundation: Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT), proposed by Venkatesh et al., integrates multiple prominent technology acceptance models into a unified framework [12]. This comprehensive model combines key determinants from earlier acceptance models such as the Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB), and Diffusion of Innovation (DOI), offering robust explanatory power to predict user behaviors towards new technologies [13-14].

The UTAUT model identifies four principal constructs influencing technology adoption intentions: performance expectancy, effort expectancy, social influence, and facilitating conditions. Each construct has been validated across various contexts, including healthcare, finance, and education [15].

Performance expectancy (PE) refers to the extent to which individuals believe that using the technology will help them achieve improved outcomes and enhance job performance. Empirical studies have consistently demonstrated that performance expectancy significantly influences adoption intention, especially in educational contexts where tangible improvements in teaching effectiveness are highly valued by educators [13].

Effort expectancy (EE) describes the perceived ease of use associated with a technology. The easier and more intuitive a technology is perceived, the greater its adoption likelihood. Multiple studies confirm that perceived complexity is a major barrier to educators' acceptance, indicating that simplicity and user-friendly interfaces critically shape teachers' technology integration decisions [16-17].

Social influence (SI) captures the degree to which individuals perceive that important others—such as colleagues, peers, and institutional leaders—believe they should use the new technology. Social influence often plays a pivotal role in technology adoption within educational institutions, where organizational culture, institutional policies, and peer recommendations significantly impact educators’ decisions to adopt innovative teaching methods [18].

Facilitating conditions (FC) represent the degree to which individuals perceive that organizational and technical infrastructure exists to support technology use. Facilitating conditions encompass technical support, training programs, clear guidelines, and adequate infrastructure. The availability of robust facilitating conditions consistently emerges as a strong predictor of educators' continued use of educational technologies, as shown in various contexts ranging from online learning platforms to smart classrooms.

Despite UTAUT’s widespread application, researchers increasingly argue for extending the original model to incorporate additional factors that capture unique user concerns, particularly when addressing emerging technologies such as artificial intelligence [13, 15]. In recent years, perceived risk has been identified as a critical variable influencing the acceptance of new, potentially disruptive technologies. Perceived risk encompasses concerns related to data privacy, algorithmic transparency, ethical considerations, potential job displacement, and reliability issues [19]. Educators may hesitate to adopt AI-driven technologies due to worries about data misuse, negative implications on pedagogical autonomy, and broader ethical dilemmas [1].

Given these considerations, scholars advocate explicitly integrating perceived risk into the UTAUT model to better reflect the nuanced adoption behaviors specific to AI-enabled educational tools [11]. Recent empirical evidence indicates that perceived risks significantly moderate educators’ adoption intentions, making it essential to include perceived risk as a core element within technology acceptance frameworks when examining AI integration in education.

Furthermore, the original UTAUT framework emphasizes that demographic variables—including age, gender, experience, and education level—moderate the relationships among core determinants and behavioral intentions [12, 14]. Subsequent research confirms that these demographic factors can significantly influence adoption behaviors by affecting users' technological familiarity, risk tolerance, and willingness to change established practices [16, 20]. Understanding these demographic moderating effects is particularly valuable in educational settings, as it allows policymakers and educational leaders to craft tailored interventions that address diverse educator segments effectively [18].

In conclusion, this study extends the UTAUT model by explicitly incorporating perceived risk as a critical factor, alongside rigorous consideration of demographic moderators. Such a comprehensive theoretical approach offers a deeper understanding of educators' complex attitudes and behaviors toward adopting AI-enabled teaching methods within the dynamic context of contemporary education (Figure 1).

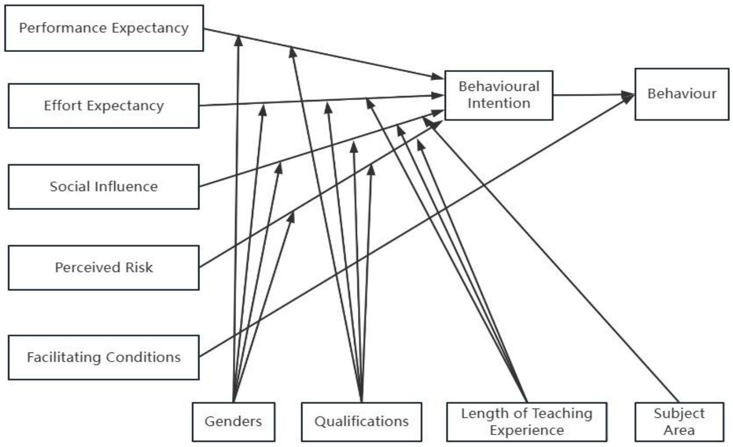

Figure 1 AI-Enabled Education Approach Acceptance Model

2.3 Hypothesis Development

2.3.1 Performance expectancy (PE)

Performance expectancy (PE) refers to the extent to which an individual perceives that using a particular technology will significantly improve their job performance and effectiveness [12]. Within educational contexts, performance expectancy primarily concerns educators' perceptions of how AI-enabled teaching tools can enhance instructional quality, improve teaching efficiency, and positively impact students' learning outcomes [21].

Multiple empirical studies indicate that educators are significantly more inclined to adopt educational technologies if they perceive clear performance benefits, such as reduced workload, increased instructional effectiveness, and improved student engagement [17]. For example, adaptive learning technologies leveraging AI-driven analytics enable educators to provide personalized instruction tailored to individual student needs, thereby enhancing student performance and overall teaching effectiveness [1]. Similarly, intelligent tutoring systems (ITS) have been documented to reduce educators' instructional workload significantly by providing tailored feedback, thus enabling them to concentrate on higher-order pedagogical activities and personalized student interactions [3, 5].

Recent research by Chiu and Chai highlights that when educators perceive AI-enabled teaching methods as improving their ability to deliver timely, personalized, and adaptive feedback, their acceptance of these technologies increases markedly. This finding aligns with earlier studies, demonstrating the direct correlation between educators' perceived performance gains and their behavioral intentions to adopt and continuously use innovative educational technologies [18].

Performance expectancy is also influenced by the perceived quality and accuracy of the technology itself. For instance, educators who observe that automated grading systems provide consistent, objective, and accurate assessments of student performance tend to report increased job satisfaction and reduced assessment-related workload, thus exhibiting higher acceptance rates for such technologies [7]. Moreover, Baker and Smith found that AI-driven virtual teaching assistants, which accurately address student queries and effectively facilitate learning processes, significantly enhance educators' teaching performance by freeing up time for more strategic, high-value educational tasks [8].

However, educators' perceived performance expectancy may vary according to their familiarity and previous experience with technology, institutional culture, and the availability of evidence demonstrating the tangible effectiveness of AI applications [6]. Empirical studies suggest that providing educators with clear evidence and demonstrable outcomes through targeted professional training programs can significantly enhance their performance expectancy perceptions and overall acceptance of AI-enabled educational tools.

Given these findings and empirical insights, it is evident that performance expectancy is a critical predictor of educators' intentions to adopt AI-enabled teaching methods. Educators who recognize the potential of AI to positively transform their instructional practices and enhance teaching effectiveness are more likely to adopt and actively integrate these innovative methods into their professional routines.

Therefore, based on these theoretical insights and empirical evidence, we propose the following hypothesis:

Hypothesis 1 (H1): Performance expectancy positively influences educators' behavioral intention to adopt AI-enabled teaching methods.

