

The impact of teachers' artificial intelligence literacy and online prosocial behavior on teaching innovation: evidence from China

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Abstract

With the rapid development of artificial intelligence, teaching innovation has emerged as a critical challenge for educators worldwide. However, the psychological mechanisms through which artificial intelligence–related competencies translate into innovative teaching practices remain insufficiently understood. Grounded in Social Cognitive Theory, this study develops and tests a moderated chain-mediation model linking artificial intelligence literacy and online prosocial behavior to teaching innovation behavior through technological self-efficacy and teaching anxiety. Data were collected through a questionnaire survey of teachers in China, and structural equation modeling was employed to test the hypothesized relationships and indirect effects. The results indicate that artificial intelligence literacy and online prosocial behavior significantly and positively predict teaching innovation behavior. Moreover, technological self-efficacy and teaching anxiety operate as sequential mediators that transmit these effects. In addition, subjective workload functions as a boundary condition that moderates the strength of key psychological pathways. By integrating cognitive, affective, and contextual mechanisms within a unified analytical framework, this study extends the literature on teaching innovation and offers theoretical and practical implications for promoting sustainable teaching innovation in technology-intensive educational contexts.

1. Introduction

With the rapid development of artificial intelligence (AI), educational systems worldwide are experiencing profound structural and pedagogical transformation. AI-enabled technologies are increasingly reshaping instructional design, teaching delivery, assessment practices, and teacher–student interaction, thereby placing unprecedented demands on teachers' professional competencies (Huang, 2025). Within this context, teaching innovation has emerged as a central concern in contemporary educational research and practice, as educators are expected not only to adopt new technologies but also to creatively integrate them into pedagogically meaningful instructional approaches (Zou et al., 2025).

Despite the growing emphasis on technology integration, teachers frequently encounter cognitive, emotional, and contextual challenges when adopting AI-enabled technologies (Aydin et al., 2021). These challenges may inhibit teachers' willingness and ability to engage in innovative teaching practices, ultimately limiting the transformative potential of artificial intelligence in education. Consequently, understanding the psychological mechanisms that facilitate or constrain teaching innovation has become an important scholarly and practical issue (Yang et al., 2025b).

Existing research has examined a range of antecedents of teaching innovation, including technological, organizational, and individual factors. At the individual level, prior studies have highlighted the role of technological competence or digital literacy in shaping teachers' innovative behavior, while others have emphasized affective factors, particularly technology-related anxiety. However, much of the existing literature examines these factors in isolation, and the integrative psychological mechanisms through which cognitive and affective processes jointly shape teaching innovation remain underexplored. In particular, limited attention has been paid to how emerging AI-related competencies translate into innovative teaching behavior through dynamic cognitive–emotional pathways.

Artificial intelligence literacy (AIL) represents a critical capability enabling teachers to understand, evaluate, and effectively apply AI technologies in educational contexts (Wang et al., 2023). Unlike general digital literacy, AI literacy emphasizes not only operational skills but also conceptual understanding, ethical awareness, and informed decision-making regarding AI applications (Peña-García et al., 2026). In parallel, online prosocial behavior (OPB)—defined as voluntary, altruistic behavior conducted within digital environments—has attracted increasing attention

as a socially embedded behavior within professional online communities. Through knowledge sharing, emotional support, and collaborative problem-solving, online prosocial behavior may provide teachers with valuable social resources that enhance confidence and reduce anxiety in technology-enhanced teaching contexts (Magtalas & Eduvala, 2024). Nevertheless, empirical research examining the joint influence of artificial intelligence literacy and online prosocial behavior on teaching innovation remains scarce.

Social Cognitive Theory provides a robust theoretical framework for examining the dynamic interplay among environmental, cognitive, affective, and behavioral factors (Khuhro, 2024). From this perspective, teachers' innovative behavior is shaped not only by external technological conditions but also by internal cognitive appraisals and emotional regulation processes (Salessi & Etchevers, 2020). Drawing on this theory, the present study develops a moderated chain-mediating model to explain how artificial intelligence literacy and online prosocial behavior influence teaching innovation behavior (TIB) through technological self-efficacy (TSE) and teaching anxiety (TA), while accounting for the boundary role of subjective workload (SW).

This study contributes to the literature in three important ways. First, it extends research on teaching innovation by integrating artificial intelligence literacy and online prosocial behavior into a unified analytical framework, thereby responding to calls for more comprehensive models of technology-driven innovation in education. Second, by identifying technological self-efficacy and teaching anxiety as sequential mediators, this study advances understanding of the cognitive–affective mechanisms through which AI-related competencies translate into innovative teaching behavior. Third, by incorporating subjective workload as a moderating factor, this research highlights the importance of contextual resource constraints in shaping the effectiveness of individual psychological resources. Collectively, these contributions enhance the theoretical precision and international relevance of research on teaching innovation in AI-driven educational environments.

2. Theoretical background and research hypothesis

2.1. Social cognitive theory

This study adopts Social Cognitive Theory (Bandura, 2001) as its theoretical foundation, emphasizing the reciprocal interactions among personal, behavioral, and environmental factors. The core mechanism of SCT is triadic reciprocal determinism, which posits that personal factors, behaviors, and the environment interact dynamically to shape individuals' psychological states and behavioral expressions (Khuhro, 2024). In the context of the AI-driven digital transformation of education, artificial intelligence literacy and online prosocial behavior are conceptualized as dual-attribute constructs—manifested as proactive behaviors while simultaneously reflected as personal competencies or predispositions (Shao et al., 2025). These dual-attribute variables promote teaching innovation by influencing key psychological mechanisms, specifically by enhancing technological self-efficacy and reducing teaching anxiety. The proposed model delineates the sequential mediating pathway AIL/OPB → TSE → TA → TIB, illustrating how behavioral and personal characteristics are transformed into psychological states and subsequently into innovative teaching behaviors. Furthermore, subjective workload serves as a contextual boundary condition that moderates the transformation of psychological states into innovative outcomes—high workload weakens the positive influence of technological self-efficacy while intensifying the negative effect of teaching anxiety. The overall theoretical framework is illustrated in Fig. 1.

Note

Personal = P; Behavioural = B; Environmental = E; Artificial Intelligence Literacy = AIL; Online Prosocial Behavior = OPB; Technological Self-efficacy = TSE; Teaching anxiety = TA; Subjective Workload = SW; Teaching Innovation Behavior = TIB

Figure 1 Framework of the theoretical research

2.2. Artificial intelligence literacy, online prosocial behavior, and teaching innovation behavior

Artificial intelligence literacy refers to teachers' capacity to understand, pedagogically apply, and critically evaluate AI technologies across multiple dimensions, including awareness, technical knowledge, application, social responsibility, and professional development (Wang et al., 2024). It emphasizes the transformation from factual knowledge to higher-order pedagogical reasoning through the integration of engineering, computational, and systems thinking (Sperling et al., 2024). In practice, artificial intelligence literacy enables teachers to strategically employ intelligent tools, such as digital platforms and virtual laboratories, to optimize instructional design and curriculum development (Tenberga & Daniela, 2024). This competency allows teachers to reconceptualize instructional content, cultivate students' AI-assisted problem-solving skills, and transition from knowledge transmitters to facilitators of learning and pedagogical innovators. Through artificial intelligence literacy, teachers can systematically analyze instructional data, identify latent educational patterns, and inform instructional reform. Moreover, artificial intelligence literacy enables teachers to guide students in developing a critical and responsible understanding of technology while cultivating an innovative mindset (Ding et al., 2024). In the AI era, artificial intelligence literacy therefore constitutes a foundational professional competence for educational innovation, enhancing interactivity and personalization (Choi et al., 2025). Accordingly, the following hypothesis is proposed:

H1a: Artificial intelligence literacy positively influences teaching innovation behavior.

Online prosocial behavior refers to voluntary, technology-mediated actions intended to benefit others and sustain constructive social relationships. Its core elements—sharing, helping, and social concern—are shaped by distinctive online norms, including virtuality, anonymity, and spatiotemporal flexibility (Bosancianu et al., 2013). Prior research indicates that online prosocial engagement strengthens social connections and facilitates information exchange, thereby expanding access to diverse resources and perspectives (Lin et al., 2025). In educational contexts, teachers' online prosocial behavior, such as sharing teaching resources or collaboratively solving instructional problems, stimulates pedagogical innovation by increasing exposure to heterogeneous knowledge sources. Such interactions broaden professional networks and encourage knowledge exchange, creating socially embedded conditions conducive to innovation (Su & Wang, 2022). From a psychological perspective, participation in online prosocial behavior evokes positive affective states that build emotional resources and promote higher levels of innovative teaching. Accordingly, the following hypothesis is proposed:

H1b: Online prosocial behavior positively influences teaching innovation behavior.

