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Exploring the factors influencing the adoption of artificial intelligence technology by university teachers: the mediating role of confidence and AI readiness

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Abstract

Objectives This study aims to explore the mediating role of confidence and artificial intelligence (AI) readiness in university teachers' behavioral intention to adopt AI technology, providing empirical support for enhancing teachers' willingness to use AI technology from both theoretical and practical perspectives.

Methods This study used a random sampling method to conduct an online survey of 504 university teachers, assessing the impact of subjective norms on behavioral intention. The survey included scales for subjective norms, confidence, AI readiness, and behavioral intention. Data analysis was performed using AMOS 26, SPSS Statistics 27 software and Model 6 from the PROCESS 4.0 plugin, aiming to investigate the mediating role of confidence and AI readiness between subjective norms and behavioral intention.

Results Subjective norms were found to have a significant positive correlation with behavioral intention. Subjective norms indirectly influenced behavioral intention through confidence or AI readiness. Confidence and AI readiness played a chain-mediating role in the relationship between subjective norms and behavioral intention ($\beta = 0.0324$, 95% CI: [0.0129, 0.0551]), accounting for 12.87% of the total effect.

Conclusions and implications This study reveals the positive role of subjective norms in university teachers' behavioral intention to adopt AI technology, indicating that subjective norms not only directly enhance behavioral intention but also exert indirect effects through both single and chain mediation of confidence and AI readiness. The findings highlight the critical role of confidence and AI readiness in the relationship between subjective norms and behavioral intention, suggesting that to effectively increase university teachers' willingness to use AI technology, it is important to focus on improving their confidence in and readiness for AI technology, thereby strengthening the positive impact of subjective norms.

Keywords AI technology, Subjective norms, Confidence, AI readiness, Behavioral intention

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Introduction

In recent years, AI technology is being increasingly utilized in education, encompassing various forms such as intelligent tutoring systems [1], online learning platforms [2], and chatbots [3]. These technologies have not only optimized the presentation of instructional content but also demonstrated immense potential in areas such as student assessment and the personalized distribution of teaching resources, significantly improving the efficiency and flexibility of higher education [4]. AI technology has brought many new opportunities to higher education, effectively addressing the shortcomings of traditional teaching methods and enhancing both teaching effectiveness and the student learning experience [5]. Currently, AI technology has been applied in various educational areas, including automated grading systems, teacher feedback, online instructors, personalized learning, virtual reality, precision reading, smart campuses, and remote learning [6]. However, the effective integration and application of AI technology not only depends on the maturity of the technology itself but also on the active involvement of teachers, who serve as the driving force for educational transformation, and their BI to using AI technology [7]. Behavioral intention (BI) reflects a person's personal belief or expectation regarding their likelihood of performing a specific action in the future [8]. Teachers' BI to adopt AI technology is crucial influencing the adoption and application of AI in tertiary education, directly impacting teaching quality and student learning outcomes [9–11]. However, the complexity of AI technology places high demands on teachers' technical abilities, particularly in adopting AI tools and mastering coding. Teachers may encounter technological barriers that can, consequently affect their willingness to use AI technology [8]. Additionally, the practical utilization of AI technology faces multiple challenges, which can be categorized into individual-level factors (such as insufficient technical skills and lack of confidence (CON)), ethical issues (such as data protection and ethical security issues), and resource-related issues (such as inadequate technical training and limited equipment support) [12, 13]. These factors both limit teachers' BI to adopt AI technology and increase the complexity of technology adoption.

Currently, research on university instructors' willingness to adopt AI technology remains relatively limited, with most existing studies based on classic theoretical models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) [14–17]. These models mainly emphasize the technology's usability, with less emphasis on the critical role of individual factors (such as CON and readiness) in the technology acceptance process. Social cognitive theory suggests that factors such as teachers' CON, technological readiness, and external support from colleagues and management strongly affect their attitudes towards and adoption of AI technology. However, existing research has yet to fully explore how these factors influence university teachers' BI to use AI technology, particularly within the specific cultural context of Chinese higher education. Specifically, how psychological factors, social support, and cultural adaptability affect teachers' adoption of AI technology remains underexamined. This study aims to fill this gap by systematically investigating the factors influencing university teachers' BI to use AI technology, as well as the underlying mechanisms. In addition to focusing on the ease of use of the technology, we place particular emphasis on how individual factors (such as CON and AI readiness (AIRE)) and social factors jointly shape teachers' attitudes toward and adoption of AI technology. By deeply analyzing these psychological and social factors, we hope to provide precise theoretical support and practical guidance for universities in the implementation of AI technologies. This study not only offers new theoretical perspectives and depth for the application of AI in education but also provides practical insights for university administrators, teacher trainers, and policymakers. Through an in-depth exploration of teachers' psychological and social factors, we aim to offer references for the development of effective strategies to advance AI technology application in higher education, thereby promoting innovation in educational technology and improving education quality.