2.3.2 Effort expectancy (EE)

Effort expectancy (EE) refers to the perceived ease or convenience associated with using a specific technology or innovation [12]. In the context of educational technology adoption, effort expectancy relates specifically to educators'

perceptions of how easily they can learn to operate, integrate, and manage AI-enabled teaching tools within their existing instructional practices [17]. This construct is especially significant in education, where technology complexity often poses substantial barriers to widespread adoption and sustained integration.
Research consistently demonstrates that effort expectancy is a strong predictor of educators' willingness to adopt new educational technologies. Educators are more likely to adopt AI-enabled teaching methods if they perceive the tools as intuitive, straightforward to use, and compatible with their existing teaching practices and technological skills [16]. Conversely, educators perceive complex or cumbersome technologies as barriers to adoption, leading to resistance, frustration, and ultimately lower acceptance rates [13].
For instance, a recent study by Šumak and Šorgo indicated that teachers who find interactive digital technologies, such as smartboards or automated grading software, easy to learn and operate tend to report significantly higher adoption rates and satisfaction levels compared to their peers [18]. Similar findings were confirmed by Teo et al., who highlighted that Chinese educators' perceived ease of use significantly influenced their willingness to integrate innovative instructional technologies, such as digital learning platforms and educational software [17].
Effort expectancy is particularly crucial in the context of AI-enabled teaching methods due to their inherent complexity, algorithmic functionalities, and sophisticated user interfaces [5]. Chiu and Chai argued that educators often lack confidence or motivation to use new technologies unless they clearly perceive that these technologies can be adopted with minimal effort and disruption to their established teaching routines. They emphasized that reducing cognitive and operational complexity through user-friendly designs and targeted training significantly facilitates the acceptance and continued use of AI-based instructional tools.
Moreover, the relevance of effort expectancy extends beyond initial adoption. Teo et al. suggested that sustained and long-term integration of educational technologies significantly depends on educators' continuous perception of ease and convenience. Their study showed that ongoing technical support, user-friendly design, and systematic training markedly enhance teachers' sustained engagement with educational technology.
Previous studies further indicate that effort expectancy interacts closely with facilitating conditions, where the availability of robust institutional support and accessible technical assistance significantly reduces educators' perceived effort in adopting new technologies. Conversely, insufficient support mechanisms and overly complex interfaces increase perceived difficulty, discouraging educators from integrating technology into their pedagogical practices [16].
The critical role of effort expectancy also aligns with empirical evidence from broader acceptance studies outside the educational context. For example, Dwivedi et al. and Alalwan et al. found that perceived ease of use substantially influences users' adoption behaviors across various technologies, including mobile banking, online services, and innovative consumer technologies [13, 19]. Thus, the insights derived from these studies further underscore the importance of addressing ease of use explicitly when introducing complex AI-enabled teaching methods.
Given this comprehensive evidence and critical analysis, it is clear that educators' perceived ease of adopting and using AI-enabled teaching technologies significantly affects their acceptance and sustained integration intentions. Therefore, this study formulates the following hypothesis:
Hypothesis 2 (H2): Effort expectancy positively influences educators' behavioral intention to adopt AI-enabled teaching methods.

2.3.3 Social influence (SI)

Social influence (SI) is defined as the extent to which individuals perceive that significant others—such as colleagues, supervisors, professional peers, and institutions—believe they should adopt a particular technology or behavior [12]. In the context of educational technology acceptance, social influence encapsulates how educators' decisions to integrate new technologies, including AI-enabled teaching methods, are influenced by institutional norms, peer recommendations, leadership endorsement, and broader professional communities [17, 21].
Research consistently highlights that educators do not operate in isolation but within complex social and organizational contexts. These social contexts significantly shape their attitudes toward adopting innovative technologies in education [16]. For example, institutional leadership and organizational culture have been found to significantly impact educators' willingness to experiment with and integrate new technologies. Institutions promoting a culture of innovation and technological exploration often achieve higher levels of educator acceptance, largely driven by supportive peer norms and clearly articulated institutional expectations [20].
Empirical studies further demonstrate that peer influence and recommendations significantly enhance educators' adoption intentions. For instance, teachers who perceive strong peer endorsement of educational technologies report higher confidence levels in technology effectiveness, leading to increased adoption rates. A study by Šumak and Šorgo on the adoption of interactive whiteboards revealed that teachers were significantly influenced by peer behaviors and opinions, particularly in early adoption stages [18]. Educators reported greater willingness to adopt new technologies if colleagues they respected or admired demonstrated successful integration experiences [5].
Leadership endorsement from school administrators and educational policymakers also substantially affects educators' acceptance behaviors. Research by Teo et al. demonstrated that explicit support from educational administrators and school leadership significantly increased teachers' technology acceptance and use intentions, primarily because it conveyed institutional commitment and legitimacy to the adoption process [17]. Similarly, Antonio and Martina argued that educators are more likely to adopt and effectively integrate new technologies when institutional leaders explicitly articulate support, provide necessary resources, and consistently encourage innovation.
Beyond institutional and peer influences, broader professional communities, including professional development networks and online educational forums, have increasingly emerged as powerful social influences shaping educators'

technology acceptance behaviors. Professional development programs, workshops, and seminars play a critical role in facilitating the exchange of best practices and enhancing teachers' perceptions of technology effectiveness. Educators who participate regularly in professional communities tend to have higher levels of social validation and perceived legitimacy regarding technology use.

Social influence becomes particularly critical in the context of AI-enabled educational technologies due to their novelty, complexity, and perceived risks associated with privacy and ethical issues. Educators' uncertainty regarding new and disruptive technologies increases their reliance on social cues and normative expectations from trusted colleagues, educational leaders, and professional communities [1]. A recent empirical study by Kong et al. on generative AI tools revealed that educators' intentions to adopt AI methods were strongly correlated with perceptions of peer and leadership support, highlighting the decisive role social influence plays in acceptance decisions [21].

Additionally, the moderating effects of demographic factors, such as age and experience, may significantly influence the strength of social influence. For example, younger educators or those newer to the teaching profession often demonstrate heightened sensitivity to peer opinions and social expectations, making social influence an even stronger determinant of their technology acceptance behaviors [16, 20]. This observation underscores the necessity of understanding and leveraging social influence strategically within educational institutions to promote broader and more inclusive technology adoption.

Given the extensive empirical support and theoretical considerations outlined above, social influence emerges as a critical predictor of educators' acceptance of AI-enabled teaching methods. Educators' technology adoption behaviors are strongly shaped by perceived social norms, peer endorsements, institutional leadership support, and professional community validation.

Therefore, based on these insights, the following hypothesis is formulated:

Hypothesis 3 (H3): Social influence positively influences educators' behavioral intention to adopt AI-enabled teaching methods.

2.3.4 Facilitating conditions (FC)

Facilitating conditions (FC) refer to individuals' perceptions of available resources, infrastructure, organizational support, and knowledge necessary to successfully implement and use new technologies [12]. Within educational settings, facilitating conditions include technical infrastructure, administrative support, comprehensive professional development, reliable technical assistance, and institutional policies that collectively enable educators to effectively adopt and integrate innovative technologies such as AI-enabled teaching tools.

Empirical research consistently demonstrates that robust facilitating conditions significantly increase educators' intentions to adopt educational technologies. According to Šumak and Šorgo, teachers who perceive that their schools provide strong institutional support, including adequate training and reliable technical resources, show higher levels of willingness and confidence in adopting new technologies such as interactive whiteboards and adaptive learning platforms [18]. Conversely, inadequate institutional resources, lack of training, and poor technological infrastructure consistently emerge as major barriers impeding successful adoption and sustainable integration of educational innovations [17].

Technical infrastructure, such as stable internet connectivity, reliable hardware, and appropriate software platforms, forms a critical component of facilitating conditions. A robust technological infrastructure substantially reduces the barriers associated with using advanced educational technologies, thereby directly enhancing educators' perceived ease and confidence in adoption [5]. Recent studies indicate that educators' perceptions of technology usability and reliability are significantly influenced by their institutions' technical readiness and overall technological ecosystem.

Institutional support through targeted professional development and ongoing training programs further significantly strengthens facilitating conditions. Effective training programs increase educators' technological competencies, directly enhancing their confidence and willingness to adopt and continuously utilize new AI-based educational tools [16]. Chao emphasized that regular professional development workshops and comprehensive training sessions significantly reduce educators' apprehensions about adopting new technologies, particularly AI-driven educational systems, by providing clear demonstrations, hands-on practice, and continuous support.