2.3. Artificial intelligence literacy, technological self-efficacy, and teaching anxiety

Technological self-efficacy refers to teachers' belief in their capability to use digital technologies to enhance professional competence and improve student learning outcomes (Rayburn et al., 2021). This concept stems from Bandura's self-efficacy construct in Social Cognitive Theory, which emphasizes individuals' domain-specific judgments of their capabilities to organize and execute actions. In educational technology research, technological

self-efficacy has been shown to shape teachers' acceptance of emerging technologies and sustain their motivation for continuous professional learning (Sharma & Saini, 2022).

With the increasing integration of AI in education, researchers have increasingly examined the multidimensional structure of artificial intelligence literacy and its underlying influence mechanisms. Artificial intelligence literacy encompasses technical understanding, critical evaluation, and practical application competencies (Choi et al., 2025). This multidimensional framework requires the integration of conceptual understanding with practical operational skills. Research indicates that improving technological literacy enhances cognitive representations of technology, whereas technological self-efficacy develops through mastery experiences and cognitive restructuring (Rachbauer et al., 2024; Ding & Xie, 2026). As teachers' artificial intelligence literacy strengthens their technical understanding, operational uncertainty is reduced, while improved critical evaluation enhances the quality of technological decision-making (Wang et al., 2023; Wu & Zhang, 2025). The accumulation of such cognitive resources systematically reshapes teachers' perceptions and appraisals of technological challenges. Consistent with Social Cognitive Theory, individuals with higher self-efficacy invest greater effort in exploring the educational value of technology (Shao et al., 2025). Accordingly, the following hypothesis is proposed:

H2a: Artificial intelligence literacy positively influences technological self-efficacy.

Teaching anxiety is a situationally induced negative affective state that arises when teachers feel tense or helpless in challenging instructional situations (Ganley et al., 2019). As AI becomes integrated into education, teachers face simultaneous challenges of technological adaptation and professional role transformation (Parsons, 1973). According to the Technology Acceptance Model, individuals' perceptions of usefulness and ease of use shape behavioral intentions; teachers unfamiliar with AI may therefore perceive greater work complexity and experience heightened concerns regarding professional autonomy (Kong et al., 2024). Empirical evidence reveals heightened teaching anxiety among teachers, largely driven by concerns regarding role displacement and professional obsolescence (Hopcan et al., 2024). This anxiety is closely associated with insufficient understanding of AI technologies and their pedagogical implications.

Prior research suggests that enhanced AI competence can attenuate anxiety and facilitate its transformation into motivation for technological adaptation (Beirat et al., 2025). This indicates that artificial intelligence literacy mitigates negative affective responses by strengthening perceived technological mastery and control. Moreover, higher awareness of AI ethics reduces anxiety levels (Sharma & Saini, 2022), thereby reinforcing the negative association between artificial intelligence literacy and teaching anxiety. Drawing on the Technology Acceptance Model and anxiety-transformation mechanisms, artificial intelligence literacy may reduce teaching anxiety through three complementary pathways, namely by enhancing perceived usefulness, lowering configuration barriers, and strengthening ethical awareness (Moulavinafchi et al., 2026). Therefore, the following hypothesis is proposed:

H3a: Artificial intelligence literacy negatively influences teaching anxiety.

2.4. Online prosocial behavior, technological self-efficacy, and teaching anxiety

Online prosocial behavior not only fosters interpersonal trust and collaboration but also enhances domain-specific technological self-efficacy by reinforcing teachers' beliefs in their capacity to manage digitally mediated instructional tasks (Bosancianu et al., 2013). Within educational settings, teachers' online prosocial behavior represents intentional, technology-mediated engagement in altruistic activities that contribute to collective digital knowledge-sharing and instructional problem-solving (Lin et al., 2025). The reciprocal nature of such prosocial

interactions strengthens teachers' sense of competence and social connectedness, which function as mastery and vicarious experiences that systematically enhance technological self-efficacy (Mieres-Chacaltana et al., 2025). Teachers who frequently engage in online prosocial behavior are more likely to cognitively reframe technological challenges as opportunities for professional contribution and skill development rather than as sources of stress or threat (Yang et al., 2025b). Moreover, the social recognition and positive feedback derived from online prosocial behavior reinforce perceived technological competence and intrinsic motivation for technology integration (Shao et al., 2025). Consequently, online prosocial behavior strengthens technological self-efficacy through mechanisms of emotional reinforcement, social reciprocity, and observational learning (Wang et al., 2024). Accordingly, the following hypothesis is proposed:

H2b: Online prosocial behavior positively influences technological self-efficacy.

Conversely, online prosocial behavior may alleviate teaching anxiety by reducing uncertainty and emotional tension associated with technology-enhanced instruction (Dahri et al., 2023). The emotional support and resource exchange embedded in online prosocial networks help teachers develop a sense of belonging, perceived control, and emotional security within digital teaching environments (Aydin & Aslan, 2021). When teachers receive peer assistance or recognition, their anxiety related to technological failure, evaluation, and professional adequacy tends to decrease (Parker & Welch, 2021). Empirical evidence further suggests that social support buffers technology-related stress and enhances emotional resilience in professional contexts (Nazir, 2026; Yang et al., 2025a). Therefore, online prosocial behavior is expected to mitigate teaching anxiety by activating emotional buffering and cognitive reappraisal mechanisms that enhance teachers' adaptive responses to technology integration. Accordingly, the following hypothesis is proposed:

H3b: Online prosocial behavior negatively influences teaching anxiety.

2.5. Technological self-efficacy, teaching anxiety, and teaching innovation behavior

Technological self-efficacy reflects teachers' confidence in successfully employing technology to design, implement, and evaluate teaching activities (Hopcan et al., 2024). High levels of technological self-efficacy suggest that teachers perceive themselves as capable of overcoming technical challenges and maintaining positive attitudes toward innovation (Sofiyani et al., 2022). Based on social cognitive theory, self-efficacy determines how individuals use cognitive and behavioral resources to meet situational demands (Bandura, 2001). In the context of educational technology, teachers with stronger self-efficacy are more proactive in experimenting with innovative instructional methods and integrating new tools into their classrooms (Shao et al., 2025). High technological self-efficacy also enhances teachers' resilience in the face of technological uncertainty, helping them remain persistent in pedagogical reform (Wu & Zhang, 2025). Conversely, low self-efficacy often leads to avoidance behaviors and resistance to instructional innovation (Mieres-Chacaltana et al., 2025). Previous studies have confirmed that self-efficacy serves as a significant predictor of teachers' innovative behavior (Sofiyani et al., 2022). Accordingly, the following hypothesis is proposed:

H4: Technological self-efficacy positively influences teaching innovation behavior.

Teaching anxiety refers to the negative emotional response teachers experience when they perceive themselves as unable to meet instructional or technological expectations (Ganley et al., 2019). Teaching anxiety triggers avoidance tendencies, undermines intrinsic motivation, and limits teachers' engagement in innovative practices (Van et al., 2014). According to the emotion–cognition interaction theory, negative emotions impair cognitive resources,

thereby reducing problem-solving efficiency and creative thinking (Magtalas & Eduvala, 2024). Teachers experiencing anxiety tend to rely on traditional teaching methods and demonstrate less willingness to adopt innovative practices (Zhao et al., 2026). Empirical studies have shown that anxiety negatively affects teachers' professional development and innovative behavior. Therefore, the following hypothesis is proposed:

H5: Teaching anxiety negatively influences teaching innovation behavior.