Subjective norms and BI

Subjective norms (SN) are defined as an individual's understanding of the expectations or social pressure exerted by important others regarding their behavior. In the teaching community, SN primarily stem from the attitudes and expectations of authoritative colleagues, leaders, and superiors [1]. Studies have demonstrated a strong positive relationship between SN and the BI to adopt AI technology [18]. When colleagues and leaders within an organization support AI technology, teachers are more inclined to actively embrace and utilize it [19]. In other words, when individuals perceive stronger SN, they tend to develop more positive behavioral attitudes, which in turn enhances their willingness to use AI technology [20]. For example, an empirical study by Zhang and Hou [21], based on the TAM and Diffusion of Innovations Theory, found that SN are a key factor influencing university teachers' use of AI-assisted teaching systems. The study highlighted that if the teacher community holds negative attitudes toward AI technology, such negative SN can significantly reduce teachers' BI to use the technology. Conversely, positive SN can effectively promote their willingness to use it. Additionally, high expectations and strict requirements from surrounding groups can reinforce the SN perceived by individuals, thereby influencing their willingness to adopt the technology [22, 23]. These studies indicate that the role of SN is not only reflected in the presence of social support but also in the specific impact mechanisms of this support on teachers' behavioral attitudes. In the process of encouraging teachers to adopt AI technology, the supportive attitudes and expectations of authoritative figures within the organization often play a crucial role, significantly enhancing teachers' intention to adopt AI technology.

The mediating role of CON

CON in AI technology reflects teachers' belief in their capability to learn and master AI-related knowledge and skills [24]. Studies have found a strong positive correlation between CON and the BI to adopt AI technology [25, 26]. For instance, Jatileni et al. [25] performed a survey on the application of AI technology among in-service teachers and found that when teachers are confident about integrating AI technology into their classrooms, they are more inclined to integrate the technology into their teaching materials. CON is regarded as a crucial factor in teachers' adoption of AI technology. Teachers tend to teach AI-related knowledge to students in the classroom and enhance their willingness to use the technology when they have sufficient CON in mastering new technologies [27, 28]. Conversely, if teachers perceive themselves as lacking the skills to master AI technology, they may experience discomfort or anxiety, leading them to avoid integrating AI technology into their teaching or even reduce its actual use [29, 30]. Such avoidance behavior not only reduce the use of AI technology in the classroom but may also have a negative impact on enhancing students' technological literacy [31]. In contrast, teachers with higher levels of CON not only feel more assured in mastering AI technology but are also more willing to actively engage in professional development activities related to AI technology. This positive learning attitude further strengthens their willingness to apply AI technology in the classroom [32]. Therefore, enhancing teachers' CON in AI technology can increase their willingness to use it.

In addition, studies show a strong positive relationship between SN and teachers' CON in AI technology. The more positive SN individuals perceive, the stronger their CON in AI technology [33, 34]. Based on social cognitive theory, when teachers witness successful cases of colleagues utilizing AI technology or receive recognition and support from leadership, these external factors often strengthen their CON [35]. At the same time, SN from colleagues or school administrators—such as expectations and pressures regarding the use of AI technology—often transform into intrinsic motivation for teachers, driving them to enhance their own capabilities and further strengthening their CON in AI technology [33, 36]. The enhancement of SN is often accompanied by increased opportunities for learning and experimenting with AI technology. For example, schools can provide training and professional support focused on AI technology, helping teachers overcome barriers to its use, accumulate successful experiences, and thereby boost their CON in integrating AI technology into their classrooms (Liu et al., 2024). Moreover, CON serves as a mediator between SN and BI. For example, Chai et al. [33], in research drawing on the theory of planned behavior, found that SN enhance students' CON in new technologies, thereby strengthening their intention for continued use. This mechanism similarly applies to teachers, as SN indirectly promote their BI to use AI technology by boosting their CON.

The mediating role of AI readiness

AIRE encompasses the knowledge, skills, and mental preparedness of teachers to successfully integrate and utilize AI technology [24]. Research indicates that teachers' AIRE is a critical factor influencing their embrace of new technologies [37, 38]. Given the high professional competency requirements associated with AI technology, teachers need a solid theoretical and technical foundation—indicative of a high level of AIRE—when using AI technology to impart academic knowledge or AI-related content to students. This readiness improves teachers' views on the technology's ease of use and utility, thereby strengthening their BI to use it [39, 40]. For instance, Ayanwale et al. [41], in their study on teachers' BI to apply AI in teaching, identified AIRE as a significant predictor of their intention. Specifically, when teachers believe they are well-prepared in terms of knowledge and skills, they are more inclined to incorporate AI technology into classroom teaching. Furthermore, an increase in AIRE can help teachers overcome psychological barriers to technology adoption. When faced with technological complexity or uncertainty, well-prepared teachers demonstrate higher adaptability and resilience, enabling them to quickly understand the features of the technology and effectively apply it in teaching practices [41, 42]. This further highlights that enhancing AIRE among university teachers can significantly strengthen their BI to use AI technology.