Furthermore, facilitating conditions encompass reliable and easily accessible technical support, enabling educators to promptly address technical challenges encountered while implementing innovative educational technologies [1]. For example, a study conducted by Nikolopoulou et al. demonstrated that rapid, accessible, and responsive technical assistance significantly increased educators' perceived control over technology usage, ultimately improving their willingness and commitment to sustained technology integration.

Institutional policies and clearly articulated guidelines are also integral aspects of facilitating conditions. Clear, supportive institutional policies provide educators with explicit expectations, objectives, and structured incentives for technology adoption, thereby significantly enhancing their adoption intentions [13]. A recent study by Wang et al. indicated that institutions with clearly established policies supporting technology adoption and innovation tend to achieve significantly higher levels of sustained technology use among educators.

Facilitating conditions are especially critical when considering the integration of advanced AI-driven educational tools due to their complexity, specialized knowledge requirements, and potential ethical and privacy-related challenges. Recent studies have highlighted that the successful implementation of AI in education significantly depends on the holistic support ecosystem provided by educational institutions, including infrastructure readiness, extensive professional training, clear policy guidance, and comprehensive risk management practices [11].

Moreover, empirical evidence suggests that facilitating conditions can moderate and amplify the positive effects of other key technology acceptance determinants, such as performance expectancy and effort expectancy. Educators who perceive strong facilitating conditions are more likely to translate perceived performance benefits and ease of use into actual adoption behaviors [17]. Conversely, inadequate facilitating conditions can undermine even high levels of perceived usefulness and ease, significantly reducing educators' adoption intentions [16, 18].

Given the extensive empirical evidence and theoretical analysis presented, it is clear that facilitating conditions represent a critical determinant of educators' intentions and behaviors towards adopting AI-enabled teaching methods. Therefore, based on these insights, we propose the following hypothesis:

Hypothesis 4 (H4): Facilitating conditions positively influence educators' behavioral intention to adopt AI-enabled teaching methods.

2.3.5 Perceived risk (PR)

Perceived risk (PR) is defined as the extent to which individuals perceive potential adverse outcomes or uncertainties associated with adopting a particular technology [22]. In educational contexts, perceived risk encompasses educators' concerns regarding data privacy breaches, ethical dilemmas, algorithmic bias, loss of pedagogical autonomy, and broader implications on teaching quality associated with the adoption of AI-enabled technologies [1].

In the context of adopting AI-enabled teaching methods, educators' perceived risks often relate explicitly to data security and privacy concerns. For instance, AI tools typically require access to large datasets involving sensitive student information, such as academic performance, behavior records, and personal details. Educators may fear unauthorized data sharing, privacy violations, or potential misuse of sensitive information, leading to considerable hesitation or resistance toward adopting such advanced technologies [11].

Algorithmic transparency and ethical concerns also significantly contribute to perceived risk. Educators frequently question the accuracy, fairness, and interpretability of AI-generated recommendations or automated assessments [5]. Algorithmic biases, such as racial, socioeconomic, or gender biases, may unintentionally emerge from AI tools, potentially disadvantaging particular student groups. Such biases can result in serious ethical dilemmas, undermining educators' trust in AI-driven educational technologies and negatively affecting their intentions to integrate these technologies into teaching practices [1, 21].

Loss of pedagogical autonomy represents another critical dimension of perceived risk. Educators may fear that reliance on AI-driven systems could diminish their professional judgment, reduce flexibility in instructional decisions, and undermine their autonomy as educators. The perception of AI tools as overly prescriptive or limiting can significantly reduce educators' willingness to embrace these technologies, particularly among experienced teachers accustomed to personalized and flexible teaching approaches [17].

Moreover, the perception of risks associated with potential job displacement or reduced relevance of teaching roles due to automation is increasingly recognized in educational settings. Educators' concerns regarding the perceived threat to their professional roles and job security represent significant psychological barriers to adoption [13]. Empirical evidence highlights that educators often resist technological innovations when they perceive the technology as potentially replacing rather than enhancing their professional capabilities [18].

Recent studies have shown that perceived risk negatively impacts educators' intentions to adopt innovative educational technologies, including AI-driven solutions. For instance, a study by Raza et al. demonstrated that perceived risk associated with privacy and security significantly inhibited user acceptance of AI-based online tools. Similarly, in educational contexts, Chen et al. identified perceived risk as a key negative determinant influencing educators' adoption decisions regarding generative AI technologies, highlighting the critical role that perceived uncertainty and potential adverse outcomes play in technology acceptance [1].

To mitigate these perceived risks, educational institutions are advised to implement transparent policies, robust data security protocols, clear ethical guidelines, and systematic risk communication strategies. Clear communication and institutional transparency regarding data handling processes, algorithmic fairness, and the pedagogical role of AI can significantly reduce perceived risks, enhancing educators' confidence and willingness to adopt AI-enabled teaching tools. Moreover, providing educators with active involvement in the adoption process, including collaborative training programs and participatory decision-making opportunities, can effectively address autonomy-related concerns and reduce psychological barriers to adoption.

Given the extensive empirical evidence and theoretical considerations presented, perceived risk emerges as an essential construct that significantly influences educators' acceptance intentions toward AI-enabled teaching methods. Consequently, educators' perceptions of potential negative outcomes must be explicitly addressed when aiming for successful and sustainable integration of advanced educational technologies.

Thus, we propose the following hypothesis:

Hypothesis 5 (H5): Perceived risk negatively influences educators' behavioral intention to adopt AI-enabled teaching methods.

2.4 Moderating Effects

In addition to examining the primary determinants of technology acceptance, this study considers various demographic moderators that potentially influence educators' acceptance behaviors towards AI-enabled teaching methods. Prior literature consistently suggests that demographic variables—such as gender, educational background, age, and teaching experience—may significantly moderate relationships between technology acceptance determinants (performance expectancy, effort expectancy, social influence, facilitating conditions, perceived risk) and adoption intentions [12-13]. Understanding these moderating effects provides nuanced insights into how diverse educator groups perceive and adopt innovative educational technologies, thus allowing institutions to tailor interventions more effectively [18].

2.4.1 Gender

Previous research on technology acceptance frequently investigates gender as a potential moderator, given that gender differences can influence attitudes, risk perceptions, and technology adoption intentions. According to the UTAUT framework initially proposed by Venkatesh et al., gender moderates technology acceptance determinants, with differences observed in how men and women perceive and respond to technology use [12].

Empirical findings regarding gender effects in educational technology acceptance contexts remain mixed. Some studies suggest that male educators are generally more willing to experiment with new technological tools, displaying higher perceived ease of use and confidence in technology integration [18]. In contrast, other studies indicate that female educators often express greater caution, emphasizing privacy concerns, perceived risks, and potential impacts on pedagogical approaches when considering new technologies [16].

For example, in a study on mobile learning adoption among teachers, Nikolopoulou et al. found significant gender differences in perceptions of facilitating conditions and perceived risks, suggesting that female educators demonstrated greater sensitivity to the presence or absence of institutional support and clarity of risk mitigation measures. Similarly, Teo et al. indicated that male educators typically reported higher performance expectancy and perceived ease of technology use, contributing to higher overall acceptance rates among this group.

Understanding these gender-based nuances is particularly crucial when introducing AI-enabled educational tools, which often pose complex privacy, ethical, and autonomy-related issues. Institutions can address these gender-specific perceptions by implementing tailored professional development programs, targeted communication strategies, and differentiated support structures to foster more equitable and effective technology integration across genders [21].

Based on these empirical insights and theoretical considerations, we propose the following hypothesis:

Hypothesis 6 (H6): Gender significantly moderates the relationships between UTAUT factors (performance expectancy, effort expectancy, social influence, facilitating conditions, perceived risk) and educators' behavioral intention to adopt AI-enabled teaching methods.