2.6. The mediating roles of technological self-efficacy

As a core competency that enables teachers to integrate intelligent technologies effectively, the mechanism by which Artificial Intelligence Literacy influences behavior must be examined within the framework of Social Cognitive Theory (Shao et al., 2025). Social cognitive theory emphasizes the central role of cognitive factors in shaping behavior, highlighting that self-efficacy—defined as an individual's belief in their ability to complete specific tasks—directly affects behavioral choices and persistence (Rachbauer et al., 2024). In educational technology, Technological Self-efficacy refers to teachers' confidence in using technological tools to achieve instructional goals, which serves as a critical cognitive driver of teaching practice (Rayburn et al., 2021). In AI-integrated contexts, teachers' mastery of technical principles, ethical norms, and practical methods enhances their technological self-efficacy through cognitive pathways (Choi et al., 2025). The Technology Acceptance Model posits that individuals' perceptions of technological characteristics significantly shape their attitudes toward technology use. Accordingly, a deeper understanding of AI technology enhances teachers' confidence in their ability to master it (Sharma & Saini, 2022). Empirical studies have demonstrated that a higher level of artificial intelligence literacy is positively associated with teachers' confidence in using AI tools for instruction (Su & Wang, 2022). Sarun et al. (2026) found that technology training enhances teachers' efficacy beliefs through the expansion of their technological knowledge base. Social cognitive theory further posits that technological self-efficacy functions as a cognitive conversion mechanism through which teachers internalize technological knowledge into capability beliefs that, in turn, drive innovative teaching practices (Kong et al., 2024). Therefore, artificial intelligence literacy indirectly promotes innovative behaviors—such as designing new instructional activities and developing AI-based teaching resources—by strengthening teachers' beliefs in their technological mastery. Accordingly, this study proposes the following hypothesis:

H6a: Technological Self-efficacy mediates the relationship between Artificial Intelligence Literacy and Teaching Innovation Behavior.

As educators increasingly engage in proactive social interactions in virtual environments, the mechanisms by which Online Prosocial Behavior influences educational practice warrant in-depth exploration. Social Cognitive Theory posits a triadic interaction among individual, behavioral, and environmental factors, in which cognitive processes mediate the relationship between external stimuli and behavioral responses (Bandura, 2001). Within this framework, positive interactions inherent in online prosocial behavior—such as knowledge sharing and collaborative support—may shape teachers' professional practices by modifying their cognitive appraisal processes (Aydin & Aslan, 2021). Specifically, consistent engagement in altruistic online behaviors can gradually strengthen teachers' beliefs in their ability to cope with technological challenges. Technological Self-efficacy is defined as an individual's confidence in using technology to complete specific tasks (Lv et al., 2021). In technology-integrated education, teachers with higher technological self-efficacy are more inclined to experiment with new instructional methods, since their confidence in mastering technological tools reduces the perceived risks of innovation (Lotfalian et al., 2025). This efficacy belief arises from accumulated successful technological experiences and is reinforced through observations of peers' technology use. The mutual-supportive environments fostered by online prosocial behavior

provide vicarious experiences, thereby establishing social conditions that nurture efficacy beliefs (Lin et al., 2025). Individuals with high technological self-efficacy tend to undertake challenging tasks and maintain sustained engagement in innovative practices. Empirical evidence in education demonstrates that teachers' technological confidence directly influences their willingness to engage in innovative teaching. When teachers believe they can effectively utilize intelligent tools, they are more likely to transcend traditional teaching models (Wang et al., 2025; Yordudom et al., 2026). Empirical analysis by Sofiyan et al. (2022) further confirms that technological self-efficacy is a key antecedent of teachers' innovative behavior. Accordingly, this study proposes the following hypothesis:

H6b: Technological Self-efficacy mediates the relationship between Online Prosocial Behavior and Teaching Innovation Behavior.

2.6. The mediating roles of technological teaching anxiety

Social Cognitive Theory emphasizes the triadic interaction among individual, behavioral, and environmental factors. When teachers encounter technological transformations, their level of literacy influences how they cognitively appraise teaching situations (Khuhro, 2024). Prior research indicates that enhancing AI ethical awareness can significantly reduce technological anxiety (Zhao et al., 2026), and that teaching anxiety typically manifests as concerns about technological adaptability and doubts regarding personal capability (Ganley et al., 2019). This emotional state may stem from an imbalance in self-efficacy resulting from limited technological understanding, thereby acting as a behavioral inhibition mechanism. Moreover, anxiety can hinder teachers' engagement in innovative teaching practices (Kataoka, 2025). Although empirical data show that AI-related anxiety negatively affects cognitive factors, its direct influence on literacy is not statistically significant (Hopcan et al., 2024). High anxiety levels weaken teachers' initiative to explore new teaching methods, as they often avoid uncertain technological risks (Wang et al., 2024). When teachers possess sufficient Artificial Intelligence Literacy, their positive appraisal of technological complexity can reduce anxiety, while lower anxiety levels free cognitive resources that facilitate innovative teaching practices. Therefore, the following hypothesis is proposed:

H7a: Teaching anxiety mediates the relationship between Artificial Intelligence Literacy and Teaching Innovation Behavior.

In intelligent education contexts, where teachers frequently engage in online interactive environments, Online Prosocial Behavior—as a form of supportive online interaction—may influence educational practice through psychological mechanisms (Yordudom et al., 2026). Social Cognitive Theory posits that environmental stimuli regulate behavioral responses through cognitive mediation. Individuals' prosocial interactions in online settings can reshape their self-efficacy beliefs, thereby influencing subsequent behavioral decisions (Mieres-Chacaltana et al., 2025). Previous research has identified a link between positive online behaviors and anxiety levels. For instance, exposure to negative online public opinion may heighten technological anxiety, as misleading information amplifies perceived technological threats. Conversely, supportive online systems can alleviate anxiety and reduce uncertainty by providing accurate decision-making resources, suggesting that Online Prosocial Behaviors such as mutual assistance and knowledge sharing may buffer external stressors and reduce cognitive load (Dahri et al., 2023). Furthermore, as a negative psychological state, teaching anxiety has been shown to hinder educational innovation. High anxiety levels reduce teachers' learning motivation and willingness to explore by triggering avoidance mechanisms that discourage risk-taking (Parker & Welch, 2021). Evidence further shows that anxious individuals tend to maintain the status quo and avoid adopting new teaching methods to minimize cognitive conflict. Therefore, the following hypothesis is proposed:

H7b: Teaching anxiety mediates the relationship between Online Prosocial Behavior and Teaching Innovation Behavior.

2.7. The chain-mediating effect of technological self-efficacy and teaching anxiety

Grounded in the triadic reciprocal determinism of Social Cognitive Theory, dynamic interactions occur among environmental, personal, and behavioral factors, with cognitive appraisal processes functioning as the proximal drivers of behavioral decision-making. Empirical research identifies Technological Self-Efficacy as a central cognitive resource that systematically alleviates anxiety in technology-integrated teaching contexts (Filippelli et al., 2026). Specifically, when teachers positively evaluate their technological abilities, their perceived controllability of technology-related demands increases, leading to a systematic reduction in psychological pressure. This cognitive-buffering effect of self-efficacy on anxiety has been consistently validated across interdisciplinary educational settings (Sofiyani et al., 2022). Further analysis clarifies the sequential mechanism through which Technological Self-Efficacy promotes Teaching Innovation Behavior via the attenuation of Teaching Anxiety (Awan & Ahmad, 2024). High levels of self-efficacy lower perceived risk and increase teachers' willingness to experiment with challenging yet high-reward innovative strategies (Ding et al., 2024). In this process, Teaching Anxiety, as an inhibitory emotional state, directly constrains innovative behavior by limiting exploratory and risk-taking tendencies. When anxiety decreases as a result of heightened self-efficacy, psychological barriers to departing from traditional teaching models diminish, thereby fostering the cognitive–emotional conditions necessary for innovation.

Integrating these mechanisms, this study posits that Artificial Intelligence Literacy influences Teaching Innovation Behavior through a sequential cognitive–affective mediating process. Enhanced artificial intelligence literacy strengthens teachers' conceptual understanding and operational mastery of technological tools, thereby enhancing Technological Self-Efficacy (Mieres-Chacaltana et al., 2025). The resulting self-efficacy reduces anxiety arising from technological uncertainty, while the psychological resources released through anxiety reduction are reallocated toward innovative teaching efforts (Wu et al., 2022). This sequential pathway aligns with the environmental stimulus–cognitive processing–emotional regulation–behavioral output framework of Social Cognitive Theory, wherein Technological Self-Efficacy and Teaching Anxiety function as ordered mediators.