In addition, research shows a significant positive correlation between SN and AIRE [43, 44]. Fundi et al. [43], in their exploration of teachers' preparedness for AI-based curricula, found that in highly collaborative and structured educational environments, teachers tend to be more influenced by the views of their colleagues and administrators. These positive SN significantly and positively impact their readiness behaviors. The successful practices of colleagues play a role-modeling effect in enhancing teachers' AIRE. When teachers observe their peers successfully integrating AI technology into classroom teaching and significantly improving teaching efficiency, they are more inclined to acknowledge the potential benefits of AI technology and proactively work to improve their own AI-related skills [45]. School leadership is key to amplifying the influence of SN. By implementing mandatory policies to promote the use of AI technology, providing resource support, and organizing systematic training, schools create favorable conditions that encourage teachers to actively engage in learning about AI technology, thereby improving their AIRE [24]. In addition, SN can not only directly enhance AIRE but also exert indirect effects through related variables [46, 47]. This suggests that SN, as a social influence mechanism, operate through multiple pathways to promote teachers' readiness for AI technology.

The chain mediating role of CON and AIRE

Studies show a strong positive relationship between teachers' CON and their AIRE [47, 48]. Dai et al. [47], in their study on factors influencing individuals' AIRE, found that those with higher CON levels are more apt to actively participate in related learning activities, acquire new knowledge, and engage in necessary technological practices, thereby enhancing their AIRE. At the same time, CON can effectively alleviate the anxiety and uncertainty teachers may experience when confronting AI technology. This psychological improvement further enhances their learning motivation and encourages them to invest more effort in preparing for AI technology [49]. CON enhances teachers' views on the usability and value of AI technology, providing them with a clearer understanding of its value. This, in turn, promotes an increase in their AIRE [50]. Therefore, teachers with stronger CON tend to demonstrate greater proactivity in knowledge acquisition and technical preparation, leading to higher levels of AIRE.

According to social cognitive theory, when teachers perceive high expectations and pressure from colleagues and school management, this external drive can foster their "I can" belief, thereby enhancing their CON in AI technology [1, 35]. This CON directly influences teachers' proactivity and level of engagement in learning and applying AI technology. Teachers with stronger CON often exhibit higher technical skills and knowledge reserves, which are reflected in greater AIRE [42, 51]. In addition, CON enhances teachers' recognition of the practical application effects of AI technology in teaching, improving their ability to adapt to technological complexity and reducing their concerns about the technology. This, in turn, boosts their BI to use AI technology [52, 53]. For example, Ayanwale et al. [41], in their survey of in-service teachers' BI to use AI, found that CON in AI technology significantly enhanced teachers' AIRE, as a result, this positively affected their intention to adopt AI. In summary, this study posits that SN, by boosting teachers' CON, not only improve their AIRE but also further promote their BI to integrate AI technology into classroom teaching.

In summary, building on existing literature, this study seeks to develop a framework that demonstrates the influence of SN on teachers' BI to adopt AI technology, as illustrated in Fig. 1. The following hypotheses are put forward:

H1 SN have a significant positive effect on BI.

H2 CON mediates the relationship between SN and BI.