2.4.2 Educational background

Educational background, encompassing educators' levels of academic qualification and specialized training, represents another potentially significant moderator influencing technology acceptance behaviors. Educators with advanced academic qualifications or extensive professional training in technology-related disciplines may perceive AI-enabled teaching methods more favorably due to higher digital literacy levels and greater familiarity with innovative technologies.

Empirical evidence indicates that educators' educational backgrounds significantly influence their attitudes, risk perceptions, and adoption intentions toward advanced educational technologies. Educators possessing specialized degrees, training, or certification in educational technology or related fields typically exhibit higher confidence, lower perceived complexity, and more positive performance expectations regarding technology integration [18].

For instance, Nikolopoulou et al. observed that educators with formal training in information and communication technology (ICT) expressed significantly more favorable perceptions of facilitating conditions and performance expectancy when adopting digital learning tools. Similarly, a study by Antonio and Martina highlighted that educators with higher academic qualifications or technology-related training demonstrated significantly lower levels of perceived effort, leading to increased adoption intentions and sustained technology use.

Educators without specialized technological training or advanced academic qualifications, however, often perceive technology integration as more complex and challenging. They are more likely to require substantial institutional support, including extensive training programs, mentoring, and continuous technical assistance, to build confidence and effectively integrate innovative AI-driven educational tools into their teaching practices [16].

Educational institutions can therefore strategically tailor training programs and support mechanisms according to educators' educational backgrounds, ensuring targeted professional development opportunities that build necessary skills, reduce perceived effort, and enhance overall acceptance of AI-enabled teaching methods [21].

Given these theoretical insights and empirical evidence, the following hypothesis is formulated:

Hypothesis 7 (H7): Educational background significantly moderates the relationships between UTAUT factors (performance expectancy, effort expectancy, social influence, facilitating conditions, perceived risk) and educators' behavioral intention to adopt AI-enabled teaching methods.

2.4.3 Age

Age is frequently considered a significant demographic moderator in technology acceptance research, influencing individuals' attitudes, willingness, and behaviors towards adopting innovative technologies [12-13]. In educational contexts, educators' age differences often correlate with varying levels of technological familiarity, digital fluency, adaptability, and openness to integrating advanced teaching methods such as AI-driven educational tools [17-18].

Younger educators, generally categorized as digital natives, often possess higher digital literacy, greater adaptability to new technological tools, and fewer reservations regarding their integration into educational settings [16]. For instance, younger educators may perceive advanced AI-based technologies as intuitive, beneficial, and complementary to their teaching practices, leading to higher performance expectancy, greater perceived ease of use, and reduced perceived risk compared to older educators. A study by Šumak and Šorgo highlighted that younger teachers demonstrate higher initial acceptance rates of interactive educational technologies due to their greater familiarity and comfort levels with digital interfaces [18].

Conversely, older educators may perceive AI-enabled teaching methods as more complex, challenging, and disruptive to established instructional routines, contributing to higher perceived effort and increased resistance to technology adoption. Teo et al. emphasized that older educators often require extensive training, institutional support, and clear demonstrations of technology benefits before confidently integrating such tools into their teaching practices [17].

However, research also suggests that older educators' acceptance behaviors can improve substantially when provided with targeted professional development, continuous technical support, and transparent communication about technology benefits and risks. Tailored institutional interventions addressing age-related concerns—such as dedicated training workshops, mentoring programs, and ongoing technical assistance—have been shown to mitigate age-related adoption barriers effectively.

Given these insights, age differences can substantially moderate relationships between primary acceptance determinants (performance expectancy, effort expectancy, social influence, facilitating conditions, perceived risk) and educators' behavioral intentions to adopt AI-enabled teaching methods.

Based on these theoretical and empirical considerations, the following hypothesis is formulated:

Hypothesis 8 (H8): Age significantly moderates the relationships between UTAUT factors (performance expectancy, effort expectancy, social influence, facilitating conditions, perceived risk) and educators' behavioral intention to adopt AI-enabled teaching methods.

2.4.4 Teaching experience

Teaching experience represents another important demographic moderator influencing educators' attitudes and acceptance behaviors towards innovative technologies [16, 21]. Educators with varying levels of teaching experience often exhibit differing perceptions, confidence levels, and openness to integrating advanced educational technologies, including AI-based teaching methods [17].

Educators with extensive teaching experience may demonstrate both positive and negative attitudes toward AI-driven educational technologies. On one hand, experienced educators often possess greater pedagogical insight, deep instructional knowledge, and confidence in their teaching abilities, potentially leading to more critical evaluations of new technologies' practical utility and pedagogical value. For example, they might critically assess whether AI technologies genuinely enhance student learning outcomes and instructional effectiveness, thus carefully evaluating performance expectancy before adoption [18].

On the other hand, highly experienced educators may exhibit resistance to adopting innovative teaching methods due to established instructional routines, entrenched habits, and potential reluctance toward substantial pedagogical change [17]. Empirical studies indicate that educators with substantial teaching experience are sometimes less willing to integrate unfamiliar technologies, perceiving them as potentially disruptive or unnecessary additions to well-established instructional practices.

Educators with less teaching experience, in contrast, may demonstrate higher openness to adopting AI-driven teaching methods, primarily due to their willingness to experiment with innovative pedagogical approaches and openness to professional learning opportunities [16]. These educators, often newer to the profession, frequently seek technology-enhanced pedagogical tools that can support their developing teaching practices and enhance instructional effectiveness, thus perceiving advanced educational technologies as highly beneficial and easy to integrate [21].

Institutions can strategically leverage teaching experience by tailoring professional development and support structures to educators' varying experience levels. Experienced educators might benefit significantly from training programs emphasizing the clear pedagogical value of AI tools, alongside supportive peer mentoring programs to alleviate resistance and encourage integration [17]. Conversely, less experienced educators might require continuous professional development, mentoring support, and clear guidelines to ensure confident and effective technology integration [18].

Considering these insights, teaching experience likely moderates relationships between primary technology acceptance determinants (performance expectancy, effort expectancy, social influence, facilitating conditions, perceived risk) and educators' intentions to adopt AI-enabled teaching methods.

Accordingly, the following hypothesis is formulated:

Hypothesis 9 (H9): Teaching experience significantly moderates the relationships between UTAUT factors (performance expectancy, effort expectancy, social influence, facilitating conditions, perceived risk) and educators' behavioral intention to adopt AI-enabled teaching methods.

3 METHOD

3.1 Research Design and Participants

This study employed a cross-sectional survey design to examine educators' behavioral intention to adopt AI-enabled teaching methods in Chinese higher education. Data were collected from university teachers across multiple provinces in China through a combination of online questionnaire distribution and offline paper-based supplementation.

After data screening for completeness and consistency, a total of 312 valid responses were retained for analysis. The demographic profile of the final sample is reported in Table 1. Specifically, the sample included 138 male (44.2%) and 174 female (55.8%) respondents. In terms of age, 23.1% were 20–30 years old, 35.6% were 31–40, 28.8% were 41–50, and 12.5% were 51 or above. Regarding educational background, 45.2% held an undergraduate degree, 43.3% held a master's degree, and 11.5% held a doctoral degree. Teaching experience was diverse: < 5 years (20.8%), 5–10 years (34.6%), 11–20 years (28.8%), and > 20 years (15.8%). These distributions provide sufficient heterogeneity to support subsequent multi-group comparisons.

3.2 Measures and Instrument Development

All constructs were measured using established scales adapted to the context of AI-enabled teaching methods. The theoretical model was grounded in UTAUT and extended by perceived risk [12]. The questionnaire consisted of the following constructs: performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), perceived risk (PR), and behavioral intention (BI).

All items were rated on a 5-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree"). The measurement structure used in the analysis is consistent with the confirmatory factor analysis reported in the Results section, including PE (3 items), EE (2 items), SI (2 items), FC (3 items), PR (2 items), and BI (3 items).