Existing evidence further supports the systematic inverse relationship between self-efficacy and anxiety. In AI-driven educational contexts, Technological Self-Efficacy indirectly enhances teachers' adaptive capacity by attenuating job-related and technology-induced anxiety (Maas et al., 2021). Teaching Anxiety thus functions as both an outcome of technological self-efficacy and a proximal constraint on innovative practice. According to Social Cognitive Theory (Bandura, 2001), external support and social interactions shape self-beliefs through observational learning and social persuasion. Accordingly, Online Prosocial Behavior may strengthen teachers' Technological Self-Efficacy by providing emotional reinforcement and technical assistance, thereby facilitating the internalization of successful technology-use experiences (Dahri et al., 2023; Yang et al., 2026). Enhanced self-efficacy subsequently reduces anxiety, enabling teachers to adopt innovative teaching methods as cognitive resources are freed for creative exploration. This results in the sequential pathway "OPB → TSE → TA → TIB," capturing the progressive interaction between cognitive appraisal and emotional regulation processes.

H8a: Technological Self-Efficacy and Teaching Anxiety play a serial mediating role between Artificial Intelligence Literacy and Teaching Innovation Behavior.

H8b: Technological Self-Efficacy and Teaching Anxiety play a serial mediating role between Online Prosocial Behavior and Teaching Innovation Behavior.

2.8. The moderating role of subjective workload

Subjective workload refers to individuals' perceived cognitive, emotional, and temporal demands arising from task performance within specific contextual constraints (Kramer et al., 2017). In educational settings, teachers' subjective workload is often heightened by technology integration, instructional complexity, and expanding administrative responsibilities (Magtalas & Eduvala, 2024). Prior research indicates that excessive workload undermines teachers' psychological well-being and constrains professional performance (Lotfalian et al., 2025). From a conservation of resources perspective, high subjective workload consumes limited cognitive and emotional resources, thereby reducing individuals' capacity to engage in adaptive, effortful, and innovative behaviors (Dogan & Arslan, 2026). In the context of teaching innovation, subjective workload may systematically condition the effectiveness of individual psychological resources by altering resource availability.

Specifically, when subjective workload is high, the positive effects of technological self-efficacy on teaching innovation are likely to be attenuated, as teachers experiencing heavy workload tend to prioritize efficiency and task completion over experimentation with innovative instructional approaches (Kramer et al., 2017). Conversely, under conditions of low subjective workload, teachers retain greater cognitive flexibility and discretionary resources, enabling them to translate technological self-efficacy into innovative practice more effectively (Maas et al., 2021). Similarly, subjective workload may moderate the strength of the relationship between teaching anxiety and teaching innovation behavior (Awan & Ahmad, 2024). When workload is high, anxiety-related resource depletion may intensify, further inhibiting innovation. In contrast, when workload is low, the negative impact of anxiety on innovation may be partially buffered. Therefore, subjective workload functions as a critical boundary condition shaping teachers' innovative behavior in technology-enhanced educational contexts.

H9: Subjective workload negatively moderates the relationship between technological self-efficacy and teaching innovation behavior.

H10: Subjective workload positively moderates the relationship between teaching anxiety and teaching innovation behavior.

Building on these findings, this study develops the theoretical model as illustrated in Fig. 2.

Note

Artificial Intelligence Literacy = AIL; Online Prosocial Behavior = OPB; Technological Self-efficacy = TSE; Teaching anxiety = TA; Subjective Workload = SW; Teaching Innovation Behavior = TIB

Figure 2. Theoretical model

3. Research design

3.1 Sample selection and data collection

This study employed a convenience sampling approach, selecting in-service teachers from various regions in China as participants. Data were primarily collected by distributing structured questionnaires through online platforms. The questionnaire included items assessing the core variables—Artificial Intelligence Literacy, Online Prosocial

Behavior, Technological Self-Efficacy, Teaching Anxiety, Teaching Innovation Behavior, and Subjective Workload—along with demographic information such as gender, subject taught, professional title, age, educational level, and teaching experience. The survey instrument comprised 59 items in total. The scale items were phrased in objective and neutral terms to minimize social desirability bias, including six items related to participants' basic information. A total of 480 questionnaires were distributed. After excluding 31 invalid or incomplete responses, 449 valid questionnaires were retained, yielding a response rate of 93.54%. The sample characteristics are presented in Table 1.

Table 1 Statistical characteristics							
Variable		N	PCT(%)	Variable		N	PCT(%)
Gender	Male	247	55.01	Sub.	Arts	197	43.88
	Female	202	44.99		Science	252	56.12
Age	Under 30	20	4.45	Exp.	Under 5	18	4.01
	31-40	281	62.58		6-15	35	7.80
	41-50	86	19.15		16-25	84	18.71
	Over 51	62	13.81		Over26	312	69.49
Prof.	Junior	270	60.13	Degree	Associate & below	69	15.37
	Intermediate	129	28.73		Bachelor	97	21.60
	Senior	50	11.14		Postgraduate	283	63.03
Note: Professional Title=Prof. ; Subject Taught = Sub. ; Teaching Experience = Exp.							

3.2. Variables measurement

All variables in this study were measured using validated, well-established scales from previous research. The items were appropriately adapted to the contexts of higher education and AI-assisted teaching. Each construct was measured using a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree").

(1) Artificial Intelligence Literacy. This variable was measured using the 12-item scale developed by Wang et al. (2023) for the quantitative assessment of AI literacy. The scale measures Artificial Intelligence Literacy across four dimensions: awareness, use, evaluation, and ethics. Sample items include: "I know how to prepare and organize data for training AI models" and "I am skilled at integrating AI tools into my workflow to improve efficiency." This helps researchers understand how users' competence with AI technology influences human–AI interactions.

(2) Online Prosocial Behavior. This variable was measured using a short version of the Internet Altruistic Behavior Scale (Bosancianu et al., 2013). The short version consisted of 10 items. Sample items include: "How often do you provide information and help to people you do not know on MSN, Yahoo Messenger, etc.?" and "How often do you willingly complete questionnaires or surveys on the Internet to help other people or organizations?" The total score of all items represents the level of Online Prosocial Behavior. A Confirmatory Factor Analysis (CFA) of the original 14-item IABS yielded satisfactory goodness-of-fit statistics.

(3) Teaching Innovation Behavior. This variable was measured using the 12-item scale developed by Salessi and Etchevers (2020). Example items include: "I systematically search for new methods, techniques, or work

instruments" and "I obtain the necessary resources to put my ideas into practice." Factor analyses indicated a four-factor structure explaining 69% of the total variance. The final version of the scale comprised twelve items with high reliability. Evidence of convergent, discriminant, and concurrent validity was also confirmed.

(4) Technological Self-Efficacy. This variable was measured using the four-item scale developed by Rayburn et al. (2021). A representative item is "I possess the knowledge necessary to use technology." The scale is concise, easy to understand, and applicable to employees across various industries and job levels. It has been validated in previous research, demonstrating strong reliability and validity.

(5) Teaching Anxiety. Although the Teaching Anxiety Scale developed by Parsons (1973) remains a widely used and effective instrument, this study adapted it by drawing on Ganley et al. (2019) Mathematics Teaching Anxiety Scale and Novak et al. (2022) Science Teaching Anxiety Scale, tailoring it to the specific context of this research. The adapted scale consisted of nine items, including statements such as "I would start to panic if I had to solve challenging teaching problems" and "My mind goes blank when I am about to start a challenging teaching problem."

(6) Subjective Workload. This variable was measured using the nine-item Integrated Workload Scale (IWS) developed by Kyriazos and Poga (2023). The IWS is designed for the real-time assessment of individuals' subjective workload. It features nine anchor points describing workload levels—ranging from "not demanding" to "too demanding"—and captures its multidimensionality by incorporating items reflecting time, demand, and effort.

(7) Control Variables. Drawing on the study by Wu et al. (2022) on innovation behavior in rural teachers' technology integration, this study included Gender, professional title, age, educational level, and teaching experience as control variables. Furthermore, given this study's focus on teachers' Artificial Intelligence Literacy and Online Prosocial Behavior, the subject taught was also included as a control variable to examine its potential influence on Teaching Innovation Behavior. This configuration allows for a more accurate estimation of the net effects of the core independent variables on Teaching Innovation Behavior.

3.3 Common method bias and reliability and validity test

Harman's single-factor test was conducted on the collected data to assess potential common method bias. An unrotated exploratory factor analysis of all scale items (excluding control variables) yielded six factors with eigenvalues greater than one. The largest factor accounted for 33.97% of the variance, which is below the 40% threshold, indicating that common method bias was not a significant concern in this study (Tehseen et al., 2017).