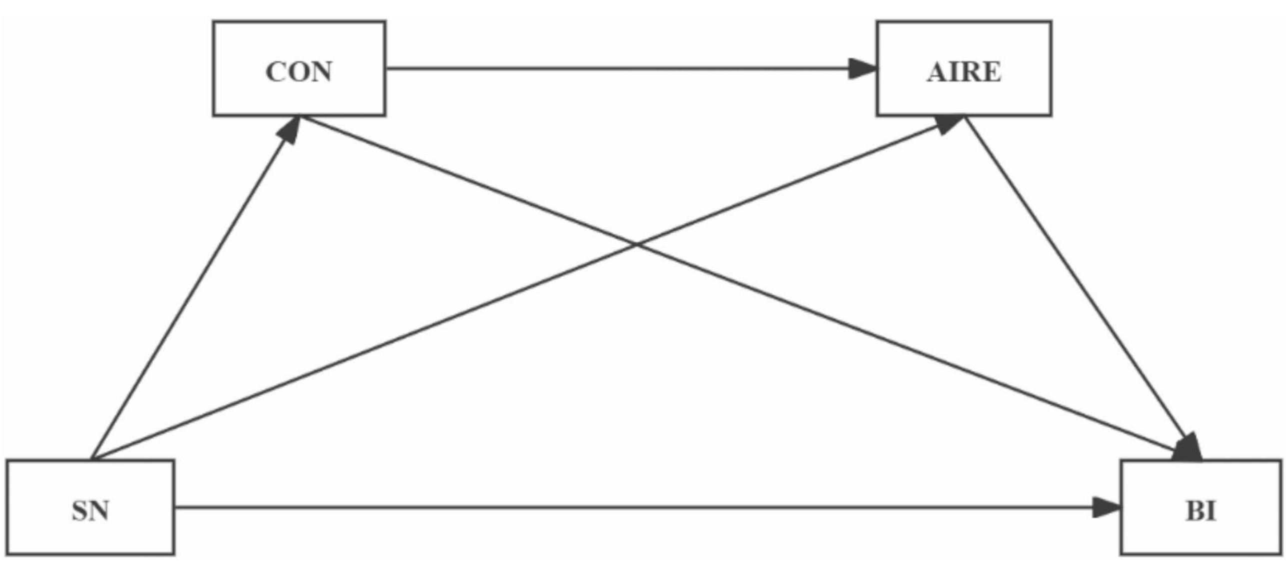

Fig. 1 Model diagram

H3 AIRE mediates the relationship between SN and BI.

H4 CON and AIRE jointly serve as a chain mediation in the relationship between SN and BI.

Research methods

Sample and data collection procedure

To ensure the representativeness of the sample and reduce selection bias, this study employed a random sampling method to recruit university teachers for the survey, the random sampling method effectively ensures the representativeness of the sample, reduces selection bias, and enhances the external validity and reliability of the research findings. The participants included in-service teachers from various departments of Anshan Normal University. To improve the representativeness of the sample, the research team first selected multiple departments to ensure the inclusion of teachers from various academic disciplines. Within each department, teachers with different teaching experiences were randomly selected. To improve the external validity and applicability of the study findings, the research team collaborated with department heads to clarify the aim and importance of the survey in detail to the teachers and invite them to participate. All teachers participated voluntarily and completed the questionnaire independently. The survey link was distributed via the Wenjuanxing platform (https://www.wjx.cn/). According to the sample size calculation method proposed by Kline [54], each questionnaire item requires responses from at least 10 participants. The questionnaire used in this study contained 18 items. Considering an approximate 20% sample attrition rate, the sample size needed was calculated to be 216 participants (18 items × 10 respondents + 20% × 18 items × 10 respondents). A total of 504 questionnaires were collected, of which 10 were invalid. Thus, 494 valid questionnaires were retained, yielding an effective response rate of 98.02%, the teaching experience of the participants was primarily concentrated in the ranges of 2–5 years (33.4%) and 6–10 years (42.1%), with 57.7% holding a master's degree (see Table 1 for details). The criteria for excluding invalid questionnaires were as follows: (1) Questionnaires with missing responses in more than 5 items (a valid questionnaire was defined as one with ≥ 80% of the items completed; missing responses ≥ 20% were considered invalid); (2) Questionnaires in which ≥ 80% of the items were rated as "strongly agree" or "strongly disagree" to avoid severe floor or ceiling effects that could compromise the accuracy of data analysis. All participants provided informed consent prior to completing the questionnaire, ensuring that the study adhered to ethical standards and respected participants' privacy and autonomy.

Table 1 Descriptive statistics

	Category	Number	Percentage (%)
Gender	Male	210	42.5
	Female	284	57.5
Age	Below 30 years	111	22.5
	31–40 years	299	60.5
	Above 40 years	84	17.0
Years of service	Less than 2 years	68	13.8
	2–5 years	165	33.4
	6–10 years	208	42.1
	More than 10 years	53	10.7
Educational background	Undergraduate	86	17.4
	Master's degree	285	57.7
	Doctoral degree	97	19.6
	Postdoctoral	26	5.3
Professional background	Humanities & social sciences	492	99.6
	Science & engineering	2	0.4

Measurement tools

The questionnaire is divided into two sections: the first section collects demographic information, while the second includes measurement items for various variables. This study employed validated scales to assess each variable, ensuring consistency with the original scales; hence, no modifications were made to the content or structure of the items. In addition to basic demographic information, the questionnaire measured four variables: SN, CON, AIRE, and BI. Each variable was measured using a 6-point scale, ranging from (1) "Strongly Disagree" to (6) "Strongly Agree." These scales have been proven to possess good reliability and validity. The scale for SN was adapted from the study by Fundi et al. [43] and includes 4 items, with a Cronbach's alpha of 0.756, and *McDonald's* Ω is 0.757, indicating high reliability. The exploratory factor analysis shows a KMO value of 0.752, and Bartlett's test of sphericity has a $P < 0.001$, indicating good structural validity. The scales for CON, AIRE, and BI were based on the study by Ayanwale et al. [41]. CON consists of 4 items, while AIRE and BI each consist of 5 items, with Cronbach's alphas of 0.807, 0.830, and 0.821, while *McDonald's* Ω values are 0.796, 0.829, and 0.819, indicating good reliability. The exploratory factor analysis shows that the structural validity for CON (KMO = 0.713, Bartlett's test $P < 0.001$), AIRE (KMO = 0.843, Bartlett's test $P < 0.001$), and BI (KMO = 0.833, Bartlett's test $P < 0.001$) is also good.