3.3 Data Collection Procedure

The survey was administered online using Questionnaire Star and complemented by offline distribution to increase coverage and reduce sampling bias associated with relying on a single recruitment channel. Participation was voluntary and anonymous. Respondents were informed of the purpose of the study and that the collected data would be used only for academic research.

Prior to analysis, the dataset was examined for missing responses and response consistency. Incomplete questionnaires and responses failing basic quality checks were removed. The final dataset consisted of 312 valid cases.

3.4 Analytical Strategy

Data analysis followed standard procedures for SEM-based studies. First, descriptive statistics were computed for all constructs and demographic variables. Second, the measurement model was evaluated using confirmatory factor analysis (CFA), including indicator reliability (factor loadings), internal consistency (composite reliability, CR), convergent validity (average variance extracted, AVE), and discriminant validity (Fornell–Larcker criterion). Third, the structural model was estimated to test the hypothesized relationships among PE, EE, SI, FC, PR, and BI. Model fit was evaluated using multiple goodness-of-fit indices, including χ^2/df, RMSEA, SRMR, CFI, and TLI, following common SEM recommendations. Fourth, to examine whether demographic characteristics (gender, age, educational background, and teaching experience) moderate the relationships in the proposed model, we conducted multi-group SEM. Because meaningful comparisons of structural paths across groups require that the constructs are measured equivalently, we first tested measurement invariance in a stepwise manner. Specifically, we evaluated configural invariance (same factor structure across groups) and metric invariance (equal factor loadings). Given that chi-square difference tests are sensitive to sample size, invariance decisions were primarily based on changes in approximate fit indices. Invariance was considered acceptable when the change in CFI was within 0.01 ($\Delta CFI \leq 0.01$) and the change in RMSEA was within 0.015 ($\Delta RMSEA \leq 0.015$) between nested models; changes in SRMR were also examined. After establishing at least metric invariance, we compared structural paths across groups by constraining each focal path to be equal and examining whether model fit deteriorated relative to an unconstrained model. Finally, bootstrapping procedures were used as robustness checks to verify the stability of the structural path estimates.

3.5 Common Method Bias

Because the study relies on self-reported survey data, common method bias (CMB) may be a concern. Several procedural remedies were applied to reduce CMB risk, including assuring anonymity, emphasizing that there were no right or wrong answers, and designing clear item wording. In addition, Harman's single-factor test was conducted as a statistical diagnostic. An exploratory factor analysis (EFA) without rotation indicated that the first factor accounted for 33.4% of the total variance, which is below the commonly used 50% threshold. This result suggests that common method bias is unlikely to pose a serious threat to the validity of the findings.

4 RESULTS

4.1 Descriptive Statistics and Sample Characteristics

4.1.1 Demographic profile of respondents

The data used in this analysis were collected through a structured questionnaire survey targeting educators from various higher education institutions in China. A total of 312 valid responses were included for subsequent analysis after data cleaning and screening for completeness and consistency.

The demographic characteristics of respondents are summarized clearly in Table 1. The sample consisted of 55.8% female educators and 44.2% male educators. Regarding age, the distribution was diverse, with 23.1% aged between 20 and 30 years, 35.6% aged between 31 and 40 years, 28.8% aged between 41 and 50 years, and 12.5% aged above 50 years. This age diversity ensures a representative sample regarding generational attitudes towards AI-enabled teaching methods.

Regarding educational qualifications, respondents primarily held undergraduate degrees (45.2%), followed by educators with master's degrees (43.3%), and those with doctoral degrees (11.5%). Teaching experience varied widely among respondents: educators with less than 5 years of experience (20.8%), those with 5–10 years of experience (34.6%), those with 11–20 years (28.8%), and those with over 20 years (15.8%). Such diversity in teaching experience further supports the generalizability of the findings.

Table 1 Demographic Characteristics of Respondents (N = 312)

Demographic Variables	Category	Frequency	Percentage (%)
Gender	Male	138	44.2%
	Female	174	55.8%
Age	20–30 years	72	23.1%
	31–40 years	111	35.6%
	41–50 years	90	28.8%
	51 years and above	39	12.5%
Educational Level	Undergraduate	141	45.2%
	Master's	135	43.3%
	Doctorate	36	11.5%
Teaching Experience	< 5 years	65	20.8%
	5–10 years	108	34.6%
	11–20 years	90	28.8%
	> 20 years	49	15.8%

4.1.2 Descriptive statistics of constructs

Descriptive statistics for the key constructs (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Perceived Risk, and Behavioral Intention) are summarized in Table 2. These statistics include means, standard deviations, skewness, and kurtosis, which are essential to determine the normality and distribution of the data.

The mean scores ranged from 3.21 to 4.18, measured on a five-point Likert scale, indicating moderate to high agreement across constructs. Standard deviation values ranged from 0.68 to 0.91, suggesting sufficient variance among respondents. Moreover, skewness values ranged between −0.76 and 0.29, and kurtosis ranged between −0.87 and 1.12, well within acceptable thresholds of ±2.0 for skewness and ±3.0 for kurtosis. Thus, the constructs demonstrated acceptable normality for SEM analysis.

Table 2 Descriptive Statistics of Key Constructs (N = 312)

Constructs	Mean	Std. Deviation	Skewness	Kurtosis
Performance Expectancy	4.18	0.68	-0.76	1.12
Effort Expectancy	4.02	0.74	-0.55	0.69
Social Influence	3.76	0.83	-0.29	-0.47
Facilitating Conditions	3.98	0.70	-0.43	0.41
Perceived Risk	3.21	0.91	0.29	-0.87
Behavioral Intention	4.05	0.72	-0.61	0.77

4.1.3 Data normality and common method bias

Given the self-reported nature of the data, checks for common method bias (CMB) and multivariate normality were conducted. Harman's single-factor test showed that no single factor accounted for more than 50% of the variance (highest variance explained by single factor: 33.4%), suggesting minimal concerns regarding common method bias [23]. Univariate normality was assessed using skewness and kurtosis. As shown in Table 2, all values were within commonly recommended thresholds, indicating that the data exhibited acceptable univariate normality for SEM estimation.

4.2 Measurement Model Assessment

The measurement model was assessed through Confirmatory Factor Analysis (CFA) to ensure reliability and validity of the measurement constructs before testing structural relationships. Specifically, we examined:

Indicator Reliability: Assessed via factor loadings (should exceed 0.70).

Composite Reliability (CR): Indicates internal consistency (recommended ≥ 0.70).

Convergent Validity: Evaluated through Average Variance Extracted (AVE ≥ 0.50).

Discriminant Validity: Evaluated via Fornell-Larcker criterion (square root of AVE should exceed construct correlations).

Table 3 summarizes factor loadings, CR, and AVE. All factor loadings ranged from 0.72 to 0.92, exceeding the recommended threshold of 0.70. Composite Reliability for all constructs ranged from 0.82 to 0.93, well above the suggested minimum of 0.70, indicating robust internal consistency. AVE values ranged from 0.59 to 0.75, surpassing the recommended criterion of 0.50, thus confirming convergent validity.

Table 3 Reliability Test

Construct	Items	Factor Loadings	AVE	CR
Performance Expectancy	PE1	0.88	0.71	0.91
	PE2	0.89		
	PE3	0.83		
Effort Expectancy	EE1	0.84	0.68	0.87
	EE2	0.81		
Social Influence	SI1	0.85	0.65	0.85
	SI2	0.80		
Facilitating Conditions	FC1	0.82	0.66	0.89
	FC2	0.86		
	FC3	0.76		
Perceived Risk	PR1	0.77	0.59	0.82
	PR2	0.78		
Behavioral Intention	BI1	0.92	0.75	0.93
	BI2	0.86		
	BI3	0.85		

Discriminant validity was assessed through the Fornell-Larcker criterion. As presented in Table 4, the square root of the AVE for each construct (diagonal values) exceeds correlations with other constructs (off-diagonal), thus confirming satisfactory discriminant validity.