Reliability and validity analyses were conducted using SPSSAU, and the results are presented in Table 2. The results indicate that for Artificial Intelligence Literacy, Online Prosocial Behavior, Technological Self-Efficacy, Teaching Anxiety, Subjective Workload, and Teaching Innovation Behavior, the standardized factor loadings (SFL) all exceeded 0.80, the average variance extracted (AVE) values surpassed 0.70, and the composite reliability (CR) values exceeded 0.90. These results demonstrate strong convergent validity of the research model (Kyriazos & Poga, 2023; Que, Zhang & Wan, 2024). The Cronbach's alpha coefficients all exceeded 0.90, indicating excellent internal consistency among the scale items.

Validity was further assessed using the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity. The KMO value was 0.94, exceeding the recommended threshold of 0.90, indicating that the data were highly suitable for factor analysis. Furthermore, the model fit indices were within acceptable ranges: RMSEA = 0.077 (< 0.10), RMR = 0.025 (< 0.05), and SRMR = 0.027 (< 0.10). The square roots of the AVE values on the diagonal were greater than

the corresponding Pearson correlation coefficients between variables, confirming strong discriminant validity (Okoye & Hosseini, 2024).

Table 2 Reliability and validityCFA

Variable	SFL	CR	AVE	α	KMO	1	2	3	4	5	6
AIL	0.848 0.954	0.985	0.850	0.990	0.942	0.922					
OPB	0.808 0.904	0.962	0.717	0.968		0.408	0.847				
TSE	0.803 0.914	0.931	0.772	0.945		0.255	0.315	0.879			
TA	0.827 0.875	0.940	0.724	0.952		-0.288	-0.307	-0.329	0.851		
SW	0.802 0.939	0.969	0.776	0.967		-0.139	-0.172	-0.168	0.162	0.881	
TIB	0.868 0.968	0.987	0.866	0.990		0.220	0.239	0.275	-0.349	-0.170	0.931

Note: Artificial Intelligence Literacy= AIL; Online Prosocial Behavior= OPB; Technological Self-efficacy= TSE; Teaching Anxiety= TA; Subjective Workload= SW; Teaching Innovation Behavior= TIB

4. Empirical analysis and results

4.1 Correlation analysis

This study employed SPSSAU to conduct a correlation analysis. As shown in Table 3, Spearman's correlation coefficients were used to assess the strength of the relationships among the variables. Artificial Intelligence Literacy exhibited significant correlations with Technological Self-Efficacy, Teaching Anxiety, and Teaching Innovation Behavior, with correlation coefficients of 0.255, -0.288, and 0.220, respectively, all of which were statistically significant at the 0.01 level. This finding suggests that Artificial Intelligence Literacy is significantly associated with Technological Self-Efficacy, Teaching Anxiety, and Teaching Innovation Behavior. Furthermore, the correlation coefficients between Online Prosocial Behavior and Technological Self-Efficacy, Teaching Anxiety, and Teaching Innovation Behavior were also significant, suggesting that Online Prosocial Behavior is significantly associated with these three variables (Zhou & Ma, 2024).

Table 3
Correlation analysis

Variable	M	SD	AIL	OPB	TSE	TA	SW	TIB
AIL	3.545	1.053	1					
OPB	3.422	0.841	0.408***	1				
TSE	3.263	0.856	0.255***	0.315***	1			
TA	2.669	0.913	-0.288***	-0.307***	-0.329***	1		
SW	2.544	0.773	-0.139**	-0.172***	-0.168***	0.162***	1	
TIB	3.237	0.952	0.220***	0.239***	0.275***	-0.349***	-0.170***	1

Note: * $p < 0.05$, ** $p < 0.01$; Artificial Intelligence Literacy = AIL; Online Prosocial Behavior = OPB; Technological Self-efficacy = TSE; Teaching Anxiety = TA; Subjective Workload = SW; Teaching Innovation Behavior = TIB

4.2. Direct effect test

This study utilized SPSSAU to examine the direct effects. As presented in Table 4, Model 1 (M1) indicates that Artificial Intelligence Literacy has a significant positive effect on Teaching Innovation Behavior ($\beta = 0.185$). Model 2 (M2) also indicates a significant positive effect of Online Prosocial Behavior on Teaching Innovation Behavior ($\beta = 0.242$). Model 5 (M5) demonstrates a significant positive relationship between Artificial Intelligence Literacy and Technological Self-Efficacy ($\beta = 0.250$), whereas Model 7 (M7) reveals a significant negative relationship between Artificial Intelligence Literacy and Teaching Anxiety ($\beta = -0.292$). Model 6 (M6) shows a significant positive relationship between Online Prosocial Behavior and Technological Self-Efficacy ($\beta = 0.324$), and Model 8 (M8) indicates a significant negative relationship between Online Prosocial Behavior and Teaching Anxiety ($\beta = -0.315$). Furthermore, Model 3 (M3) confirms a significant positive effect of Technological Self-Efficacy on Teaching Innovation Behavior ($\beta = 0.262$), while Model 4 (M4) confirms a significant negative effect of Teaching Anxiety on Teaching Innovation Behavior ($\beta = -0.338$) (Zhou & Ma, 2024). Thus, hypotheses H1a, H1b, H2a, H2b, H3a, H3b, H4, and H5 were supported.

Table 4
Regression results analysis

Variable	TIB		TSE				TA		
	M1	M2	M3	M4	M5	M6	M7	M8	M9
Gender	0.011	-0.007	0.001	-0.019	0.003	-0.021	-0.070	-0.044	-0.054
Prof.	0.020	0.038	0.019	-0.003	0.008	0.031	-0.071	-0.094*	-0.070
Age	0.182***	0.206***	0.206***	0.193***	-0.010	0.022	-0.012	-0.052	-0.053
Sub.	-0.031	-0.038	-0.010	-0.043	-0.099*	-0.107*	-0.023	-0.013	-0.048
Degree	-0.097*	-0.128**	-0.088	-0.095	-0.060	-0.102*	0.020	0.063	0.012
Exp.	-0.000	0.007	0.006	0.009	0.009	0.019	0.010	-0.004	-0.002
AIL	0.185***				0.250***		-0.292***		
OPB		0.242***				0.324***		-0.315***	
TSE			0.262***						-0.333***
TA				-0.338***					
R2	0.085	0.111	0.120	0.165	0.079	0.123	0.093	0.109	0.120
Adj. R2	0.071	0.096	0.106	0.152	0.064	0.109	0.079	0.095	0.106
D-W	1.902	1.939	1.895	1.892	1.946	1.925	2.159	2.176	2.073

Note: *p < 0.05, **p < 0.01; Artificial Intelligence Literacy = AIL; Online Prosocial Behavior = OPB; Technological Self-efficacy = TSE; Teaching Anxiety = TA; Subjective Workload = SW; Teaching Innovation Behavior = TIB

4.3. Tests for mediating effects

The mediation effects were tested using the percentile bootstrap method. As shown in Table 5, for the path AIL → TSE → TIB, the total effect (c) of Artificial Intelligence Literacy on Teaching Innovation Behavior was 0.132. The regression coefficient (a) of Artificial Intelligence Literacy on Technological Self-efficacy was 0.124, and the regression coefficient (b) of Technological Self-efficacy on Teaching Innovation Behavior was 0.162. The mediation effect (a*b) was 0.020, while the direct effect (c') of Artificial Intelligence Literacy on Teaching Innovation Behavior was 0.067. Since both a and b were significant but c' was not, Technological Self-efficacy demonstrates a full mediation effect between Artificial Intelligence Literacy and Teaching Innovation Behavior (Dar & Chand, 2024). This is further supported by the 95% bias-corrected confidence interval from the bootstrap sampling, which did not include zero (0.005 to 0.045), confirming a significant mediation effect via the AIL → TSE → TIB path, specifically of a full mediation nature. Similarly, the results indicate significant full mediation effects for the paths AIL → TA → TIB, OPB → TSE → TIB, and OPB → TA → TIB (Qin, 2024). Therefore, hypotheses H6a, H6b, H7a, and H7b were supported.

