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The relationship between school support and teachers' perceived AI teaching application competence: the mediating roles of psychological and cognitive factors and the moderating role of practical experience

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Introduction: The rapid development of artificial intelligence (AI) in education raises an important question: What factors are associated with teachers' perceived AI teaching application competence, and under what conditions do the underlying psychological and cognitive mechanisms operate?
Methods: Drawing on the stimulus–organism–response (SOR) framework, this study used survey data from 782 primary and secondary school teachers and employed partial least squares structural equation modeling (PLS–SEM) and multigroup analysis (MGA) to examine the relationship between perceived school support and teachers' perceived AI teaching application competence (PAITAC), the mediating roles of psychological and cognitive factors, and the moderating role of practical experience.
Results: AI-TPACK, self-efficacy, psychological resilience, and practical experience were significantly positively associated with PAITAC, whereas AI anxiety was significantly negatively associated with PAITAC. Among these predictors, AI-TPACK exhibited the strongest direct path coefficient. Although the direct association between perceived school support and PAITAC was not statistically significant, multiple indirect effects through psychological resilience, AI anxiety, self-efficacy, and AI-TPACK were significant. Practical experience was not only positively associated with PAITAC but also positively moderated the relationships of AI-TPACK and self-efficacy with PAITAC. MGA revealed no statistically significant gender or urban–rural differences in structural paths after correction for multiple comparisons.
Discussion: These findings provide empirical evidence of the indirect associations between perceived school support and teachers' PAITAC and highlight the moderating role of practical experience.

KEYWORDS
AI-TPACK, perceived AI teaching application competence, perceived school support, practical experience, self-efficacy

1 Introduction

Artificial intelligence (AI) is rapidly reshaping the landscape of teaching and learning. As an important technological force driving digital transformation in education, AI has expanded the ways in which teaching practices can be supported and created new possibilities for improving instructional quality (Tan et al., 2025; Ng et al., 2025; Kohnke et al., 2025). At the same time, these developments have placed greater demands on teachers' capabilities to use AI for instructional purposes. UNESCO's AI Competency Framework for Teachers emphasizes that teachers need the capability to integrate AI into classroom instruction and pedagogical innovation (Miao and Cukurova, 2024). However, a survey conducted by the Walton Family Foundation (2025) found that 68% of teachers had not received school-provided training in the use of AI tools, while only 19% reported that their schools had established policies governing AI use. These findings indicate that the development of teachers' AI-related capabilities continues to face practical challenges, including insufficient training support and underdeveloped institutional guidance. Existing research has likewise increasingly emphasized the need to strengthen support for teachers' AI capability development and professional learning in order to facilitate the effective use of AI in teaching (Karataş and Yüce, 2024; Sperling et al., 2024). Accordingly, identifying the factors associated with teachers' Perceived AI Teaching Application Competence (PAITAC) and understanding the mechanisms through which they operate has become an important issue in research on AI-enhanced education. The term PAITAC is used throughout the remainder of this article.

Accordingly, research attention has gradually shifted from AI technologies themselves toward how teachers understand, accept, and effectively use AI, as well as the factors that shape this process. Previous studies have shown that teachers' use of AI is influenced by multiple factors, including external conditions such as school support, resource availability, professional development, and the broader social environment (Taheri et al., 2025; Molefi et al., 2024; Nazaretsky et al., 2022); individual factors such as self-efficacy, attitudes, trust, and technological perceptions (Bergdahl and Sjöberg, 2025; Viberg et al., 2025); and capability-related foundations such as technological integration knowledge and practical experience (Sofwan et al., 2023). At the same time, negative factors such as anxiety, concerns, and perceived risks may undermine teachers' confidence in using AI and, in turn, hinder their acceptance and application of AI technologies (Kiliç and Çelik, 2025).

Despite growing research on teachers' use of AI in education, several limitations remain. At the theoretical level, existing studies have primarily drawn on perspectives such as the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology, the Theory of Planned Behavior, the TPACK framework, and Self-Determination Theory to examine teachers' intentions to adopt AI and their technology-use behaviors (Wang et al., 2025; Basarmak and Ates, 2026; Zhang, 2025; Hava and Babayigit, 2024; Li et al., 2024). Although these studies have provided an important foundation for understanding teachers' AI use, they have focused largely on whether teachers are willing to use AI, while paying less attention to the continuous process through which external conditions shape internal psychological and cognitive states and ultimately relate to capability-related outcomes. In particular, limited attention has been paid to how school support is associated with the development of PAITAC through teachers' psychological and cognitive mechanisms (Hazzan-Bishara et al., 2025). At the practical level, prior research has often treated AI primarily as an emerging instructional technology and has paid relatively little attention to teachers' authentic teaching contexts or to the role of practical experience in PAITAC. More specifically, the boundary role of practical experience in the relationship between AI-related knowledge, efficacy beliefs, and PAITAC remains insufficiently understood.

In summary, drawing on the stimulus-organism-response (SOR) framework, this study develops a theoretical model to examine the relationship between school support and teachers' PAITAC. Within this framework, school support is conceptualized as an external stimulus; psychological resilience, AI anxiety, self-efficacy, and AI-TPACK are conceptualized as organismic factors; and PAITAC is treated as the response variable. This model allows us to examine the psychological and cognitive pathways underlying the association between school support and PAITAC. Furthermore, practical experience is incorporated into the SOR framework to examine its direct association with PAITAC and its moderating effects on the relationships of AI-TPACK and self-efficacy with PAITAC, thereby identifying potential boundary conditions for these associations. Methodologically, partial least squares structural equation modeling (PLS-SEM) is employed to assess the structural relationships, mediation effects, and moderation effects, while multigroup analysis (MGA) is used to explore potential differences across teacher groups. This study aims to advance our understanding of the multiple indirect associations between school support and PAITAC and provide empirical evidence regarding the conditional role of practical experience.

2 Literature review and research hypotheses

2.1 Teachers' perceived AI teaching application competence and its influencing factors

As artificial intelligence increasingly enters educational settings, whether teachers can effectively integrate AI into instructional practice has become an important prerequisite for realizing the potential value of intelligent education. Teachers' Perceived AI Teaching Application Competence (PAITAC) reflects teachers' subjective evaluations of their own capability to use AI tools to support instructional practice. In this study, PAITAC is defined as teachers' self-judgments regarding their capability to integrate AI tools around instructional goals and to carry out activities such as instructional design, classroom implementation, learning assessment, and feedback-based improvement in specific teaching contexts.

The factors influencing teachers' PAITAC can be understood from three levels: environmental support, psychological and cognitive factors, and practical experience. These three categories correspond, respectively to the external conditions, internal states, and practical foundations of teachers' AI use, and together shape the development of PAITAC, providing an important perspective for understanding teachers' professional capability development in the AI era.

School support is an important environmental factor associated with teachers' PAITAC. The integration of AI into teaching depends not only on teachers' individual exploration, but also on sustained support from schools in areas such as technological resources, training opportunities, and policy provision. Previous studies have shown that supportive conditions at the school level can facilitate the development of teachers' technology integration competence and digital teaching competence (Bowman et al., 2022; Chen et al., 2025; Tondeur et al., 2025). In the context of AI-supported teaching, Nazaretsky et al. (2022) further found that professional development support related to AI educational technologies can enhance teachers' understanding of and trust in AI tools, while also strengthening their willingness to use such tools in the classroom. Therefore, school support not only provides external conditions for teachers' AI-related instructional practices, but may also shape their psychological responses and cognitive readiness when confronting AI-driven changes in teaching.

Psychological and cognitive factors constitute important internal conditions associated with the development of teachers' PAITAC, mainly including psychological resilience, AI anxiety, self-efficacy, and AI-TPACK. Psychological resilience, as a positive psychological resource, can help teachers maintain continued effort, reflection, and improvement when they encounter difficulties in using AI for teaching (Lu et al., 2024). In contrast, AI anxiety, as a negative psychological response, may lead teachers to experience tension, worry, and avoidance when using AI tools, thereby limiting their willingness to further explore AI-supported teaching practices (Darancik et al., 2025; Hopcan et al., 2024). Thus, psychological resilience and AI anxiety represent, respectively, positive coping resources and negative emotional burdens when teachers engage with AI-supported teaching, and together form an important psychological foundation associated with PAITAC. Self-efficacy reflects teachers' confidence in their ability to complete AI-supported teaching tasks. Teachers with higher levels of self-efficacy are more likely to actively experiment with AI tools and apply them to specific instructional tasks (Collie et al., 2024; Kong et al., 2024). At the same time, teachers with stronger AI-TPACK are better able to select appropriate AI tools and instructional strategies according to pedagogical needs, thereby improving the appropriateness of AI-supported teaching applications (Celik, 2023). Accordingly, self-efficacy and AI-TPACK are associated with the development of PAITAC from the perspectives of capability beliefs and knowledge integration, respectively.