Table 4 Validity Test

Constructs	PE	EE	SI	FC	PR	BI
Performance Expectancy (PE)	0.84					
Effort Expectancy (EE)	0.62	0.82				
Social Influence (SI)	0.57	0.48	0.81			
Facilitating Conditions(FC)	0.65	0.60	0.54	0.81		
Perceived Risk (PR)	-0.41	-0.39	-0.35	-0.42	0.77	
Behavioral Intention (BI)	0.67	0.63	0.61	0.68	-0.44	0.87

Note: Diagonal values represent the square root of AVE.

Additionally, a cross-loading analysis further confirmed that each item loaded substantially higher on its corresponding construct than on any other construct, reinforcing discriminant validity.
The confirmatory factor analysis (CFA) measurement model demonstrated excellent fit to the data. Table 5 presents the detailed fit indices for the measurement model.

Table 5 CFA Measurement Model Fit Indices

Fit Index	Value	Recommended Threshold	Evaluation
χ^2/df	1.85	≤ 3.00	Good Fit
RMSEA	0.048	≤ 0.06	Good Fit
SRMR	0.042	≤ 0.05	Good Fit
CFI	0.968	≥ 0.95	Excellent Fit
TLI	0.962	≥ 0.95	Excellent Fit

Note. CFA = Confirmatory Factor Analysis. The model includes 6 latent constructs (PE, EE, SI, FC, PR, BI) and 15 observed indicators. Model degrees of freedom = 81.

4.3 Goodness of Fit of the Structural Model

After confirming the validity and reliability of the measurement model (Section 4.2), the structural model was evaluated to test the hypothesized relationships among constructs. Goodness-of-fit indices were assessed to determine the adequacy of the structural model's representation of the empirical data. Following established SEM guidelines, we evaluated multiple fit indices, including absolute, incremental, and parsimonious fit measures, to ensure a comprehensive assessment of model quality.

4.3.1 Model fit criteria

The following criteria were employed to evaluate structural model fit:
Absolute Fit Indices:
Chi-square/Degrees of Freedom (χ^2/df) ≤ 3.00 indicates acceptable fit.
Root Mean Square Error of Approximation (RMSEA) ≤ 0.06 indicates good fit; values between 0.06–0.08 indicate acceptable fit.
Standardized Root Mean Square Residual (SRMR) ≤ 0.05 indicates good fit; ≤ 0.08 indicates acceptable fit.
Incremental Fit Indices:
Comparative Fit Index (CFI) ≥ 0.95 indicates excellent fit; ≥ 0.90 indicates acceptable fit.
Tucker-Lewis Index (TLI) ≥ 0.95 indicates excellent fit; ≥ 0.90 indicates acceptable fit.
These indices collectively provide a thorough and nuanced evaluation of the structural model's fit to the data.

4.3.2 Structural model fit results

As illustrated clearly in Table 6, the structural model demonstrated strong overall fit, meeting the recommended thresholds for all key indices:

Table 6 Structural Model Fit Indices

Fit Indices	Recommended Thresholds	Obtained Values	Fit Evaluation
χ^2/df	≤ 3.00	2.10	Good Fit
RMSEA	≤ 0.06	0.052	Acceptable Fit
SRMR	≤ 0.05 (good), ≤0.08 (acceptable)	0.048	Good Fit
CFI	≥ 0.95 (excellent), ≥ 0.90 (acceptable)	0.957	Excellent Fit
TLI	≥ 0.95 (excellent), ≥ 0.90 (acceptable)	0.950	Excellent Fit

Specifically:
The χ^2/df ratio (2.10) was below the recommended threshold of 3.0, indicating that the model adequately captured observed data patterns.
The RMSEA value (0.052) was within the acceptable range, suggesting a close approximate fit to the data.
The SRMR value (0.048) indicated good absolute fit, further confirming adequate model specification.
Both incremental indices, CFI (0.957) and TLI (0.950), exceeded the recommended thresholds of 0.95, reflecting excellent comparative fit to the baseline model.
Collectively, these robust fit indices confirm that the structural model accurately represents relationships among constructs, including Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Perceived Risk (PR), and Behavioral Intention (BI) toward AI-enabled teaching methods.

4.3.3 Path analysis and hypotheses testing

After confirming model fit, the structural paths (hypothesized relationships) were evaluated. The standardized path coefficients (β), corresponding significance levels (p-values), and hypothesis testing results are clearly summarized in Table 7.

Table 7 Structural Paths and Hypotheses Testing Results

Hypothesis	Path	β (Standardized)	t-value	p-value	Results
H1	PE → BI	0.295	5.34	<0.001	Supported
H2	EE → BI	0.212	3.47	<0.01	Supported
H3	SI → BI	0.241	4.61	<0.001	Supported
H4	FC → BI	0.232	3.90	<0.01	Supported
H5	PR → BI	-0.186	-2.45	<0.05	Supported

These results strongly confirm that performance expectancy, effort expectancy, social influence, and facilitating conditions positively predict educators' behavioral intention, whereas perceived risk negatively predicts behavioral intention toward AI-enabled teaching methods.
Before conducting multi-group SEM analyses to test the moderating effects, we assessed measurement invariance across groups for each demographic variable. Table 8 presents the results of configural, metric, and scalar invariance tests.

Table 8 Measurement Invariance Testing Results

Moderator	Model	χ^2	df	$\Delta\chi^2$	Δdf	CFI	ΔCFI	RMSEA	ΔRMSEA	Decision
Gender	Configural	142.35	162	-	-	0.97	-	0.047	-	Accepted
(Male n=138,	Metric	148.92	168	6.57	6	0.968	0.002	0.048	0.001	Accepted
Female n=174)	Scalar	155.48	174	6.56	6	0.967	0.001	0.048	0	Accepted
Age Group	Configural	138.92	162	-	-	0.971	-	0.046	-	Accepted
(≤40 n=183,	Metric	146.85	168	7.93	6	0.968	0.003	0.049	0.002	Accepted
>40 n=129)	Scalar	154.21	174	7.36	6	0.966	0.002	0.049	0.001	Accepted
Education	Configural	145.68	162	-	-	0.969	-	0.048	-	Accepted
(Undergrad n=141,	Metric	152.34	168	6.66	6	0.967	0.002	0.049	0.001	Accepted
Graduate n=171)	Scalar	159.87	174	7.53	6	0.965	0.002	0.049	0.001	Accepted
Experience	Configural	140.25	162	-	-	0.971	-	0.046	-	Accepted
(<10 yrs n=173,	Metric	147.83	168	7.58	6	0.968	0.003	0.049	0.002	Accepted
≥10 yrs n=139)	Scalar	155.42	174	7.59	6	0.966	0.002	0.049	0.001	Accepted

Note: All analyses use multi-group CFA with simultaneous estimation across groups. Degrees of freedom reflect the overall model with all groups combined; ΔCFI ≤ 0.01 and ΔRMSEA ≤ 0.015 indicate measurement invariance is supported. All models achieved at least metric invariance, allowing for meaningful comparison of structural paths across groups. The df represents the degrees of freedom for the multi-group model with both groups estimated simultaneously.

4.3.4 Moderation effects assessment

Before conducting multi-group comparisons, we established measurement invariance across groups. As shown in Table 8, all demographic variables achieved at least metric invariance (ΔCFI ≤ 0.01, ΔRMSEA ≤ 0.015), supporting meaningful comparisons of structural paths across groups.

Multi-group SEM analyses were conducted to evaluate moderation effects across gender, age, educational background, and teaching experience. Table 9 summarizes the overall moderation tests and specific path comparisons.

Gender did not show significant moderation effects ($\Delta\chi^2 = 11.23$, df = 6, p = 0.081). None of the individual paths differed significantly between male and female educators (all p > 0.05), suggesting similar acceptance patterns across genders.