Table 5
Results of mediation effect size

Path	c	a	b	a*b	z	95% BootCI	c'	Conclusion
AIL→TSE→TIB	0.132**	0.124**	0.162**	0.020	1.978	0.005–0.045	0.067	full mediation
AIL→TA→TIB	0.132**	-0.169***	-0.265***	0.045	3.207	0.024–0.079	0.067	full mediation
OPB→TSE→TIB	0.204***	0.258***	0.162**	0.042	2.929	0.012–0.068	0.097	full mediation
OPB→TA→TIB	0.204***	-0.247***	-0.265***	0.065	3.981	0.029–0.093	0.097	full mediation
Note: *p < 0.05, **p < 0.01; Artificial Intelligence Literacy = AIL; Online Prosocial Behavior = OPB; Technological Self-efficacy = TSE; Teaching Anxiety = TA; Subjective Workload = SW; Teaching Innovation Behavior = TIB								

The mediation analysis employed a bootstrap sampling method with 5,000 iterations. Results in Table 6 indicate that, for the AIL → TSE → TIB mediation path, the 95% confidence interval did not include zero (0.005 to 0.045), confirming a significant mediation effect. Similarly, for the paths AIL → TA → TIB, OPB → TSE → TIB, and OPB → TA → TIB, the 95% confidence intervals did not include zero, indicating significant mediation effects across all pathways. Furthermore, analysis of the serial mediation path AIL → TSE → TA → TIB indicated that the 95% confidence interval did not include zero (0.003 to 0.018), confirming a significant serial mediation effect that accounted for 2.38% of the total effect. Similarly, for the OPB → TSE → TA → TIB serial mediation path, the 95% confidence interval did not include zero (0.007 to 0.026), confirming a significant serial mediation effect accounting for 5.06% of the total effect (Qin, 2024). Thus, hypotheses H8a and H8b were supported.

Table 6
Chain mediation effect analysis

	Path	Effect	SE	t	p	95% CI	Proportion
Total Effect	AIL⇒TIB	0.132	0.045	2.933	0.004	0.044~0.221	100.00%
	OPB⇒TIB	0.204	0.056	3.606	0.000	0.093~0.315	
Direct Effect	AIL⇒TIB	0.067	0.044	1.534	0.126	-0.019~0.154	48.81%
	OPB⇒TIB	0.097	0.056	1.723	0.086	-0.014~0.207	
Total Indirect Effect	AIL = > TIB	0.065	0.017	3.779	0.000	0.040~0.108	51.19%
	OPB = > TIB	0.107	0.021	5.007	0.000	0.056~0.140	
Indirect Effect	AIL→TSE→TIB	0.020	0.010	1.978	0.048	0.005~0.045	5.95%
	AIL→TA→TIB	0.037	0.013	2.774	0.006	0.017~0.068	11.01%
	AIL→TSE→TA→TIB	0.008	0.004	2.215	0.027	0.003~0.018	2.38%
	OPB→TSE→TIB	0.042	0.014	2.929	0.003	0.012~0.068	12.5%
	OPB→TA→TIB	0.048	0.015	3.227	0.001	0.016~0.075	14.29%
	OPB→TSE→TA→TIB	0.017	0.005	3.426	0.001	0.007~0.026	5.06%

Note: *p < 0.05, **p < 0.01; Artificial Intelligence Literacy = AIL; Online Prosocial Behavior = OPB; Technological Self-efficacy = TSE; Teaching Anxiety = TA; Subjective Workload = SW; Teaching Innovation Behavior = TIB

4.4. Tests for moderating effects

As shown in Table 7, Models 3 (M3) and 6 (M6) tested the moderating effects of Subjective Workload on the relationships between Technological Self-Efficacy and Teaching Innovation Behavior, and between Teaching Anxiety and Teaching Innovation Behavior, respectively. The results indicated that the interaction term between Technological Self-Efficacy and Subjective Workload had a significant negative effect on Teaching Innovation Behavior ($\beta = -0.116$, $p < 0.05$). Similarly, the interaction term between Teaching Anxiety and Subjective Workload had a significant positive effect on Teaching Innovation Behavior ($\beta = 0.111$, $p < 0.05$). These findings suggest that Subjective Workload negatively moderates the relationship between Technological Self-Efficacy and Teaching Innovation Behavior, while positively moderating the relationship between Teaching Anxiety and Teaching Innovation Behavior (Zhou & Ma, 2024). Thus, hypotheses H9 and H10 were empirically supported.

Table 7
Regression results analysis

Variable	TIB					
	M1	M2	M3	M4	M5	M6
Gender	0.001	-0.007	-0.008	-0.019	-0.026	-0.031
Prof.	0.019	0.018	0.034	-0.003	-0.003	0.016
Age	0.206 ^{***}	0.199 ^{***}	0.206 ^{***}	0.193 ^{***}	0.187 ^{***}	0.187 ^{***}
Sub.	-0.010	-0.019	-0.008	-0.043	-0.049	-0.030
Degree	-0.088	-0.092 [*]	-0.095 [*]	-0.095 [*]	-0.098 [*]	-0.096 [*]
Exp.	0.006	-0.011	-0.017	0.009	-0.007	-0.008
TSE	0.262 ^{***}	0.241 ^{***}	0.226 ^{***}			
TA				-0.338 ^{**}	-0.320 ^{***}	-0.327 ^{***}
SW		-0.123 ^{**}	-0.120 ^{**}		-0.115 [*]	-0.125 ^{**}
TSE*SW			-0.116 [*]			0.111 [*]
TA*SW	0.085	0.111	0.120	0.093	0.109	0.120
R2	0.120	0.134	0.147	0.165	0.178	0.189
Adj. R2	0.106	0.119	0.130	0.152	0.163	0.172
Note: *p < 0.05, **p < 0.01; Artificial Intelligence Literacy = ALL; Online Prosocial Behavior = OPB; Technological Self-efficacy = TSE; Teaching Anxiety = TA; Subjective Workload = SW; Teaching Innovation Behavior = TIB						

Given the significant moderating effects of Subjective Workload identified in the previous analysis, a simple slopes analysis was subsequently conducted. As shown in Table 8, when the moderator (Subjective Workload) was at a high level, the 95% confidence interval (CI) included zero (-0.034 to 0.270), indicating that the relationship between Technological Self-Efficacy and Teaching Innovation Behavior was not significant under high-workload conditions. For the relationship between Teaching Anxiety and Teaching Innovation Behavior, the regression coefficients at low, medium, and high levels of Subjective Workload were - 0.235, -0.341, and - 0.446, respectively, demonstrating a significant and progressively stronger negative association as workload increased. These results further confirm the moderating role of Subjective Workload in the relationships between Technological Self-Efficacy and Teaching Innovation Behavior, and between Teaching Anxiety and Teaching Innovation Behavior (Zhou & Ma, 2024). The results of the simple slopes analyses are visually presented in Figs. 3 and 4. Thus, hypotheses H9 and H10 were further empirically supported.

Table 8
Simple slope analysis

Variable	Levels of moderating	RC	SE	t	p	95% CI
TSE	AVG	0.252	0.051	4.967	0.000	0.152–0.351
	HIGH(+ 1SD)	0.118	0.077	1.522	0.129	-0.034–0.270
	LOW(-1SD)	0.386	0.068	5.658	0.000	0.252–0.520
TA	AVG	-0.341	0.046	-7.449	0.000	-0.431–0.251
	HIGH(+ 1SD)	-0.235	0.060	-3.890	0.000	-0.354–0.116
	LOW(-1SD)	-0.446	0.065	-6.917	0.000	-0.573–0.319
Note: *p < 0.05, **p < 0.01; Artificial Intelligence Literacy = ALL; Online Prosocial Behavior = OPB; Technological Self-efficacy = TSE; Teaching Anxiety = TA; Subjective Workload = SW; Teaching Innovation Behavior = TIB						

5. Conclusion and implications

5.1. Research conclusions and theoretical contributions

This study examined the joint effects of teachers' artificial intelligence literacy and online prosocial behavior on teaching innovation through a moderated chain-mediation framework grounded in Social Cognitive Theory. The findings indicate that both artificial intelligence literacy and online prosocial behavior significantly promote teaching innovation directly and indirectly by enhancing technological self-efficacy and alleviating teaching anxiety. Specifically, technological self-efficacy and teaching anxiety function as sequential cognitive–affective mechanisms through which AI-related competencies and social engagement are transformed into innovative teaching practices. Moreover, subjective workload conditions the effectiveness of these psychological processes by weakening the positive influence of self-efficacy and intensifying the inhibitory effect of anxiety under high workload conditions.