Practical experience provides an important contextual foundation for applying AI-related knowledge to specific instructional tasks. Previous research has indicated that the development of teachers' technology integration competence depends not only on training and knowledge acquisition, but also on continued accumulation and adjustment through concrete teaching practice (Huang et al., 2024; Tseng et al., 2019). Practical experience provides teachers with contextualized opportunities for application, enabling them to gradually develop an understanding of and judgment about the pedagogical value, appropriate conditions, and modes of use of AI tools in authentic instructional tasks (Farjon et al., 2019). At the same time, prior studies have shown that teachers' technology-use experience, capability beliefs, and technology integration practices are closely related, and that actual teaching experience can shape how teachers apply their existing knowledge and beliefs in technology-supported instructional activities (Liu et al., 2017; Nelson and Voithofer, 2022). Therefore, practical experience is not only related to the instructional application of teachers' AI-related knowledge, but may also influence how their capability beliefs are enacted in specific teaching contexts, making it an important practical foundation for understanding the development of teachers' PAITAC.

Based on the above discussion, it is necessary to further explain the mechanisms underlying teachers' PAITAC from the three perspectives of the external environment, psychological and cognitive factors, and practical experience.

2.2 Stimulus-organism-response theory

The stimulus-organism-response (SOR) theory, originally proposed by Mehrabian and Russell (1974), explains the relationships among external environmental stimuli, individuals' internal states, and behavioral responses. The theory comprises three core components: stimulus (S), organism (O), and response (R). Stimuli refer to external environmental factors, such as resource support, organizational policies, and training opportunities. The organism represents individuals' internal psychological and cognitive states in response to external stimuli, including emotions, attitudes, and perceptions. Responses refer to behaviors or outcomes associated with external stimuli and internal states (Bigne et al., 2020).

In educational research, the SOR framework has been widely applied to examine the relationships between external factors, such as learning environments, technological conditions, and instructional resources, and learners' psychological states, learning behaviors, technology adoption, and usage intentions (Dahri et al., 2025; Zhou et al., 2022; Ning, 2025; Wang and Long, 2025; Zhou et al., 2026; Cheng, 2023). Unlike studies that primarily focus on technology acceptance intentions or usage behaviors, the present study employs the SOR framework to distinguish among external support, teachers' internal psychological and cognitive states, and perceived teaching application competence. Specifically, school support is conceptualized as an external stimulus; psychological resilience, AI anxiety, self-efficacy, and AI-TPACK are treated as organismic factors; and PAITAC is positioned as the response variable. These four organismic factors represent teachers' psychological adaptability, negative emotional experiences, efficacy beliefs, and self-assessed knowledge of AI integration in teaching. In particular, self-efficacy refers to teachers'

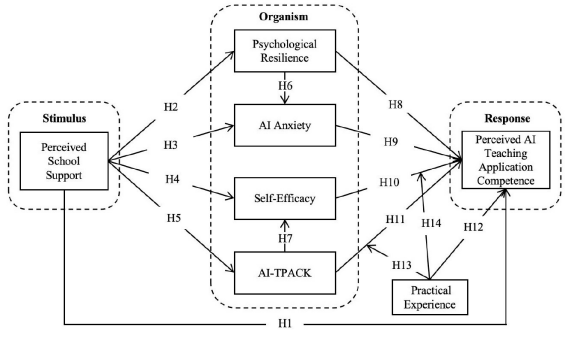

FIGURE 1
Research framework.

beliefs in their ability to accomplish AI-supported teaching tasks, whereas PAITAC concerns their self-assessed capability to use AI to perform specific instructional tasks. Although both constructs are measured through self-reports, they differ in their conceptual emphasis and theoretical roles within the model.

Building on this framework, the present study examines both the direct association between school support and PAITAC and the indirect associations through psychological and cognitive factors. Practical experience is further incorporated as a contextual condition to examine its direct association with PAITAC and its moderating effects on the relationships of AI-TPACK and self-efficacy with PAITAC. Practical experience may shape the extent to which teachers' AI integration knowledge and efficacy beliefs are reflected in their perceived teaching application competence. It is therefore important to examine whether these relationships vary across different levels of practical experience. Accordingly, the SOR framework not only provides a structure for organizing the study variables but also offers a theoretical perspective for understanding the multiple associations between school support and PAITAC and their potential boundary conditions. The research framework is presented in Figure 1.

2.2.1 Stimulus

As the stimulus variable in the SOR framework of this study, Perceived School Support (PSS) refers to teachers' subjective evaluations of the resources, training, technical assistance, and opportunities for practice provided by their schools. Although these forms of support originate from the school environment, this study focuses on teachers' individual perceptions of such support rather than on the objective level of support provided at the school level. School support as perceived by teachers may influence their psychological and cognitive states during AI-supported teaching through resource provision, training and guidance, and opportunities for practice.

First, school support may have a direct positive effect on teachers' PAITAC. The digital resources, technical assistance, and professional learning opportunities provided by schools can reduce the resource-related and operational barriers teachers encounter when implementing AI-supported teaching. Chiu et al. (2024) found that school-based learning support promoted the development of teachers' digital competence, while Han and Zhou (2026) further found that the school environment had a significant direct positive effect on the digital teaching competence of rural teachers in China. Accordingly, the following hypothesis is proposed:

H1. School support positively influences teachers' PAITAC.

Second, school support may influence teachers' psychological adaptation and emotional responses. Specifically, school support can contribute to the development of teachers' psychological resilience, which refers to their capacity to adapt flexibly, cope with challenges, and recover from difficulties in changing AI teaching contexts. Previous research has identified supportive school environments as an important condition for fostering teacher resilience (Lu et al., 2024). Chen and Lee (2022) suggested that job resources, including school support, can strengthen teacher resilience and help teachers cope more effectively with everyday teaching challenges. Similarly, Journell et al. (2025) found that teachers with higher levels of resilience tended to perceive greater school support.

School support may also help alleviate teachers' AI anxiety, which refers to negative emotional experiences, such as tension, worry, and stress, arising from operating AI technologies or completing AI-supported teaching tasks. Zhang and Cao (2025) found that teachers' positive perceptions of AI integration were significantly associated with lower levels of educational anxiety, suggesting that technological adaptation and support may help reduce psychological stress during AI-driven educational transformation. Accordingly, the following hypotheses are proposed:

H2. School support positively influences teachers' psychological resilience.

H3. School support negatively influences teachers' AI anxiety.

Finally, school support may influence teachers' efficacy beliefs and knowledge base. First, school support can enhance teachers' self-efficacy, which refers to their confidence in using AI tools to accomplish teaching-related tasks. It primarily reflects teachers' beliefs in their ability to operate AI tools, access instructional information, and use AI to support problem-solving. In the context of generative AI (GenAI) integration in teaching, Collie et al. (2024) found that school-based GenAI support was positively associated with teachers' GenAI self-efficacy and perceived value of GenAI, suggesting that school support may strengthen teachers' confidence in using AI for teaching.

Second, school support provides an important external condition for the development of teachers' AI-TPACK. AI-TPACK refers to teachers' self-perceived knowledge of how to integrate AI technologies, subject content, and pedagogical strategies to meet instructional objectives and students' needs. Previous research has shown that professional development programs and personalized learning support can improve teachers' TPACK (Chaipidech et al., 2022). Furthermore, Cao et al. (2026) indicated that school digital transformation can facilitate the development of teachers' AI-TPACK, suggesting that a supportive school digital environment may help teachers integrate AI into subject-specific teaching. Accordingly, the following hypotheses are proposed:

H4. School support positively influences teachers' self-efficacy.

H5. School support positively influences teachers' AI-TPACK.

2.2.2 Organism

At the organism level, O represents the internal states formed in response to external stimuli, mainly including psychological resilience, AI anxiety, self-efficacy, and AI-TPACK.

Psychological resilience, as a positive psychological resource, can help teachers maintain adaptability and sustained engagement when facing difficulties in AI-supported teaching. Previous research has shown that teachers' psychological resilience enables them to cope with challenges in complex teaching contexts and provides an important psychological foundation for the development of teaching competence (Liu and Chu, 2022). In AI-related educational contexts, psychological resilience may also help alleviate anxiety triggered by AI technologies. Liu (2025) found that higher levels of psychological resilience were associated with lower levels of AI anxiety among students. In contrast, AI anxiety, as a negative emotional response, may reduce teachers' willingness to engage with AI (Schiavo et al., 2024). For example, Tekin (2024) found that AI anxiety had a significant negative effect on teachers' behavioral intention to use AI technologies for teaching, suggesting that anxiety may constitute an important barrier to teachers' acceptance of AI-supported instruction. Accordingly, the following hypotheses are proposed:

H6. Psychological resilience negatively influences AI anxiety.