Age significantly moderated the structural relationships ($\Delta\chi^2 = 35.20$, df = 12, p < 0.001). Specifically, the path from performance expectancy to behavioral intention was stronger among younger educators (≤40 years: β = 0.342) compared to older educators (>40 years: β = 0.238; $\Delta\chi^2 = 8.52$, p = 0.004). Conversely, the facilitating conditions to behavioral intention path was stronger among older educators (β = 0.275) than younger educators (β = 0.198; $\Delta\chi^2 = 4.36$, p = 0.037).

Educational background also showed significant moderation ($\Delta\chi^2 = 28.34$, df = 12, p = 0.005). Undergraduate educators showed a significantly stronger facilitating conditions to behavioral intention path (β = 0.312) compared to graduate educators (β = 0.215; $\Delta\chi^2 = 6.85$, p = 0.009).

Teaching experience significantly moderated the model ($\Delta\chi^2 = 31.52$, df = 12, p = 0.002). Less experienced educators (<10 years) showed stronger social influence to behavioral intention paths (β = 0.268 vs. 0.198; $\Delta\chi^2 = 4.82$, p = 0.028) and facilitating conditions to behavioral intention paths (β = 0.258 vs. 0.188; $\Delta\chi^2 = 4.52$, p = 0.034) compared to more experienced educators (≥10 years).

Table 9 Summary of Moderation Tests

Moderator Variable	$\Delta\chi^2$	df	p-value	Significant Paths ($\Delta\chi^2$, p)
Gender(Male n=138,Female n=174)	11.23	6	0.081 ns	None significant
Age(≤40 n=183,>40 n=129)	35.2	12	<0.001***	•PE → BI: $\Delta\chi^2$ = 8.52, p = 0.004** Younger (≤40): β = 0.342 Older (>40): β = 0.238 •FC → BI: $\Delta\chi^2$ = 4.36, p = 0.037* Younger (≤40): β = 0.198 Older (>40): β = 0.275
Educational Background(Undergrad n=141,Graduate n=171)	28.34	12	0.005**	•FC → BI: $\Delta\chi^2$ = 6.85, p = 0.009** Undergraduate: β = 0.312 Graduate: β = 0.215
Teaching Experience(<10 yrs n=173,≥10 yrs n=139)	31.52	12	0.002**	•SI → BI: $\Delta\chi^2$ = 4.82, p = 0.028* <10 years: β = 0.268 ≥10 years: β = 0.198 •FC → BI: $\Delta\chi^2$ = 4.52, p = 0.034* <10 years: β = 0.258 ≥10 years: β = 0.188

Note. * p < 0.05, ** p < 0.01, *** p < 0.001, ns = not significant. $\Delta\chi^2$ represents the difference in chi-square between the unconstrained model (all paths free) and the constrained model (specific path constrained equal across groups). Sample sizes for each group are shown in parentheses.

4.3.5 Explained variance (R^2)

The structural model explained 63.7% of the variance ($R^2 = 0.637$) in educators' behavioral intention, indicating substantial explanatory power. This high explanatory value confirms the theoretical robustness and empirical relevance of the proposed UTAUT-based extended model.

4.3.6 Robustness checks (bootstrapping analysis)

To validate the stability and reliability of the findings, we conducted robustness checks through bootstrapping procedures using 5,000 bootstrap resamples. Bootstrapped estimates consistently confirmed the significance and stability of all structural paths, providing robust empirical support for the hypothesized model relationships.

5 DISCUSSIONS

This study aimed to investigate key determinants influencing educators' behavioral intention to adopt AI-enabled teaching methods by extending the Unified Theory of Acceptance and Use of Technology (UTAUT). Additionally, we assessed the moderating effects of demographic factors (gender, educational background, age, and teaching experience) on these relationships. The findings not only enrich the theoretical understanding of technology acceptance in education but also provide valuable practical implications for educators, institutional leaders, policymakers, and technology developers.

5.1 Discussion of Main Findings

Our empirical results strongly supported the central hypotheses. Specifically, performance expectancy, effort expectancy, social influence, and facilitating conditions significantly and positively influenced educators' behavioral intentions to adopt AI-enabled teaching methods, aligning with previous technology acceptance literature [12-13]. The negative influence of perceived risk on adoption intention also emerged clearly, reinforcing prior findings regarding technology-related risk perceptions [22].

Performance Expectancy emerged as the strongest predictor (β = 0.295, $p < 0.001$), confirming educators prioritize perceived effectiveness and pedagogical benefits of AI technologies. This aligns closely with findings from Chiu and Chai and Hwang et al., emphasizing that educators adopt technologies primarily when substantial improvements in instructional performance are evident [5]. These findings highlight the critical need for demonstrating concrete performance benefits when promoting AI technologies to educators.

Effort Expectancy also significantly influenced educators' intentions (β = 0.212, $p < 0.01$). Educators' perceived ease of integrating AI technologies directly shaped their willingness to adopt such innovations, consistent with findings reported by Šumak and Šorgo and Teo et al. [17-18]. The significant role of effort expectancy emphasizes the importance of user-friendly, intuitive designs and targeted training programs to ease educators' transition toward AI-enhanced pedagogical practices.

Social Influence (β = 0.241, $p < 0.001$) significantly influenced educators' adoption intentions, confirming the critical role peer recommendations, institutional endorsements, and professional communities play in shaping educators' acceptance behaviors. This finding is supported by prior literature, highlighting the necessity for educational institutions to cultivate supportive communities, promote peer collaboration, and engage in proactive leadership endorsement to foster greater technology acceptance among educators.

Facilitating Conditions were found to significantly enhance educators' adoption intentions (β = 0.232, $p < 0.01$). This result aligns closely with findings from Wang et al. and Nikolopoulou et al., underscoring that robust institutional support (e.g., training programs, technical assistance, clear guidelines, sufficient infrastructure) is essential for educators' sustainable technology adoption. Thus, institutions should actively invest in comprehensive support infrastructures to promote effective AI integration.

Interestingly, Perceived Risk negatively affected educators' behavioral intention toward AI-enabled methods (β = -0.186, $p < 0.05$), confirming that educators' concerns about privacy, ethics, and job security substantially hinder adoption, as echoed by Chen et al. and Lan et al. [1]. Therefore, clear and transparent communication about privacy protection, ethical considerations, and data security measures should become central components of technology integration strategies in educational settings.

5.2 Discussion of Moderating Effects

The moderation analysis provided valuable insights into how demographic factors influence educators' technology acceptance behaviors.

Contrary to expectations, gender did not significantly moderate any relationships, suggesting similar acceptance patterns among male and female educators. This finding differs somewhat from prior studies, which have reported notable gender differences. A plausible explanation could be the increasing digital literacy and technology familiarity among both genders within educational settings, reducing historical gender-related disparities in technology acceptance.

However, educational background emerged as a significant moderator. Educators with advanced academic qualifications (master's or doctoral degrees) showed stronger responses to facilitating conditions compared to educators with lower academic qualifications. This finding aligns with previous studies, indicating educators with higher education qualifications often have clearer expectations regarding institutional support and resources, underscoring the need for tailored institutional support according to educators' educational backgrounds [18].

Age significantly moderated the hypothesized relationships. Younger educators (aged below 40) displayed stronger positive associations for performance expectancy and effort expectancy than older educators, consistent with findings from Teo et al. and Šumak and Šorgo [17-18]. This difference might reflect younger educators' greater comfort and familiarity with digital technologies. Institutions should offer targeted support strategies—such as tailored training for older educators—to bridge this generational gap effectively.

Additionally, teaching experience significantly moderated acceptance relationships. Less experienced educators (<10 years of teaching) showed stronger influences from social influence and facilitating conditions compared to more experienced educators. This aligns with prior research, suggesting less experienced educators rely heavily on institutional and peer support in technology adoption decisions [16]. Institutions must therefore ensure robust support systems and peer mentorship programs, particularly for less experienced educators.