Theoretically, this study advances Social Cognitive Theory by elucidating how cognitive appraisal and emotional regulation operate jointly—rather than independently—in shaping innovative behavior within AI-driven educational contexts. By integrating individual competencies, emotional responses, and contextual constraints into a unified analytical model, this research refines existing explanations of teaching innovation and enhances their applicability to technology-intensive educational environments.

5.2. Discussion

This study advances understanding of teaching innovation by clarifying how cognitive, affective, and contextual factors interact within AI-driven educational environments. The results demonstrate that artificial intelligence literacy and online prosocial behavior emerge as robust antecedents of teaching innovation, extending prior research that focused primarily on general digital competence or technology acceptance. By emphasizing AI-specific literacy, this study highlights the importance of conceptual understanding, evaluative judgment, and informed application in translating technological potential into pedagogical innovation.

More importantly, the findings validate a structured cognitive–affective pathway through which technological self-efficacy enhances innovation by reducing teaching anxiety. This sequential mechanism advances Social Cognitive Theory by empirically demonstrating that cognitive confidence and emotional regulation operate in tandem rather

than isolation. Furthermore, subjective workload operates as a critical boundary condition, indicating that innovation is contingent not only on individual capability but also on the availability of cognitive and emotional resources. Finally, online prosocial behavior functions as a social-environmental resource that strengthens self-efficacy and buffers anxiety, underscoring the role of digitally mediated professional communities in supporting sustainable teaching innovation.

5.3. Managerial implications

The findings provide actionable insights for educational administrators seeking to promote teaching innovation in technology-enhanced learning environments. Institutions should adopt integrated, practice-oriented AI literacy development strategies that embed technical training within authentic pedagogical contexts, thereby enhancing teachers' technological self-efficacy and reducing anxiety associated with AI integration. Simultaneously, fostering online prosocial engagement can strengthen collective professional support by facilitating knowledge sharing, emotional reassurance, and collaborative problem-solving.

Equally important, workload management is essential for enabling innovation. Excessive subjective workload constrains teachers' capacity to translate psychological resources into creative instructional practices, whereas balanced workload structures preserve cognitive flexibility and emotional resilience. Accordingly, institutional policies should align professional development, collaboration incentives, and workload allocation within a coherent framework that supports sustained innovation rather than short-term technological adoption.

5.4. Limitations and Future Research Directions

Several limitations warrant consideration. First, the cross-sectional design limits causal inference; future studies could employ longitudinal or experimental designs to strengthen causal interpretation. Second, reliance on self-reported data may introduce perceptual bias, suggesting the value of incorporating multi-source data such as peer evaluations or classroom observations. Third, the generalizability of the findings is constrained by the focus on K–12 teachers within a single national context. Future research should examine diverse educational levels and cultural settings and further integrate organizational and institutional variables to refine understanding of innovation processes in AI-supported education.

Declarations

Author contributions

Conceptualization, M.Y. and Z.W.; Methodology, M.Y. and G.R.; Software, M.Y. and G.R.; Validation, M.Y., G.R. and L.G.; Formal analysis, M.Y. and G.R.; Investigation, M.Y. and S.Y.; Resources, M.Y. and Z.W.; Data curation, M.Y. and G.R.; Writing – original draft, M.Y.; Writing – review & editing, Z.W., S.Y. and L.G.; Visualization, G.R.; Supervision, Z.W. and S.Y.; Project administration, M.Y. ; Funding acquisition, M.Y.

Data Availability

All raw questionnaire data, cleaned analysis dataset, full scale items (Chinese-English bilingual coding), variable definition documents and descriptive statistical files are uploaded as supplementary supporting materials of this manuscript. Original individual survey data cannot be fully publicly released to protect participants' personal privacy in line with ethical constraints; relevant data can be provided upon reasonable request to the corresponding author.

Ethical Approval

This study involving humans was approved (Ref: JJU-IRB-2026-022) by the Ethics Committee of the School of Management, Jiujiang University. This study and all methods were carried out in accordance with the Declaration of Helsinki and relevant institutional guidelines. Written informed consent was obtained from all participants prior to their participation in this study.

Conflict of interest

The authors declare no competing interests.

Additional information

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Figures

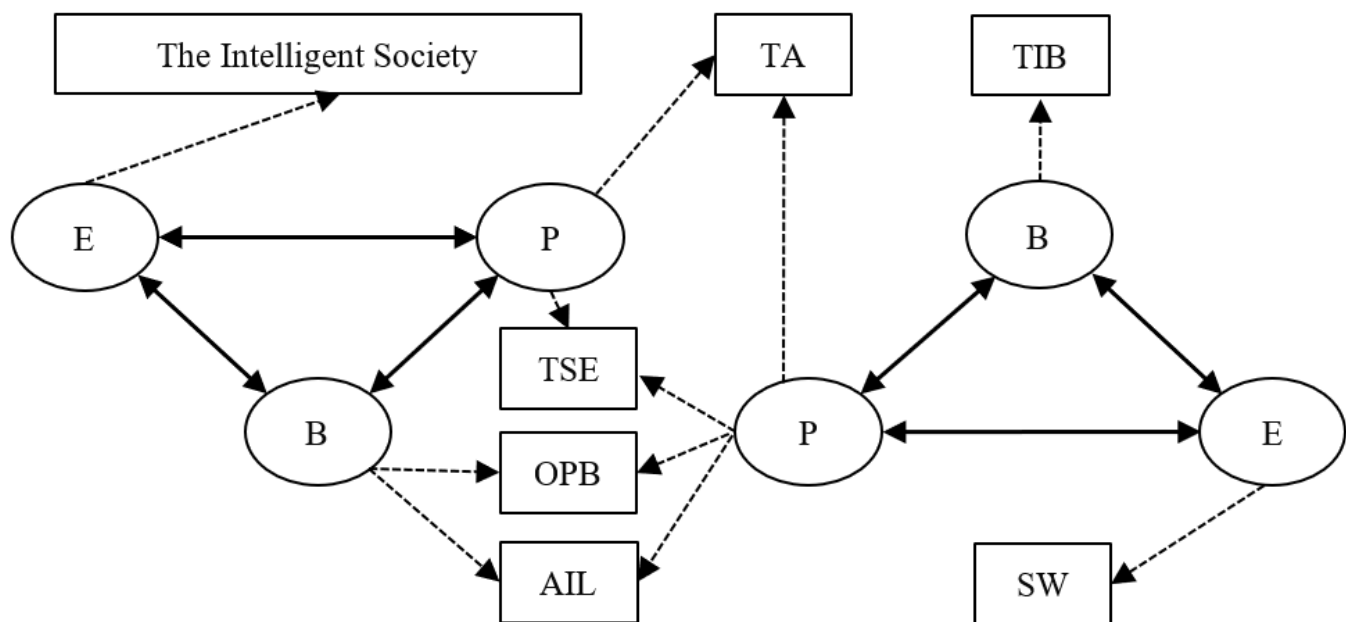


Figure 1

Framework of the theoretical research

Note: Personal=P; Behavioural=B; Environmental=E; Artificial Intelligence Literacy=AIL; Online Prosocial Behavior=OPB; Technological Self-efficacy=TSE; Teaching anxiety=TA; Subjective Workload=SW; Teaching Innovation Behavior=TIB