Data analysis

This study employed SPSS Statistics 27 and AMOS 26 for statistical analysis. Uses AMOS to conduct confirmatory factor analysis (CFA) to determine the observed variables under each latent variable and evaluate the validity of the

Table 2 Descriptive statistics of variables

	N	M ± SD	MIN	MAX	SK	Kur
SN	494	4.4347 ± 0.64967	1.5	6.00	-2.430	7.850
CON	494	4.4135 ± 0.66094	1.5	6.00	-2.410	6.568
AIRE	494	4.4911 ± 0.63925	1.4	6.00	-2.009	4.987
BI	494	4.4389 ± 0.63061	1.4	6.00	-2.295	7.123

measurement model. And descriptive statistics and correlation analyses were performed on the scale data using SPSS to examine the basic characteristics of the dataset. Subsequently, a chain mediation analysis using Model 6 in the SPSS PROCESS 4.0 plugin was performed to investigate how SN influences BI through the mediators CON and AIRE. Model 6 was selected because it provides a straightforward framework for measuring a chain mediation model, which aligns with the primary focus of our study. The mediation analysis employed the Bootstrap method with 5,000 resamples to assess the confidence intervals of the mediation effects for the key variables, the bootstrapping method was chosen because it does not assume a normal distribution of indirect effects, making it particularly robust for small to medium sample sizes. If the 95% confidence interval does not include zero, both direct and indirect effects are considered statistically significant. Additionally, to verify the reliability of the statistical analysis and the appropriateness of the methods used, tests for normality and common method bias were conducted prior to multivariate analysis.

Result

To verify that the data satisfied the assumptions necessary for multivariate analysis, thereby guaranteeing the accuracy of the results and the validity of statistical tests, this study assessed data normality using skewness and kurtosis indices. According to the guidelines suggested by Kline [55], skewness with an absolute value less than 3 and kurtosis with an absolute value less than 10 are considered acceptable standards. All key variables in this study met these criteria, indicating that the data exhibit characteristics of a normal distribution (see Table 2 for details).

Common variance bias test

This study employed Harman's single-factor test to examine common method bias in the data. The results of the exploratory factor analysis revealed four factors with eigenvalues greater than 1, with the first factor accounting for 38.467% of the variance, which is below the critical threshold of 40% (Podsakoff & Organ, 1986). This indicates that there is no significant common method bias in the data used in this study.

Table 3 Model fit indices for the structural equation models

Fit index	Reference value	Model
CMIN/DF	< 5	2.630
RMSEA	< 0.08	0.057
GFI	> 0.9	0.921
CFI	> 0.9	0.939
IFI	> 0.9	0.940
TLI	> 0.9	0.928

Note: CMIN: chi-square value, DF: degrees of freedom, RMSEA: root mean square error of approximation, GFI: goodness-of-fit index, NFI: normed fit index, CFI: comparative fit index, IFI: incremental fit index, TLI: Tucker- Lewis index

Table 4 Correlation analysis

	SN	CON	AIRE	BI
SN	1			
CON	0.532***	1		
AIRE	0.474***	0.434***	1	
BI	0.608***	0.560***	0.528***	1

Note: In this study, ** indicates $p < 0.01$, and *** indicates $p < 0.001$

Confirmatory factor analysis

In CFA, the factor loadings range from 0.62 to 0.75, all greater than 0.5 for the observed variables. The measurement model demonstrates acceptable validity (Table 3) [56].

Correlation analysis

The results of the correlation analysis showed significant positive correlations between SN and CON ($r = 0.532$, $p < 0.001$), AIRE ($r = 0.474$, $p < 0.001$), and BI ($r = 0.608$, $p < 0.001$). CON was significantly positively correlated with AIRE ($r = 0.434$, $p < 0.001$) and BI ($r = 0.560$, $p < 0.001$), while AIRE was significantly positively correlated with BI ($r = 0.528$, $p < 0.001$) (see Table 4).

Mediation analysis

This study employed Model 6 of the PROCESS macro for IBM SPSS, developed by Hayes, to explore the chain mediation effects of CON and AIRE in the relationship between SN and BI. As shown in Table 5; Fig. 2, after incorporating CON and AIRE as mediators, SN significantly positively predicted CON ($\beta = 0.5417$, $t = 13.9516$, $p < 0.001$), AIRE ($\beta = 0.3339$, $t = 7.4534$, $p < 0.001$), and BI ($\beta = 0.3385$ $t = 8.6895$, $p < 0.001$). CON significantly positively predicted AIRE ($\beta = 0.2450$, $t = 5.5640$, $p < 0.001$) and BI ($\beta = 0.2545$, $t = 6.8011$, $p < 0.001$), and AIRE significantly positively predicted BI ($\beta = 0.2439$, $t = 6.5574$, $p < 0.001$).