H8. Psychological resilience positively influences teachers' PAITAC.

H9. AI anxiety negatively influences teachers' PAITAC.

AI-TPACK serves as a cognitive foundation for teachers' AI-supported teaching and helps them understand how AI can be integrated with specific instructional tasks. When teachers are able to clearly judge how AI tools should be used according to instructional needs, they are more likely to develop confidence in completing AI-supported teaching tasks. Previous studies have shown that teachers' TPACK can significantly enhance online teaching self-efficacy and further influence their intention to engage in online teaching (Cheng et al., 2025). Xia et al. (2025) also found that, in the context of generative AI in education, both TPACK and self-efficacy were closely related to teachers' willingness to integrate GenAI. At the same time, higher AI teaching self-efficacy can encourage teachers to explore and apply AI tools more proactively and integrate them into instructional practice (Yang et al., 2024). Accordingly, the following hypotheses are proposed:

H7. AI-TPACK positively influences teachers' self-efficacy.

H10. Self-efficacy positively influences teachers' PAITAC.

H11. AI-TPACK positively influences teachers' PAITAC.

2.2.3 Response

At the response level, this study treats PAITAC as the outcome variable and incorporates practical experience into the SOR framework as an important practical factor associated with PAITAC and a contextual moderator. Practical experience refers to teachers' prior experience of using AI tools in tasks such as instructional design, resource development, classroom instruction, and student assessment. Previous research has shown that the development of teachers' digital competence is closely associated with teaching practice and technology-use experience (Claro et al., 2024). Tschönhens et al. (2024) further indicated that teachers' teaching experience influences how TPACK is applied in specific instructional contexts, highlighting the importance of practical experience in applying technology integration knowledge to teaching. Therefore, practical experience may serve as an important contextual condition shaping the relationship between AI-TPACK and PAITAC. Compared with teachers who have less practical experience, those with greater experience may be more familiar with the appropriate contexts and instructional applications of AI tools, resulting in a stronger positive association between AI-TPACK and PAITAC.

Similarly, practical experience may also influence the strength of the relationship between self-efficacy and PAITAC. Previous research has shown that positive experiences with technology-supported teaching can enhance teachers' technology integration self-efficacy and promote subsequent technology use (Paetsch et al., 2023). In AI-supported teaching contexts, mastery experiences may likewise strengthen teachers' AI technology integration self-efficacy and support their engagement in AI-supported instructional practices (Yang et al., 2024). Accordingly, greater practical experience may help teachers develop a more comprehensive contextual understanding of AI-supported teaching tasks, thereby strengthening the positive association between their efficacy beliefs and PAITAC. Based on these arguments, the following hypotheses are proposed:

H12. Practical experience positively influences PAITAC.

H13. Practical experience positively moderates the relationship between AI-TPACK and PAITAC, such that the positive association between AI-TPACK and PAITAC is stronger at higher levels of practical experience.

H14. Practical experience positively moderates the relationship between self-efficacy and PAITAC, such that the positive association between self-efficacy and PAITAC is stronger at higher levels of practical experience.

2.2.4 Group heterogeneity

Beyond the structural relationships proposed above, differences in teachers' individual characteristics and school contexts may also give rise to a certain degree of group heterogeneity in the model. Previous studies have shown that male and female teachers may differ in technology anxiety, self-efficacy, technology acceptance, and instructional use, and these differences may further affect the strength with which relevant psychological and cognitive factors are translated into teaching application competence (Wu and Wee, 2026; Scherer et al., 2026). Differences also exist between urban and rural schools in digital infrastructure, technological resources, professional development opportunities, and school support. Such contextual differences may further shape teachers' technological competence and technology integration practices, potentially resulting in urban-rural heterogeneity in the structural relationships of the model (Li, 2025; Zhao, 2024). Accordingly, this study further examines whether the structural relationships in the model differ across gender groups and between teachers in urban and rural schools, and proposes the following research questions:

RQ1. Do the structural paths in the proposed model differ significantly across teacher gender groups?

RQ2. Do the structural paths in the proposed model differ significantly according to school location?

3 Research methodology

3.1 Measurement

The measurement items used in this study were primarily adapted from established scales and appropriately modified to fit the context of AI-supported teaching. Specifically, the items measuring school support were adapted from the studies of Chiu et al. (2024), Dai (2023), and Yang and Li (2026); the items measuring psychological resilience were adapted from Jonker et al. (2024) and Piele et al. (2026); the items measuring AI anxiety were adapted from Schiavo et al. (2024); the items measuring self-efficacy were adapted from Yu et al. (2026) and Wang et al. (2024); the items measuring AI-TPACK were adapted from Celik (2023) and Xu et al. (2025); the items measuring practical experience were informed by Tondeur et al. (2015) and Farjon et al. (2019); and the PAITAC items were developed based on related studies by Chu et al. (2023), Chiu et al. (2025), and Celik (2023). All items were measured using a five-point Likert scale ranging from 1 ("strongly disagree") to 5 ("strongly agree").

To ensure the content validity and contextual appropriateness of the measurement instrument, the questionnaire underwent multiple rounds of revision. First, the research team reviewed and adapted the initial items based on the existing literature so that they could better reflect the specific context of AI-supported teaching among primary and secondary school teachers. Second, experts in education, educational technology, and the educational application of artificial intelligence, together with frontline teachers with experience in AI-supported teaching, were invited to review the items, with particular attention to clarity of wording, contextual appropriateness, and construct relevance. Third, for items adapted from English-language scales, a translation/back-translation procedure was employed to ensure semantic equivalence between the Chinese and English versions (Jin and Weber, 2013). Finally, an independent pilot test was conducted with 60 primary and secondary school teachers. The pilot results showed that one item from the initial school support scale and one item from the initial psychological resilience scale had relatively low corrected item-total correlations (CITC) and factor loadings. After jointly considering the statistical results and item content, these two items were removed, while all remaining items were retained. The formal survey questionnaire was finalized after these revisions, and the final set of items is presented in Supplementary Table S1.

3.2 Data collection and sampling

This study conducted a structured questionnaire survey through Wenjuanxing (https://www.wjx.cn/), a widely used online survey platform in China. A non-probability sampling approach was employed, with school administrators assisting in distributing the survey invitations. The questionnaire consisted of four sections. The first section provided an introduction to the study, including the research background, the importance of PAITAC in teacher education, and information regarding anonymity and voluntary participation. The second section contained screening questions used to determine whether respondents met the inclusion criteria for the target sample. Eligible participants were primary or secondary school teachers in China who had participated in at least 1 month of accumulated AI-related teaching training, professional development, or practice-based learning activities. Only respondents who met these criteria were allowed to proceed to the formal questionnaire. The third section comprised the core measurement items used to collect data on the constructs related to PAITAC. The fourth section collected demographic information, including gender, years of teaching experience, school location, and frequency of AI use.

To ensure data quality, each respondent was permitted to submit the questionnaire only once, with duplicate submissions prevented through IP address restrictions. Eligible participants who completed the questionnaire received compensation of RMB 3–5, whereas responses that did not meet the eligibility criteria were not compensated.

Prior to data collection, an a priori statistical power analysis was conducted using G*Power 3.1 (Faul et al., 2007) to estimate the minimum required sample size. A multiple linear regression model with eight predictors was specified, assuming a medium effect size ($f^2 = 0.15$), a significance level of $\alpha = 0.05$, and a desired statistical power of 0.95. The analysis indicated a minimum required sample size of 160. During the formal data collection period (March-April 2026), a total of 1,331 questionnaires were collected. After applying the predetermined eligibility criteria, 1,071 respondents met the inclusion requirements.

To ensure data quality, three screening criteria were applied following the data-cleaning procedures described by Wang et al. (2023). First, based on the pilot test results, the questionnaire typically required approximately 3–6 min to complete; therefore, responses completed in less than 2 min were excluded. Second, responses that failed the embedded attention-check question were removed. Third, questionnaires in which respondents selected the same response option across all items of the core measurement scales were excluded. Following these sequential screening procedures, 289 responses were removed, yielding a final sample of 782 valid questionnaires, exceeding the minimum sample size requirement established by the a priori power analysis.