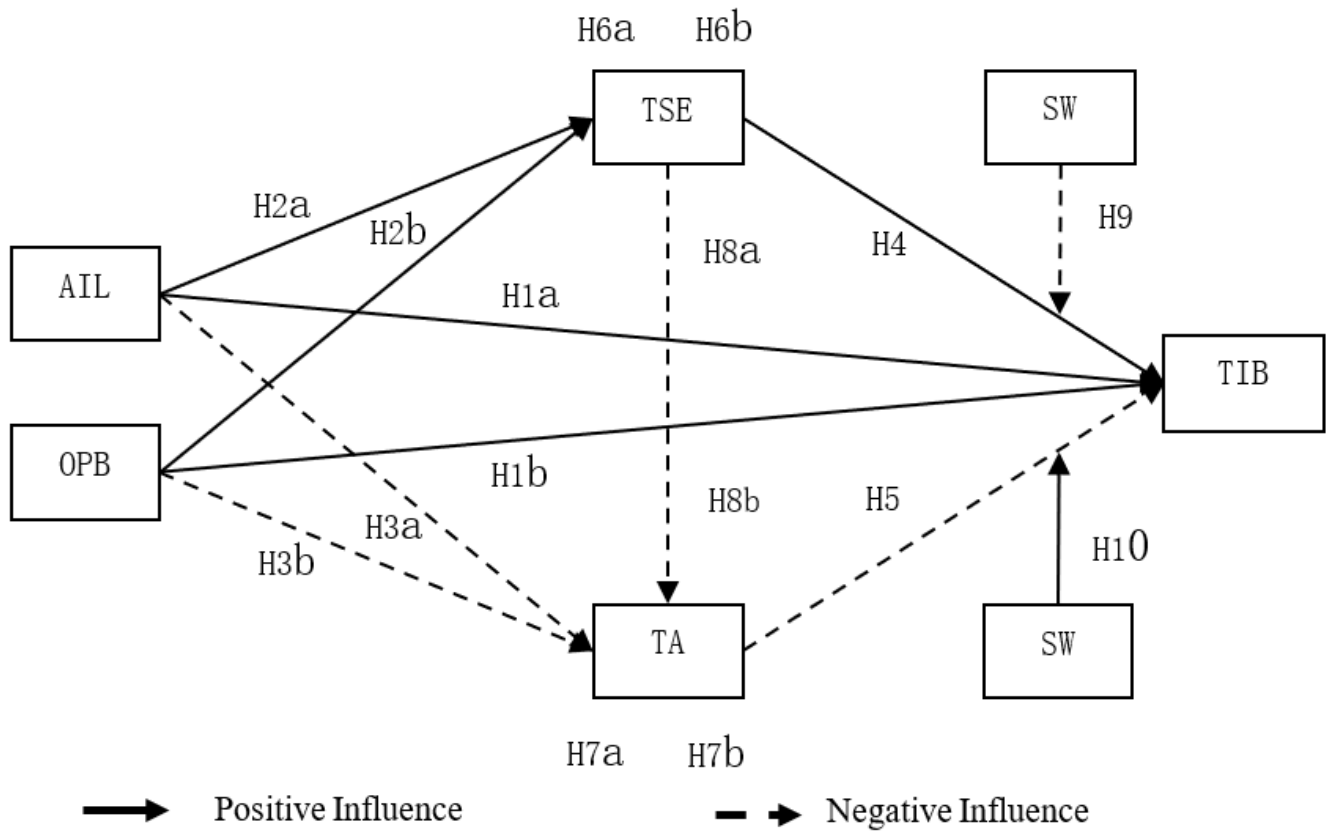


Figure 2

Theoretical model

Note: Artificial Intelligence Literacy=AIL; Online Prosocial Behavior=OPB; Technological Self-efficacy=TSE; Teaching anxiety=TA; Subjective Workload=SW; Teaching Innovation Behavior=TIB

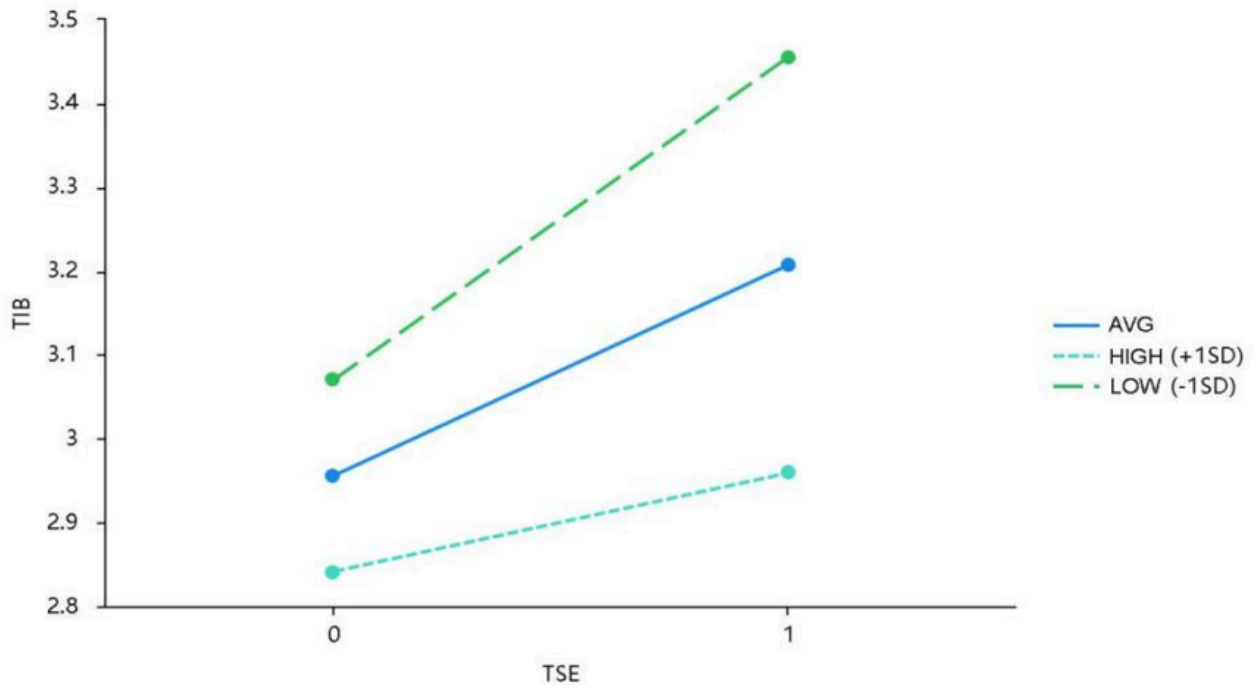


Figure 3

The moderating effect of subjective workload on technological self-efficacy and teaching innovation behavior

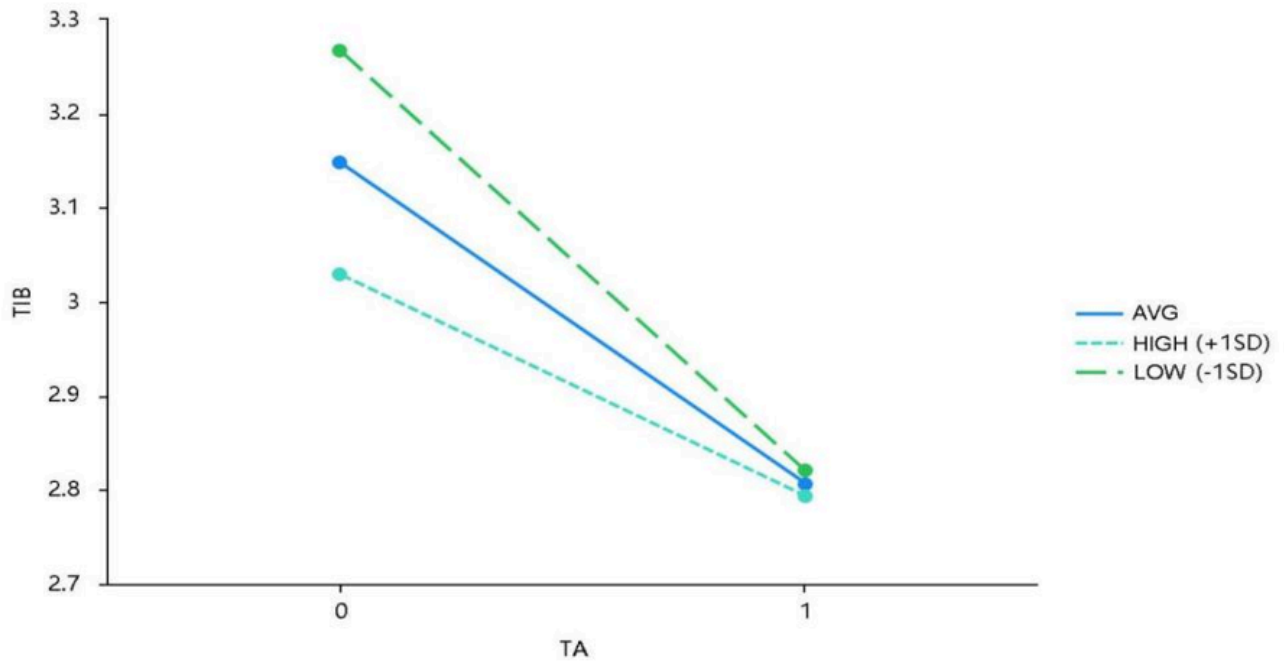


Figure 4

The moderating effect of subjective workload on teaching anxiety and teaching innovation behavior

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