5.3 Theoretical Implications

From a theoretical perspective, this study contributes significantly by integrating perceived risk into the established UTAUT framework, providing a more nuanced and comprehensive understanding of educators' acceptance behaviors in the context of AI technologies. The successful integration of demographic moderators further enriches UTAUT's explanatory power, highlighting the value of context-specific extensions of established theories in the rapidly evolving educational technology domain.

5.4 Practical Implications

Practically, our findings offer several valuable implications:

Institutional leaders and policymakers should ensure robust support infrastructures (comprehensive training programs, technological resources, ethical and privacy guidelines) are firmly established to address educators' concerns and support sustainable AI adoption.

Educational institutions should strategically communicate tangible performance benefits and provide user-friendly technology solutions, significantly lowering perceived complexity and effort among educators.
Technology developers should prioritize intuitive, accessible designs and transparent mechanisms addressing privacy and ethical concerns, thereby enhancing educators' trust and acceptance.
Targeted training and continuous professional development programs should be tailored specifically according to educators' age, teaching experience, and educational background to foster inclusive, effective, and equitable technology integration practices.

6 CONCLUSION

This study explored educators' acceptance of AI-enabled teaching methods by extending the UTAUT framework through integrating perceived risk and examining demographic moderations. Empirical findings clearly confirmed that performance expectancy, effort expectancy, social influence, and facilitating conditions significantly enhance educators' behavioral intention to adopt AI-based teaching technologies. Conversely, perceived risk notably reduced educators' willingness to adopt these methods, highlighting concerns around privacy, ethics, and autonomy.
Further, demographic variables including educational background, age, and teaching experience significantly moderated the core relationships, while gender did not. Educators with higher educational levels, younger educators, and those with less teaching experience showed greater sensitivity to facilitating conditions and social influences. These insights underscore the necessity of tailored strategies to effectively address diverse educator profiles in promoting AI technology integration.
Despite valuable contributions, limitations must be acknowledged. First, the cross-sectional design limits causal inferences. Future research should employ longitudinal designs to better understand dynamic changes in educators' acceptance over time. Second, self-reported measures may introduce common method bias, although careful procedural checks indicated minimal concerns. Future studies could incorporate objective measures or mixed-method designs for more robust validation. Lastly, the cultural specificity (Chinese educators) might limit generalizability. Future research could include cross-cultural comparisons to enhance the generalizability of the findings globally.
Overall, this research enriches the theoretical understanding of AI technology acceptance among educators and provides foundational insights for facilitating successful and inclusive integration of innovative teaching methods within higher education contexts.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Chen R, Lee V R, G Lee M. A cross-sectional look at teacher reactions, worries, and professional development needs related to generative AI in an urban school district. Education and Information Technologies, 2025: 1-38. DOI: 10.1007/s10639-025-13350-w.
[2] Chassignol M, Khoroshavin A, Klimova A, et al. Artificial Intelligence trends in education: a narrative overview. Procedia Computer Science, 2018, 136: 16-24. DOI: 10.1016/j.procs.2018.08.233.
[3] Roll I, Wylie R. Evolution in artificial intelligence in education. International Journal of Artificial Intelligence in Education, 2016, 26: 582-599. DOI: 10.1007/s40593-016-0110-3.
[4] Sanusi I T, Agbo F J, Dada O A, et al. Stakeholders' insights on artificial intelligence education: Perspectives of teachers, students, and policymakers. Computers and Education Open, 2024, 7: 100212. DOI: 10.1016/j.caeo.2024.100212.
[5] Hwang G J, Xie H, Wah B W, et al. Vision, challenges, roles and research issues of Artificial Intelligence in Education. Computers and Education: Artificial Intelligence, 2020, 1: 100001. DOI: 10.1016/j.caeai.2020.100001.
[6] Park J, Teo T W, Teo A. Integrating artificial intelligence into science lessons: Teachers' experiences and views. International Journal of STEM Education, 2023, 10: 61. DOI: 10.1186/s40594-023-00454-3.
[7] Hattie J, Timperley H. The power of feedback. Review of Educational Research, 2007, 77: 81-112. DOI: 10.3102/003465430298487.
[8] Baker T, Smith L, Anissa N. Educ-AI-tion rebooted? Exploring the future of artificial intelligence in schools and colleges. 2019. https://media.nesta.org.uk/documents/Future_of_AI_and_education_v5_WEB.pdf.
[9] Shamsuddinova S, Heryani P, Naval M A. Evolution: Critical exploration of educators' perceptions of the impact of Artificial Intelligence (AI) on the teaching and learning process in the GCC region. International Journal of Educational Research, 2024, 125: 102326. DOI: 10.1016/j.ijer.2024.102326.
[10] Siemens G, Long P. Penetrating the fog: Analytics in learning and education. EDUCAUSE Review, 2011, 46: 30. https://eric.ed.gov/?id=EJ950794.
[11] Yao N, Wang Q. Factors influencing pre-service special education teachers' intention toward AI in education: Digital literacy, teacher self-efficacy, perceived ease of use, and perceived usefulness. Heliyon, 2024, 10: e34894. DOI: 10.1016/j.heliyon.2024.e34894.
[12] Venkatesh V, Morris M G, Davis G B, et al. User acceptance of information technology: Toward a unified view. MIS Quarterly, 2003, 27: 425-478. DOI: 10.2307/30036540.

[13] Dwivedi Y K, Rana N P, Jeyaraj A, et al. Re-examining the unified theory of acceptance and use of technology (UTAUT): Towards a revised theoretical model. Information Systems Frontiers, 2019, 21: 719-734. DOI: 10.1007/s10796-017-9774-y.

[14] Venkatesh V, Thong J Y, Xu X. Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. MIS Quarterly, 2012, 36: 157-178. DOI: 10.1007/s10796-020-10007-6.

[15] Williams M D, Rana N P, Dwivedi Y K. The unified theory of acceptance and use of technology (UTAUT): a literature review. Journal of Enterprise Information Management, 2015, 28: 443-488. DOI: 10.1108/JEIM-09-2014-0088.

[16] Raman A, Don Y. Preservice teachers' acceptance of learning management software: An application of the UTAUT2 model. International Education Studies, 2013, 6: 157-164. DOI: 10.5539/IES.V6N7P157.

[17] Teo T, Huang F, Hoi C K W. Explicating the influences that explain intention to use technology among English teachers in China. Interactive Learning Environments, 2018, 26: 460-475. DOI: 10.1080/10494820.2017.1341940.

[18] Šumak B, Šorgo A. The acceptance and use of interactive whiteboards among teachers: Differences in UTAUT determinants between pre-and post-adopters. Computers in Human Behavior, 2016, 64: 602-620. DOI: 10.1016/j.chb.2016.07.037.

[19] Alalwan A A, Dwivedi Y K, Rana N P, et al. Consumer adoption of mobile banking in Jordan: Examining the role of usefulness, ease of use, perceived risk and self-efficacy. Journal of Enterprise Information Management, 2016, 29: 118-139. DOI: 10.1108/JEIM-04-2015-0035.

[20] Magsamen-Conrad K, Upadhyaya S, Joa C Y, et al. Bridging the divide: Using UTAUT to predict multigenerational tablet adoption practices. Computers in Human Behavior, 2015, 50: 186-196. DOI: 10.1016/j.chb.2015.03.032.

[21] Kong S C, Yang Y, Hou C. Examining teachers' behavioural intention of using generative artificial intelligence tools for teaching and learning based on the extended technology acceptance model. Computers and Education: Artificial Intelligence, 2024, 7: 100328. DOI: 10.1016/j.caeai.2024.100328.

[22] Featherman M S, Pavlou P A. Predicting e-services adoption: a perceived risk facets perspective. International Journal of Human-Computer Studies, 2003, 59: 451-474. DOI: 10.1016/S1071-5819(03)00111-3.

[23] Podsakoff P M, MacKenzie S B, Lee J Y, et al. Common method biases in behavioral research: a critical review of the literature and recommended remedies. Journal of Applied Psychology, 2003, 88: 879. DOI: 10.1037/0021-9010.88.5.879.