Table 5 Hierarchical regression analysis of chain mediation effects

Outcome variable	Predictor variable	*R*	R^2	F	β	SE	t
CON	SN	0.5324	0.2835	194.6459***	0.5417	0.0388	13.9516***
AIRE	SN	0.5204	0.2708	91.1847***	0.3339	0.0448	7.4534***
	CON				0.2450	0.0440	5.5640***
BI	SN	0.7014	0.4920	158.1767***	0.3385	0.0390	8.6895***
	CON				0.2545	0.0374	6.8011***
	AIRE				0.2439	0.0372	6.5574***

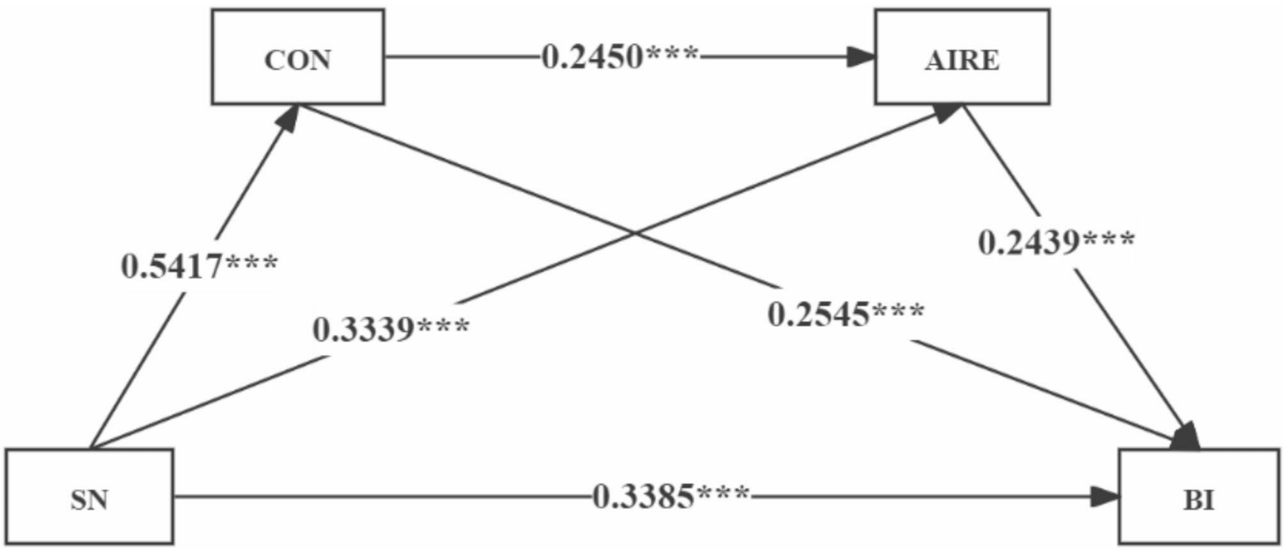

Fig. 2 Mediated pathway diagram

Table 6 Analysis of chain mediation effects between SN, CON, AIRE, and BI using the bootstrap method

		Efficiency value	Boot SE	Bootstrap 95% CI		Percentage
				LLCI	ULCI	
Total indirect effect	SN→BI	0.2517	0.0440	0.1601	0.3315	100%
Indirect effect	SN→CON→BI	0.1379	0.0295	0.0838	0.1987	54.79%
	SN→AIRE→BI	0.0814	0.0202	0.0425	0.1225	32.34%
	SN→CON→AIRE→BI	0.0324	0.0107	0.0129	0.0551	12.87%

The Bootstrap test results (Table 6) further confirmed the partial mediation effects of CON and AIRE in the relationship between SN and BI. The mediation effects were achieved through the following three indirect paths: (1) SN → CON → BI, accounting for 54.79% of the total indirect effect; (2) SN → AIRE → BI, accounting for 32.34% of the total indirect effect; and (3) SN → CON → AIRE → BI, accounting for 12.87% of the total indirect effect.

Discussion

The direct impact of SN on BI

SN significantly and positively affect BI, confirming H1. This result aligns with the findings of Zhang and Hou [21], indicating that for university teachers, positive SN can notably increase their intention to adopt AI technology. Currently, the extensive incorporation of AI technology into classroom teaching has emerged as a key research focus in education. When teachers perceive that their colleagues or school management are promoting the use of AI technology, they may feel pressure from SN, which, consequently, strengthens their intention to adopt [57, 58]. In addition, the results of this study also align with the research by Sing et al. [44], highlighting the impact of perceived subjective norms on teachers' BI to use AI technology, when teachers observe others improving work efficiency or student learning outcomes through AI technology, they may perceive this behavior as having a positive impact on overall teaching quality, hence, strengthening their own motivation to utilize AI technology. It is evident that the supportive factors of SN play a crucial role in driving teachers' technology adoption decisions. Supportive SN may also enhance personal relevance, helping teachers better recognize the importance of integrating AI technology into classroom teaching, thereby indirectly promoting their intention to use it [35]. Thus, supportive SN can increase university teachers' motivation to adopt AI technology, providing important theoretical and practical insights for promoting the comprehensive integration of AI technology into classroom teaching within education.