After completing the individual-level data quality screening, this study further considered the clustered structure of the sample at the school level. The final sample of 782 valid questionnaires was drawn from 16 primary and secondary schools. As some teachers were from the same schools, their responses might exhibit within-school correlations. To assess this possibility, intraclass correlation coefficients (ICCs) were calculated for the main study variables, ranging from 0.037 to 0.048. Accordingly, a supplementary regression analysis was conducted using school-clustered robust standard errors. The results showed that, after accounting for school-level clustering, the directions and statistical significance of the associations between psychological resilience, AI anxiety, self-efficacy, AI-TPACK, practical experience, and PAITAC were

largely consistent with those obtained from the original PLS-SEM model. Both interaction effects involving practical experience also remained statistically significant, whereas the direct association between school support and PAITAC remained non-significant (see Supplementary Table S2). These findings provide supplementary evidence supporting the robustness of the main direct associations and moderation effects.

Regarding the demographic characteristics of the 782 respondents, 44.8% were male and 55.2% were female. In terms of teaching experience, 26.3% had 0–5 years of experience, 15.6% had 6–10 years, 14.2% had 11–15 years, 20.1% had 16–20 years, and 23.8% had 21 years or more. With regard to school characteristics, 51.4% of the respondents taught in primary schools, 27.4% in junior secondary schools, and 21.2% in senior secondary schools. In addition, 51.4% taught in urban schools and 48.6% in rural schools; 72.3% were from public schools and 27.7% from private schools. The sample covered eastern (31.2%), central (26.4%), and western (42.4%) China. In terms of the frequency of AI use in teaching, 8.3% of respondents reported using AI rarely, 20.8% occasionally, 33.0% frequently, and 37.9% very frequently.

3.3 Common method variance

This study relied on single-source data, with all measurement variables assessed through self-reports provided by the same respondents. Therefore, the data may be subject to the potential risk of common method variance (CMV). To minimize its influence, several procedural remedies were implemented during questionnaire design and data collection.

First, the questionnaire underwent several rounds of revision before the formal survey to ensure that the items were clearly worded and logically structured. The order of the items was also appropriately arranged to reduce the potential influence of common method variance (Podsakoff et al., 2003). Second, demographic questions were placed at the end of the questionnaire to minimize their potential interference with the core measurement items. In addition, the introductory section clearly stated that there were no right or wrong answers and emphasized the anonymity of responses and the importance of answering honestly. These measures were intended to reduce respondents' evaluation apprehension and social desirability bias, thereby improving the authenticity and reliability of the data (Chong et al., 2018).

To assess CMV statistically, this study first conducted Harman's single-factor test following the recommendations of Podsakoff et al. (2003). The results identified seven factors with eigenvalues greater than 1, with the first factor accounting for 34.71% of the total variance in the unrotated factor solution, below the commonly used 50% threshold (Sarstedt et al., 2014).

However, Harman's single-factor test alone is insufficient to rule out potential common method bias. Therefore, a supplementary sensitivity analysis incorporating a common method factor was conducted. First, a seven-factor measurement model was estimated using confirmatory factor analysis (CFA), demonstrating good model fit ($\chi^2 = 328.589$, df = 303, $\chi^2/df = 1.084$, CFI = 0.998, TLI = 0.997, RMSEA = 0.010, SRMR = 0.024). Subsequently, a common method factor was added to the baseline measurement model, with equal unstandardized loadings across all measurement items and orthogonality constraints imposed between the method factor and the seven theoretical constructs. The results showed only minor changes in model fit after introducing the common method factor ($\chi^2 = 327.547$, df = 302, CFI = 0.998, TLI = 0.997, RMSEA = 0.010, SRMR = 0.024). These findings suggest that, under the specified constrained model, the inclusion of a common method factor did not meaningfully improve overall measurement model fit. Nevertheless, because all core variables were measured through teachers' self-reports at a single time point, this sensitivity analysis cannot entirely rule out the potential influence of common method bias.

4 Data analysis and results

Data were analyzed using SmartPLS 4.0, with partial least squares structural equation modeling (PLS-SEM) employed as the primary analytical method. Given that the data did not meet the assumption of normality, PLS-SEM was considered appropriate because of its ability to accommodate non-normally distributed data. Moreover, PLS-SEM can maintain adequate statistical power when estimating complex models involving multiple latent variables (Hair et al., 2016).

4.1 Measurement model

To assess the quality of the measurement model, the reliability and validity of the constructs were examined, with the results presented in Tables 1, 2. First, indicator reliability was assessed using the outer loadings of the measurement items. The results showed that all item loadings exceeded the recommended threshold of 0.70 (Hair et al., 2019). Second, Cronbach's alpha and composite reliability (CR) were used to evaluate internal consistency reliability. The Cronbach's alpha and CR values for all constructs were above 0.70, indicating satisfactory construct reliability (Fornell and Larcker, 1981; Hair et al., 2019). In addition, convergent validity was assessed using the average variance extracted (AVE). The AVE values of all constructs exceeded the recommended threshold of 0.50 (Fornell and Larcker, 1981). Collectively, these results demonstrate that the measurement of the latent constructs exhibited satisfactory reliability and convergent validity.

Discriminant validity was first assessed using the Fornell-Larcker criterion, which compares the square root of each construct's AVE with its correlations with the other constructs. As shown in Table 2, the square root of the AVE for each construct exceeded its correlations with all other constructs, indicating satisfactory discriminant validity (Fornell and Larcker, 1981). In addition, the heterotrait-monotrait ratio of correlations (HTMT) was used to further assess discriminant validity. The highest HTMT value was 0.688, which was below the recommended threshold of 0.85, providing further evidence of satisfactory discriminant validity for the measurement model (Kline, 2023).

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TABLE 1 Reliability and validity.

Construct	Items	Factor loading	Cronbach's alpha	CR	AVE
Perceived school support	PSS1	0.767	0.865	0.908	0.713
	PSS2	0.860			
	PSS3	0.877			
	PSS4	0.870			
Psychological resilience	PR1	0.765	0.871	0.912	0.722
	PR2	0.863			
	PR3	0.886			
	PR4	0.880			
AI anxiety	AIA1	0.901	0.879	0.925	0.804
	AIA2	0.909			
	AIA3	0.880			
Self-efficacy	SE1	0.804	0.816	0.890	0.730
	SE2	0.881			
	SE3	0.876			
AI-TPACK	AI-TPACK1	0.808	0.863	0.907	0.709
	AI-TPACK2	0.833			
	AI-TPACK3	0.866			
	AI-TPACK4	0.861			
Practical experience	PE1	0.740	0.750	0.841	0.571
	PE2	0.717			
	PE3	0.767			
	PE4	0.796			
Perceived AI teaching application competence	PAITAC1	0.773	0.873	0.908	0.664
	PAITAC2	0.794			
	PAITAC3	0.845			
	PAITAC4	0.821			
	PAITAC5	0.838			

4.2 Structural model

After evaluating the measurement model, the structural model was assessed using SmartPLS 4.0. Collinearity was first examined, followed by an assessment of the significance of the structural path coefficients. Collinearity was evaluated using the variance inflation factor (VIF). As shown in Table 3, the VIF values for all predictor variables ranged from 1.000 to 2.071, all below the recommended threshold of 3.3 (Hair et al., 2020), indicating that the structural model was not affected by serious multicollinearity.

Subsequently, bootstrapping with 5,000 resamples was used to test the significance of the hypothesized paths, with the results presented in Figure 2 and Table 3. Specifically, the effect of school support on PAITAC was not significant ($\beta = 0.010$, $p = 0.754$); therefore, H1 was not supported. School support had significant effects on psychological resilience ($\beta = 0.518, p < 0.001$), AI anxiety ($\beta = -0.466$, $p < 0.001$), self-efficacy ($\beta = 0.220$, $p < 0.001$), and AI-TPACK ($\beta = 0.548, p < 0.001$), supporting H2–H5. In addition, psychological resilience had a significant negative effect on AI anxiety ($\beta = -0.112$, $p < 0.01$), while AI-TPACK had a significant positive effect on self-efficacy ($\beta = 0.352$, $p < 0.001$), supporting H6 and H7. With regard to PAITAC, psychological resilience ($\beta = 0.130$, $p < 0.001$), self-efficacy ($\beta = 0.308$, $p < 0.001$), AI-TPACK ($\beta = 0.372$, $p < 0.001$), and practical experience ($\beta = 0.258$, $p < 0.001$) all had significant positive effects, whereas AI anxiety had a significant negative effect ($\beta = -0.111$, $p < 0.001$), supporting H8–H12. Furthermore, practical experience significantly moderated the relationship between AI-TPACK and PAITAC ($\beta = 0.258$, $p < 0.001$) and the relationship between self-efficacy and PAITAC ($\beta = 0.320$, $p < 0.001$), supporting H13 and H14.