The mediating role of CON

CON acts as a mediator between SN and BI, indicating that an increase in SN enhances teachers' CON in AI technology, which further strengthens their intention to use it. This finding confirms H2 and aligns with the study by Chai et al. [33], demonstrating that SN can boost individuals' CON in AI technology, thereby increasing their BI. This aligns with the theory of planned behavior, which posits that BI is jointly influenced by SN, attitudes, and perceived behavioral control. Perceived behavioral control includes factors such as CON and optimism, which mediate the relationship between SN and BI. When SN enhance an individual's CON in their own abilities, they are more likely to develop a positive BI [59]. When teachers perceive support or expectations from those around them (e.g., colleagues or leaders) regarding the use of AI technology, they may feel the need to align with these social expectations, thereby enhancing their CON in using AI technology, this is consistent with the findings of Liu et al. [60] and Limbu et al. [34]. However, the unique contribution of this study lies in further exploring the mediating role of CON between SN and teachers' BI to use AI technology. Previous research has indicated a positive relationship between CON and technology adoption, teachers with high CON are typically more willing to participate in technology training and learning activities, improving their adaptability to new technologies. They are better able to perceive the positive effects of integrating AI technology into classrooms, such as enhanced teaching efficiency, thereby increasing their intention to use it [25, 32]. However, this study further reveals how SN, by enhancing teachers' CON in AI technology, indirectly increase their BI to use it. This finding enriches the existing literature by demonstrating that, in promoting the application of educational technology, SN play an important role not only in providing direct technical training and support but also in boosting teachers' self-confidence and fostering their willingness to use the technology.

The mediating role of AIRE

AIRE mediates the relationship between SN and BI, indicating that an increase in SN helps enhance teachers' AIRE, which further strengthens their intention to use AI technology. This finding confirms H3 and aligns with the study by Fundi et al. [43], suggesting that SN can influence university teachers' AIRE. Higher levels of AIRE are a significant predictor of the effective integration of AI technology into classroom teaching [41]. SN, by providing AI tools and support resources that better align with teachers' instructional needs, can stimulate teachers' motivation to learn AI technology, thereby enhancing their AIRE [43, 45]. Moreover, the study by Mansor et al. [61] also found that SN serve as an external pressure for teachers, when teachers perceive the emphasis placed on AI technology by colleagues or school administrators, their sense of professional responsibility is heightened, prompting them to proactively enhance their knowledge base and improve their AIRE. Teachers with higher AIRE typically possess extensive AI-related knowledge, which helps them integrate existing teaching skills with AI technology and even innovate more efficient teaching methods, thereby increasing their intention to use AI technology [45, 46]. This study further reveals that AIRE is not only a key factor in teachers' use of AI technology but also an indirect pathway through which SN influence BI. Specifically, SN enhance teachers' AIRE, which in turn promotes their willingness to use AI technology. Therefore, this study expands on the existing literature by elaborating on the mechanism of AIRE and emphasizes the crucial role of SN in this process, as they indirectly drive teachers' intention to use AI technology by improving their AIRE.

The chain mediating role of CON and AIRE

CON and AIRE serve as a chain mediation between SN and BI. Specifically, when teachers perceive stronger SN, their CON in AI technology increases, which subsequently enhances their AIRE, ultimately boosting their BI. This finding confirms H4 and aligns with the study by Dai et al. [47], which indicates a positive correlation between university teachers' CON in AI technology and their AIRE. According to social cognitive theory, when teachers perceive positive SN from their external environment, they often enhance their CON in AI technology to meet these expectations [60]. For instance, if teachers observe colleagues successfully applying AI technology in classrooms or receive support and encouragement from school leaders, they may feel more confident and thus more willing to try these new technologies [62]. Furthermore, when teachers have high CON in AI technology, they are more likely to actively explore these technologies and participate in relevant training and learning activities, thereby improving their AIRE, this finding is consistent with the research by Dai et al. [47] and Wang and Li [48]. Furthermore, teachers' AIRE is a significant predictor of their BI to use AI technology [45]. When teachers possess a high level of AIRE, they are more capable of integrating existing teaching skills with AI technology, achieving favorable classroom outcomes, and thereby strengthening their BI to use AI technology [41, 42]. In summary, this study thoroughly explores how SN indirectly promote teachers' BI to use AI technology by enhancing their CON and improving AIRE. Compared to existing research, this study emphasizes the role of CON and AIRE as chain mediators in this process, expanding the understanding of how SN influence teachers' intention to use AI technology. This provides new theoretical perspectives and empirical support for promoting the application of AI technology in the education sector.