The explanatory power of the model was assessed using the coefficient of determination (R^2). According to Hair et al. (2019), R^2 values of 0.75, 0.50, and 0.25 generally indicate substantial, moderate, and weak explanatory power, respectively. In this study, the R^2 values of the five endogenous constructs ranged from 0.257 to 0.720, all exceeding 0.25 (see Table 4). In addition, the PLSpredict procedure in SmartPLS 4 was employed to evaluate the model's out-of-sample predictive performance. The results

TABLE 2 Discriminant validity.

Fornell-Larcker criterion	AI-TPACK	AIA	PAITAC	PE	PR	SE	PSS
AI-TPACK	**0.842**						
AI anxiety (AIA)	−0.349	**0.897**					
Perceived AI teaching application competence (PAITAC)	0.599	−0.397	**0.815**				
Practical Experience (PE)	0.400	−0.129	0.434	**0.755**			
Psychological resilience (PR)	0.339	−0.353	0.391	0.179	**0.850**		
Self-efficacy (SE)	0.472	−0.252	0.534	0.319	0.249	**0.855**	
Perceived school support (PSS)	0.548	−0.524	0.505	0.258	0.518	0.413	**0.845**
Heterotrait-monotrait ratio							
AI-TPACK							
AI anxiety (AIA)	0.397						
Perceived AI teaching application competence (PAITAC)	0.688	0.448					
Practical Experience (PE)	0.495	0.153	0.534				
Psychological resilience (PR)	0.391	0.391	0.446	0.219			
Self-efficacy (SE)	0.560	0.296	0.627	0.402	0.291		
Perceived school support (PSS)	0.630	0.593	0.580	0.316	0.590	0.485	

Values on diagonal, which are bold, are the square root of AVE. HTMT < 0.85 (Kline, 2023).

TABLE 3 Results of structural model assessment.

H	Relationship	Coefficient	*t*-value	f^2	VIF	*p*-value	Decision
H1	PSS → PAITAC	0.010	0.314	0.000	2.071	0.754	Not Supported
H2	PSS → PR	0.518	18.533	0.367	1.000	< 0.001	Supported
H3	PSS → AIA	−0.466	13.873	0.222	1.367	< 0.001	Supported
H4	PSS → SE	0.220	5.519	0.046	1.429	< 0.001	Supported
H5	PSS → AI-TPACK	0.548	22.134	0.429	1.000	< 0.001	Supported
H6	PR → AIA	−0.112	3.043	0.013	1.367	< 0.01	Supported
H7	AI-TPACK → SE	0.352	9.012	0.117	1.429	< 0.001	Supported
H8	PR → PAITAC	0.130	5.553	0.043	1.400	< 0.001	Supported
H9	AIA → PAITAC	−0.111	4.897	0.031	1.412	< 0.001	Supported
H10	SE → PAITAC	0.308	11.222	0.241	1.399	< 0.001	Supported
H11	AI-TPACK → PAITAC	0.372	11.619	0.277	1.787	< 0.001	Supported
H12	PE → PAITAC	0.258	6.656	0.189	1.260	< 0.001	Supported
H13	PE x AI-TPACK → PAITAC	0.258	8.544	0.201	1.239	< 0.001	Supported
H14	PE x SE → PAITAC	0.320	9.529	0.262	1.246	< 0.001	Supported

PSS, Perceived School Support; PR, Psychological Resilience; AIA, AI Anxiety; SE, Self-Efficacy; PE, Practical Experience; AI-TPACK, AI Technological Pedagogical Content Knowledge; PAITAC, Perceived AI Teaching Application Competence; VIF, Variance Inflation Factor.

showed that all endogenous constructs had positive Q^2_predict values, ranging from 0.168 to 0.386, indicating that the model outperformed a simple benchmark based on the training sample mean (Shmueli et al., 2019; see Table 4).

Furthermore, effect sizes (f^2) were calculated to assess the contribution of each predictor to the explained variance of its respective endogenous construct. Following Cohen (2009), f^2 values of 0.02, 0.15, and 0.35 generally represent small, medium, and large effects, respectively (see Table 3). The model also yielded a standardized root mean square residual (SRMR) of 0.040, below the recommended threshold of 0.08 (Hu and Bentler, 1999), suggesting an acceptable approximate model fit.

4.3 Mediation effects

For brevity, Table 5 reports only the specific indirect effects linking perceived school support (PSS) to PAITAC. Based on 5,000 bootstrap resamples, all six indirect effects reported in Table 5 were statistically significant (Preacher and Hayes, 2008; Nitzl et al., 2016). Specifically, school support was indirectly

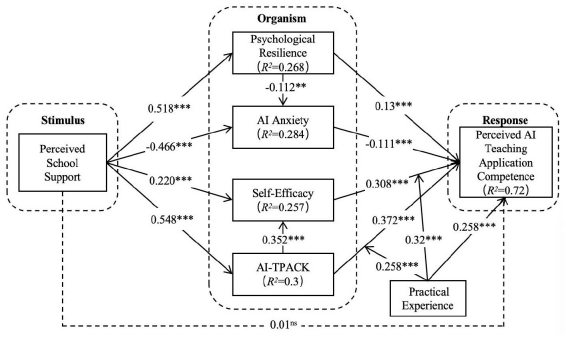

FIGURE 2
Results of path analysis. $^{*}p < 0.05$, $^{**}p < 0.01$ and $^{***}p < 0.001$; ns = non-significant ($p > 0.05$).

TABLE 4 Explanatory power and predictive relevance of endogenous constructs.

Endogenous variables	Q^2_predict	R^2
AI-TPACK	0.298	0.300
AIA	0.272	0.284
SE	0.168	0.257
PR	0.266	0.268
PAITAC	0.386	0.720

associated with PAITAC through multiple pathways involving psychological resilience, AI anxiety, self-efficacy, and AI-TPACK. Among these pathways, PSS → AI-TPACK → PAITAC exhibited the largest indirect effect ($\beta = 0.204$, $t = 9.594$, $p < 0.001$), indicating a particularly prominent mediating role of AI-TPACK in the relationship between school support and PAITAC. In addition, the PSS → SE → PAITAC, PSS → PR → PAITAC, and PSS → AIA → PAITAC pathways were all statistically significant. Further analysis revealed two statistically significant sequential mediation pathways: PSS → PR → AIA → PAITAC and PSS → AI-TPACK → SE → PAITAC. These findings suggest that the relationship between school support and PAITAC involves not only indirect associations through individual psychological or cognitive factors but also sequential indirect associations involving multiple psychological and cognitive factors.

For pathways involving relationships moderated by practical experience, Table 5 reports the indirect effect estimates at the mean level of practical experience. Given that these indirect effects may vary across levels of practical experience, Section 4.4 further presents the conditional indirect effects at low, mean, and high levels of practical experience.

4.4 Moderating effects of practical experience

To examine the moderating role of practical experience, this study employed the two-stage approach in SmartPLS 4 to construct the interaction terms. Statistical significance and 95% confidence intervals were assessed using 5,000 bootstrap resamples (Hair et al., 2022). The results showed that practical experience significantly and positively moderated the relationship between AI-TPACK and PAITAC ($\beta = 0.258$, $t = 8.544$, $p < 0.001$), as well as the relationship between self-efficacy and PAITAC ($\beta = 0.320$, $t = 9.529$, $p < 0.001$).

Simple slope analyses were subsequently conducted to examine the conditional effects at the mean and one standard deviation below and above the mean of practical experience (Aiken and West, 1991). The results indicated that the positive association between AI-TPACK and PAITAC was statistically significant at low, mean, and high levels of practical experience, with the strength of the association increasing as practical experience increased. In contrast, the association between self-efficacy and PAITAC was not statistically significant at low levels of practical experience ($\beta = -0.013$, $p = 0.773$), whereas it was significantly positive at mean and high levels. Thus, although practical experience positively moderated both relationships, the patterns of conditional associations differed across levels of practical experience (see Table 6, Panel A, and Figure 3).

Given that practical experience also moderated the latter stage of several indirect pathways, this study further examined conditional indirect effects at different levels of practical experience. The results showed that the indirect association between school support and PAITAC through AI-TPACK was statistically significant at low, mean, and high levels of practical experience, with the estimated indirect effect increasing across these levels. In contrast, the indirect association through self-efficacy and the sequential indirect association through AI-TPACK and self-efficacy were not statistically significant at low levels of practical experience but were significantly positive at mean and high levels (see Table 6, Panel B). These findings indicate that practical experience not only moderated the relationships of AI-TPACK and self-efficacy with PAITAC but was also associated with different patterns of estimated indirect effects across its levels.

4.5 Multigroup analysis

To address the research questions concerning group heterogeneity proposed above, this study further conducted multigroup analysis (MGA) to examine whether the structural paths in the model differed across teacher gender groups and school-location groups. The gender groups and school-location groups had relatively balanced sample sizes, satisfying the basic requirements for multigroup comparison. To assess path differences across subgroups, a permutation test was employed for the multigroup comparisons (Sarstedt et al., 2011). Before conducting the MGA, measurement invariance across groups was examined using the measurement invariance of composite models (MICOM) procedure. Comparisons of structural paths across groups are interpretable only when sufficient measurement invariance has been established. Following the MICOM procedure, configurational invariance (Step 1), compositional invariance (Step 2), and equality of composite means and variances (Step 3) were assessed sequentially (Henseler et al., 2016; Cheah et al., 2020).

The detailed MICOM results are presented in Supplementary Tables S3, S4. The results showed that all constructs passed both Step 1 and Step 2 for the gender and

TABLE 5 Results of mediation analysis.

M	Relationship	Coefficient	SD	*t*-value	p-value	95% BC CI
M1	PSS → PR → AIA → PAITAC	0.006	0.003	2.554	< 0.05	[0.002, 0.012]
M2	PSS → SE → PAITAC	0.068	0.013	5.060	< 0.001	[0.042, 0.094]
M3	PSS → PR → PAITAC	0.067	0.013	5.307	< 0.001	[0.043, 0.092]
M4	PSS → AIA → PAITAC	0.052	0.011	4.666	< 0.001	[0.030, 0.074]
M5	PSS → AI-TPACK → PAITAC	0.204	0.021	9.594	< 0.001	[0.162, 0.246]
M6	PSS → AI-TPACK → SE → PAITAC	0.059	0.009	6.301	< 0.001	[0.042, 0.079]

PSS, Perceived School Support; PR, Psychological Resilience; AIA, AI Anxiety; SE, Self-Efficacy; PAITAC, Perceived AI Teaching Application Competence; SD, Standard Deviation; BC CI, bias-corrected 95% bootstrap confidence interval.

TABLE 6 Conditional direct and indirect effects across levels of practical experience.

Relationship	PE level	*β*	*p*	95% BC CI
Panel A. Conditional direct effects				
AI-TPACK → PAITAC	Low (−1 SD)	0.114	0.006	[0.031, 0.190]
	Mean	0.372	<0.001	[0.311, 0.435]
	High (+1 SD)	0.631	<0.001	[0.538, 0.721]
Self-efficacy → PAITAC	Low (−1 SD)	−0.013	0.773	[−0.101, 0.077]
	Mean	0.308	<0.001	[0.255, 0.362]
	High (+1 SD)	0.628	<0.001	[0.547, 0.712]
Panel B. Conditional indirect effects				
PSS → AI-TPACK → PAITAC	Low (−1 SD)	0.062	0.007	[0.017, 0.108]
	Mean	0.204	<0.001	[0.165, 0.247]
	High (+1 SD)	0.346	<0.001	[0.286, 0.408]
PSS → SE → PAITAC	Low (−1 SD)	−0.003	0.778	[−0.023, 0.016]
	Mean	0.068	<0.001	[0.043, 0.095]
	High (+1 SD)	0.138	<0.001	[0.086, 0.193]
PSS → AI-TPACK → SE → PAITAC	Low (−1 SD)	−0.002	0.773	[−0.018, 0.016]
	Mean	0.059	<0.001	[0.043, 0.080]
	High (+1 SD)	0.121	<0.001	[0.093, 0.154]
AI-TPACK → SE → PAITAC	Low (−1 SD)	−0.005	0.772	[−0.033, 0.028]
	Mean	0.108	<0.001	[0.079, 0.144]
	High (+1 SD)	0.221	<0.001	[0.173, 0.277]

BC CI, bias-corrected 95% bootstrap confidence interval. Low, mean, and high PE correspond to mean – 1 SD, mean, and mean + 1 SD.

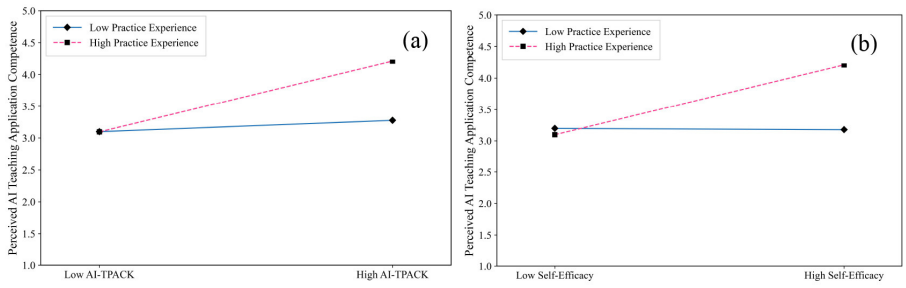

FIGURE 3
Moderating effects of practical experience on **(a)** the relationship between AI-TPACK and PAITAC and **(b)** the relationship between self-efficacy and PAITAC.

school-location groupings. In Step 1, the same measurement models, data treatment procedures, and algorithm settings were applied across groups; therefore, configurational invariance was established. In Step 2, the original correlation coefficient (c) for each construct was not lower than the 5th percentile of the permutation distribution, indicating that compositional invariance was established. Thus, partial measurement invariance, which is required for between-group comparisons of structural paths, was established for both grouping variables.

In Step 3, for the gender groups, the differences in composite means and composite variances for all constructs fell within their corresponding 95% confidence intervals, indicating full measurement invariance between male and female teachers. For the school-location groups, all constructs satisfied the equality-of-composite-means criterion. In the test of equality of composite variances, AI-TPACK, AIA, PR, SE, and PSS met the criterion, whereas PAITAC and PE did not. Therefore, full measurement invariance was not established across school-location groups. However, because configurational invariance in Step 1 and compositional invariance in Step 2 had already been established, partial measurement invariance was supported, allowing subsequent comparisons of structural paths across groups.

As shown in Table 7, the unadjusted MGA results indicated that several structural paths differed across gender and school-location groups. Because multiple between-group path comparisons were conducted simultaneously, the Holm-Bonferroni procedure was further applied to adjust the p values and control the inflation of Type I error associated with multiple testing. After adjustment, none of the between-group differences that had reached the 0.05 significance level remained statistically significant. Therefore, the following between-group differences are reported only as exploratory findings and should not be interpreted as robust evidence of group heterogeneity.

For the gender groups, the AIA → PAITAC (H9) and SE → PAITAC (H10) paths showed between-group differences before correction. Specifically, for the AIA → PAITAC path, the negative effect was stronger among female teachers ($\beta = -0.154$, $p < 0.001$), whereas the corresponding path was weaker and non-significant among male teachers ($\beta = -0.059$, $p > 0.05$). The unadjusted p value for the difference between the two path coefficients was 0.038. For the SE → PAITAC path, the effects were significantly positive for both male teachers ($\beta = 0.242$, $p < 0.001$) and female teachers ($\beta = 0.360$, $p < 0.001$), but the effect was stronger among female teachers. The unadjusted p value for the between-group difference was 0.033. After Holm-Bonferroni correction, however, neither difference remained statistically significant. These findings therefore provide only tentative indications of possible gender heterogeneity, suggesting that the group differences addressed in RQ1 were not supported by robust statistical evidence.

For the school-location groups, the PSS → AIA (H3) and PSS → SE (H4) paths showed between-group differences before correction. The PSS → AIA path was significantly negative for both urban teachers ($\beta = -0.396$, $p < 0.001$) and rural teachers ($\beta = -0.543$, $p < 0.001$), with a stronger negative effect among rural teachers. The unadjusted p value for the difference between the two path coefficients was 0.023. The PSS → SE path was significantly positive for both urban teachers ($\beta = 0.303$, $p < 0.001$) and rural teachers ($\beta = 0.129$, $p < 0.05$), with a stronger effect among urban teachers. The unadjusted p value for the between-group difference was 0.027. After Holm-Bonferroni correction, these differences likewise no longer remained statistically significant. Accordingly, these results should be regarded only as tentative indications of possible urban-rural heterogeneity, suggesting that the group differences addressed in RQ2 were not supported by robust statistical evidence.

5 Discussion

Drawing on the SOR framework, this study examined the mechanisms underlying the association between school support and PAITAC, focusing on the mediating roles of psychological resilience, AI anxiety, self-efficacy, and AI-TPACK, as well as the direct association and moderating role of practical experience. Multigroup analysis was also conducted to explore potential differences in structural relationships across teacher groups.