Research implications

This study holds significant theoretical and practical implications. From a theoretical perspective, firstly, it enriches the theoretical framework of technology adoption among university teachers. By examining the pathways through which SN influence BI to use AI technology and uncovering the mediating roles of CON and AIRE, this study broadens the research perspective of technology adoption theory and offers new insights into the psychological mechanisms underlying teachers' technology adoption behavior. Secondly, this study deepens the understanding of the role of SN in the technology adoption process. The empirical results indicate that SN not only directly influence BI but also indirectly affect it through CON and AIRE, further clarifying the critical role of social influence factors in the technology adoption process. Finally, this study integrates CON and AIRE into a chain mediation model, revealing their synergistic effects in the technology adoption process. This provides new theoretical evidence for the integrated application of the TAM and AIRE theory.

From a practical perspective, the findings of this study provide important insights for the promotion and application of AI technology among university teachers. On one hand, the mediating effects of CON and AIRE suggest that designing tiered training programs to enhance teachers' mastery of and CON in applying AI technology can effectively promote their intention to adopt the technology. Universities should emphasize the combination of hands-on practice with simulated scenarios, allowing teachers to build CON and improve their technical readiness through practical experience. On the other hand, the significant impact of SN suggests that universities can strengthen social support and motivation among teachers by fostering a supportive culture for technology application, implementing incentive policies, and organizing peer exchange and technology workshops. In addition, the chain mediation effects of CON and AIRE revealed in this study provide specific pathway recommendations for promoting educational technology. Promotion agencies can focus on enhancing teachers' CON and readiness for technology, while incorporating organizational and social support measures to optimize promotion strategies, thereby advancing the adoption and application of AI technology in the educational field.

In conclusion, this study not only deepens the theoretical understanding of technology adoption behavior among university teachers but also provides scientific evidence and practical recommendations for more effectively promoting and applying AI technology in practice.

Limitations and future research directions

This study has certain limitations in sample selection, as the sample primarily consisted of university teachers from a specific region, which may restrict the generalizability of the findings to other regions or educational contexts. Future research could broaden the scope and diversity of the sample by collecting data across different regions, various types of universities, and multidisciplinary contexts. This would help to further validate the applicability of the findings and explore differences among various groups of teachers. Additionally, this study adopted a cross-sectional design, which only revealed correlations between variables without establishing causality. Future research could employ longitudinal designs to track the dynamic changes in teachers' CON, AIRE, and BI over time. This approach would allow for a deeper analysis of the long-term mechanisms of technology adoption behavior and provide a more comprehensive understanding of the causal pathways and patterns of change between variables.

Conclusion

This study thoroughly explored the chain mediation effects of CON and AIRE in the relationship between SN and university teachers' BI to use AI technology. The findings indicate that SN significantly and positively influence teachers' BI and indirectly promote their intention by enhancing their CON and improving their AIRE. This finding suggests that CON and AIRE not only independently mediate the relationship between SN and BI but also form a chain mediation pathway, further strengthening the impact of SN on BI. This theoretical contribution extends existing TAM, particularly in the education sector, by incorporating CON and AIRE to explain the formation process of teachers' BI to use AI technology for the first time. Therefore, the study proposes that when promoting the adoption of AI technology among university teachers, attention should not only be given to the direct effects of SN but also to enhancing teachers' CON and AIRE. Specifically, educational administrators should provide more support and resources, such as professional training, technical guidance, and pilot programs, to help teachers build trust in AI technology and enhance their readiness to use it, thereby increasing their BI. Through this multidimensional support, AI technology can be promoted at a broader level within higher education.

Furthermore, the chain mediation model proposed in this study not only provides a new perspective for the academic community but also offers actionable practical guidance for policymakers and educational administrators in advancing the application of AI technology. Future research could further explore other potential mediating variables, such as teaching attitudes and technology acceptance, and investigate how they play a role in more complex processes of educational technology adoption. Overall, this study emphasizes the necessity of a comprehensive, multi-angle approach to advancing AI technology applications, making both theoretical and practical contributions to technological reform in higher education.

Author contributions

The entire research process was conducted by Nannan Liu, including conceptualization, methodology, formal analysis, and investigation. Nannan Liu also prepared the original draft, performed the review and editing, and provided supervision for the study. The author has reviewed and approved the final version of the manuscript for publication.

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Data availability

The data that support the findings of this study are available on request from the corresponding author.

Declarations

Ethics approval and consent to participate

The researchers confirms that all research was performed in accordance with relevant guidelines/regulations applicable when human participants are involved (e.g., Declaration of Helsinki or similar). **This study was approved by the Ethics Committee of Anshan Normal University.** The participants received oral and written information and provided written informed consent before participating in the study.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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