The findings identified AI-TPACK as an important cognitive factor closely associated with PAITAC. In the PLS-SEM analysis, AI-TPACK exhibited the strongest direct association with PAITAC ($\beta = 0.372$). The mediation analysis further revealed a particularly prominent indirect association between school support and PAITAC through AI-TPACK ($\beta = 0.204$). These findings suggest that the relationship between school support and PAITAC involves not only external resources and organizational conditions but also teachers' self-assessed knowledge of integrating AI technologies, subject content, and pedagogical strategies. Previous research has similarly emphasized the importance of teachers' knowledge of integrating technology, subject content, and pedagogy for technology-supported teaching practices (Celik, 2023; Ning et al., 2024). Furthermore, AI-TPACK was significantly positively associated with self-efficacy, suggesting a relationship between teachers' self-assessed AI integration knowledge and their beliefs in their ability to undertake AI-supported teaching tasks. This finding is broadly consistent with the social cognitive theory perspective on the relationship between perceived capabilities and efficacy beliefs (Bandura, 1997).

Self-efficacy was also identified as an important psychological factor closely associated with PAITAC. The PLS-SEM results showed a significant positive association between self-efficacy and PAITAC ($\beta = 0.308$). Unlike AI-TPACK, which focuses on teachers' understanding of how AI technologies can be integrated with subject content and pedagogy, self-efficacy primarily reflects teachers' beliefs in their ability to successfully accomplish AI-supported teaching tasks. This finding suggests that, beyond AI integration knowledge, teachers' efficacy beliefs are also important for understanding PAITAC. Furthermore, the significant indirect association between school support and PAITAC through self-efficacy highlights the mediating role of teachers' efficacy beliefs in the relationship between external support and perceived teaching application competence. This finding aligns with the emphasis placed on self-efficacy in social cognitive theory (Bandura, 1997) and is consistent with previous research highlighting the positive role of teachers' technology integration self-efficacy (Chiu et al., 2025; Paetsch et al., 2023).

TABLE 7 Multigroup analysis results.

H	Relationship	Path coefficient (gender)		Male—female			Path coefficient (location)		Urban-rural		
		Male 350	Female 432	Coefficient difference	Raw *p*	Holm *p*	Urban 402	Rural 380	Coefficient difference	Raw *p*	Holm *p*
H1	PSS → PAITAC	0.027	0.001	0.026	0.681	1.000	0.015	0.023	−0.008	0.892	1.000
H2	PSS → PR	0.501***	0.536***	−0.035	0.542	1.000	0.519***	0.518***	0.001	0.979	1.000
H3	PSS → AIA	−0.449***	−0.482***	0.033	0.616	1.000	−0.396***	−0.543***	0.147	0.023*	0.322
H4	PSS → SE	0.250***	0.198***	0.052	0.52	1.000	0.303***	0.129*	0.174	0.027*	0.351
H5	PSS → AI-TPACK	0.581***	0.522***	0.059	0.236	1.000	0.541***	0.556***	−0.015	0.761	1.000
H6	PR → AIA	−0.111*	−0.110*	0.001	0.992	1.000	−0.136**	−0.086	−0.050	0.495	1.000
H7	AI-TPACK → SE	0.341***	0.359***	−0.018	0.817	1.000	0.359***	0.348***	0.011	0.891	1.000
H8	PR → PAITAC	0.150***	0.111***	0.039	0.413	1.000	0.138***	0.120***	0.018	0.697	1.000
H9	AIA → PAITAC	−0.059	−0.154***	0.095	0.038*	0.494	−0.115***	−0.106**	−0.009	0.831	1.000
H10	SE → PAITAC	0.242***	0.360***	−0.118	0.033*	0.462	0.273***	0.337***	−0.064	0.255	1.000
H11	AI-TPACK → PAITAC	0.404***	0.349***	0.055	0.393	1.000	0.386***	0.351***	0.035	0.588	1.000
H12	PE → PAITAC	0.260***	0.259***	0.001	0.999	1.000	0.225***	0.300***	−0.075	0.346	1.000
H13	PE x AI-TPACK → PAITAC	0.248***	0.263***	−0.015	0.809	1.000	0.248***	0.266***	−0.018	0.758	1.000
H14	PE x SE → PAITAC	0.335***	0.299***	0.036	0.607	1.000	0.328***	0.311***	0.017	0.797	1.000

Raw *p*-values were obtained from permutation tests. Holm correction was applied separately to the 14 gender and 14 school-location comparisons. *, **, and *** indicate $p < 0.05$, $p < 0.01$, and $p < 0.001$, respectively, for both within-group path coefficients and unadjusted between-group differences. No between-group differences remained significant after correction.

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The findings further revealed that the relationship between school support and PAITAC was primarily characterized by indirect associations. Although the direct path from school support to PAITAC was not statistically significant, the indirect effects through psychological resilience, AI anxiety, self-efficacy, and AI-TPACK were all statistically significant. First, school support was significantly positively associated with psychological resilience, which, in turn, was positively associated with PAITAC. This suggests that teachers' perceptions of school resources, training, and technical support are closely related to their psychological adaptability, while higher psychological resilience is associated with higher PAITAC (Dursun et al., 2026). Meanwhile, school support was significantly negatively associated with AI anxiety, which was also negatively associated with PAITAC. These findings suggest that school support is related not only to external resource conditions but also to teachers' emotional experiences when using AI. Higher levels of school support were associated with lower AI anxiety, which, in turn, was associated with higher PAITAC. This pattern is consistent with the findings of Liu et al. (2025) concerning the relationships among institutional support, negative emotions associated with technology use, and work engagement in online teaching. Furthermore, psychological resilience was significantly negatively associated with AI anxiety, a finding consistent with stress and coping theory. According to this theory, individuals' anxiety responses are related not only to external stressors but also to their cognitive appraisals of stressful situations and available coping resources (Lazarus and Folkman, 1984). As AI technologies become increasingly integrated into educational settings, teachers may experience stress arising from uncertainties surrounding technology use and instructional adaptation (Yan et al., 2024; Holmes et al., 2019; Tan et al., 2025). Against this background, the present study found that both school support and psychological resilience were associated with lower levels of AI anxiety, providing additional evidence for understanding the relationships among external support, individual coping resources, and negative emotional experiences (Shi et al., 2025). In addition, school support was significantly positively associated with AI-TPACK, indicating that teachers' perceptions of resource availability, professional training, and opportunities for practice were closely related to their self-assessed AI integration knowledge. This finding is consistent with Maipita et al. (2023), who examined the relationship between organizational support and teachers' TPACK development. School support was also significantly positively associated with teachers' self-efficacy, suggesting that higher levels of perceived support tended to accompany stronger beliefs in their ability to undertake AI-supported teaching tasks. This finding echoes Dong et al. (2020), who highlighted the relationship between supportive technological environments and teachers' technology-related self-efficacy. Overall, the relationship between school support and PAITAC involves multiple psychological and cognitive dimensions, including psychological adaptation, emotional experiences, efficacy beliefs, and AI integration knowledge. These findings further demonstrate the value of the SOR framework as a theoretical lens for understanding the multiple indirect associations between external support and PAITAC.

The findings showed that practical experience was not only significantly positively associated with PAITAC but also positively moderated the relationships of AI-TPACK and self-efficacy with PAITAC. According to experiential learning theory, the development of knowledge and competence depends on continuous application and reflection in practice (Kolb, 1984). For teachers, AI-TPACK represents their knowledge base for integrating AI technologies, subject content, and pedagogical approaches, while practical experience provides opportunities to apply such knowledge in specific teaching contexts. Accordingly, the positive association between AI-TPACK and PAITAC was stronger among teachers with greater practical experience. This finding is consistent with previous research highlighting the important role of practical experience in teachers' technology integration (Koh et al., 2015; Ding et al., 2024; Yue et al., 2024). Similarly, self-efficacy reflects teachers' beliefs in their ability to accomplish AI-supported teaching tasks. According to Bandura's (1997) self-efficacy theory, mastery experiences are an important source of self-efficacy, and actual teaching experiences may also be closely related to teachers' assessments of their technological capabilities (Yang et al., 2024). The present study further found that the positive association between self-efficacy and PAITAC was stronger among teachers with greater practical experience. The conditional indirect effects analysis further revealed that the indirect associations between school support and PAITAC through AI-TPACK and self-efficacy exhibited different patterns across levels of practical experience. In particular, some indirect effects involving self-efficacy were not statistically significant at low levels of practical experience but were significantly positive at high levels. These findings suggest that practical experience is not only directly associated with PAITAC but also serves as an important contextual factor for understanding the conditional associations among school support, internal psychological and cognitive factors, and PAITAC.

The multigroup analysis provided some preliminary indications of group heterogeneity in the results before correction for multiple comparisons. Regarding gender, the AIA → PAITAC and SE → PAITAC paths showed between-group differences in the unadjusted analyses. Specifically, the negative association between AI anxiety and PAITAC was stronger among female teachers, as was the positive association between self-efficacy and PAITAC.

Previous research has also documented gender-related differences in AI anxiety and self-efficacy, providing a broader context for interpreting these exploratory findings (Bolívar-Cruz and Verano-Tacoronte, 2025; Wu and Wee, 2026). However, these differences were no longer statistically significant after Holm-Bonferroni correction. Accordingly, these findings should be interpreted as preliminary indications of potential gender heterogeneity rather than robust evidence of between-group differences. Regarding school location, the unadjusted results suggested potential urban-rural differences in the PSS → AIA and PSS → SE paths. Specifically, the negative association between school support and AI anxiety was stronger among rural teachers, whereas the positive association between school support and self-efficacy was stronger among urban teachers. These patterns may be understood, at least in part, in relation to differences in digital resources, technology access, and support conditions between urban and rural schools (Salemink et al., 2017; Lythreatis et al., 2022; Chiu et al., 2024). Nevertheless, these urban-rural differences also failed to remain statistically significant

after correction for multiple comparisons. Therefore, no definitive conclusions about group differences can be drawn from these findings, and further investigation using larger samples and independent datasets is needed.

6 Theoretical and practical implications

6.1 Theoretical implications

This study provides further theoretical insights into PAITAC by considering external support, internal psychological and cognitive states, and practical experience.

First, this study extends the application of the SOR framework to AI-supported teaching contexts by identifying multiple indirect associations between school support and PAITAC through distinct psychological and cognitive factors (Mehrabian and Russell, 1974). Unlike previous studies that have primarily focused on teachers' intentions to adopt technology or their technology use behaviors, the present study examines teachers' self-assessed capability to accomplish specific AI-supported teaching tasks. The results showed that although the direct association between school support and PAITAC was not statistically significant, multiple indirect effects through psychological resilience, AI anxiety, self-efficacy, and AI-TPACK were significant. Specifically, psychological resilience and AI anxiety represent teachers' psychological adaptability and negative emotional experiences when facing AI-related teaching challenges, respectively, whereas self-efficacy and AI-TPACK reflect their efficacy beliefs and self-assessed AI integration knowledge. These findings suggest that the association between school support and PAITAC involves distinct psychological and cognitive factors rather than operating solely through a direct relationship (Peng et al., 2024; Hu et al., 2025; Wang et al., 2026; Tekin, 2024). Accordingly, the theoretical contribution of this study lies not only in applying the SOR framework to AI-supported teaching but also in distinguishing different internal states within the organism component, thereby providing additional evidence for understanding the multiple indirect associations between school support and PAITAC.

Second, this study further clarifies the boundary role of practical experience in these relationships. The results showed that practical experience positively moderated the relationships of AI-TPACK and self-efficacy with PAITAC, indicating that the positive associations between teachers' self-assessed AI integration knowledge, efficacy beliefs, and PAITAC were stronger among teachers with greater practical experience. The conditional indirect effects analysis further revealed that the indirect associations between school support and PAITAC through AI-TPACK, self-efficacy, and their sequential pathway exhibited different patterns across levels of practical experience. These findings suggest that practical experience is not only directly associated with PAITAC but may also serve as an important contextual condition shaping the relationships among external support, internal psychological and cognitive factors, and PAITAC. This finding provides an additional perspective on the relationships among knowledge, efficacy beliefs, and practical experience in teachers' professional development (Darling-Hammond et al., 2017), while identifying practical experience as a boundary condition for specific relationships within the SOR framework.

Finally, the multigroup analysis explored potential group heterogeneity in the structural relationships. Although the unadjusted results suggested possible gender and urban-rural differences in certain structural paths, none of these differences remained statistically significant after Holm correction for multiple comparisons. Therefore, the current evidence is insufficient to support robust conclusions regarding between-group differences. Instead, these findings provide preliminary indications that may inform future research examining group heterogeneity in the relationships underlying teachers' AI teaching application.

6.2 Practical implications

The findings of this study offer several practical implications for supporting the development of teachers' PAITAC, particularly highlighting the importance of AI-TPACK, self-efficacy, practical experience, and school support. Schools can strengthen their support systems for AI integration in teaching by focusing on professional competence development, opportunities for practice, and psychological support.

First, schools should emphasize the integration of AI-TPACK development with practical teaching experience. AI-related professional development programs should guide teachers in selecting, integrating, and evaluating AI tools in accordance with specific instructional objectives and students' needs. Through teaching demonstrations, case-based discussions, and collaborative lesson planning, schools can help teachers develop a deeper understanding of how AI technologies can be integrated with subject content and pedagogical strategies. Schools should also provide sustained opportunities for teachers to gain experience in using AI for lesson planning, classroom instruction, and student assessment, while encouraging reflection through peer exchanges and instructional feedback. Given that practical experience positively moderated the relationships of AI-TPACK and self-efficacy with PAITAC, schools should further integrate knowledge development, efficacy beliefs, and hands-on teaching opportunities to help teachers gradually build confidence in applying AI to specific instructional tasks.

Second, schools should establish comprehensive support systems that address both resource provision and teachers' psychological needs. Schools should provide adequate AI teaching equipment, digital resources, and technical guidance to reduce the practical difficulties teachers encounter when using AI tools and integrating them into teaching. At the same time, greater attention should be paid to teachers' emotional experiences and perceptions of their capabilities in relation to AI technologies. Through differentiated training, peer support, reflective teaching practices, and progressively structured practical tasks, schools can create conditions that help strengthen teachers' self-efficacy, alleviate AI anxiety, and enhance psychological adaptability. This study found that although the direct association between school support and PAITAC was not statistically significant, multiple indirect effects through psychological and cognitive factors were

significant. These findings suggest that schools should not only improve external support conditions but also ensure that support measures are aligned with teachers' specific psychological and cognitive needs.

Finally, schools should consider teachers' individual support needs and provide flexible, targeted professional development opportunities. Given that the group differences identified in the unadjusted analyses did not remain statistically significant after correction for multiple comparisons, it would be inappropriate to develop fixed, differentiated support strategies based solely on teachers' gender or school location. Instead, schools can use needs assessments, self-assessments of competence, and feedback from teaching practice to identify teachers' specific challenges related to AI integration knowledge, confidence in using AI, technology-related stress, and access to resources. Based on these identified needs, schools can offer foundational training, advanced guidance, or ongoing technical support to better tailor professional development opportunities to individual teachers.

7 Limitations and future research

Although this study provides a systematic examination of PAITAC and its associated factors, several limitations should be acknowledged.

First, this study relied on cross-sectional survey data, which allowed us to examine statistical associations among variables and structural relationships within the proposed theoretical model. However, this design does not establish the temporal ordering of variables or rule out reverse relationships and the influence of unobserved factors. Therefore, the direct, indirect, and moderating effects reported in this study should be interpreted as statistical associations within the theoretical model rather than empirically established causal mechanisms. Future research could employ longitudinal, cross-lagged panel, or experimental designs to further examine the temporal relationships among these variables and their potential causal effects.

Second, this study relied primarily on teachers' self-reported data, which may have been affected by common method bias, social desirability bias, and biases in self-perception. Future research could incorporate classroom observations, evaluations of teaching artifacts, platform usage logs, and data on actual AI-related teaching behaviors to obtain evidence from multiple sources and further examine the correspondence between teachers' perceived competence and their actual teaching performance.

Third, this study employed a non-probability sampling approach, and the sample was restricted to teachers who met the predefined AI-related training or learning experience criteria, which may limit the representativeness of the sample and the generalizability of the findings. Furthermore, although the study accounted for school-level clustering through supplementary robustness analyses, it did not systematically incorporate objective school-level contextual factors. Future research could expand the sampling scope to include teachers with diverse AI training and practical experience backgrounds. By integrating multilevel data on school digital infrastructure, technical support conditions, and organizational environments, future studies could further examine the relationships between individual-level characteristics and school-level contextual factors.

Finally, the multigroup analysis revealed some potential gender and urban-rural differences in the unadjusted results. However, none of these differences remained statistically significant after Holm correction for multiple comparisons. Therefore, the current evidence is insufficient to support robust conclusions regarding group heterogeneity. Future research could re-examine these structural path differences using larger independent samples and explore the potentially differing support needs of teacher groups in AI-supported teaching.

Data availability statement

The original contributions presented in the study are included in the article. Further inquiries can be directed to the corresponding author.

Ethics statement

The studies involving humans were approved by Ethics Committee of Ningxia Normal University, Guyuan, Ningxia, China. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

HZ: Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Writing – original draft. YX: Funding acquisition, Project administration, Supervision, Validation, Writing – review & editing. CC: Data curation, Formal analysis, Investigation, Software, Visualization, Writing – review & editing.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/fpsyg.2026.1997903/full#supplementary-material

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