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Exploring the Sustainable Cultivation Pathways of Pre-Service Teachers' AI Literacy Based on the TAM-IDT Integrated Model

Shuai Cao * and Yanlin Zheng

School of Information Science and Technology, Northeast Normal University, Changchun 130117, China; yanlinzheng@nenu.edu.cn

* Correspondence: caos009@nenu.edu.cn

Abstract

With the deep integration of artificial intelligence technology into education, AI literacy has emerged as a core competence indispensable for pre-service teachers. However, its formation mechanisms and sustainable cultivation pathways remain to be further explored. This study integrates the Technology Acceptance Model (TAM) and Innovation Diffusion Theory (IDT) to construct a theoretical model, in which Individual Innovation (II) and Self-Efficacy (SE) serve as antecedents, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) as mediators, Behavioral Intention (BI) as a proximal variable, AI literacy as the outcome variable, gender and major as moderating variables, and grade and AI exposure time as control variables, exploring the influencing factors and mechanisms of pre-service teachers' AI literacy. Through a questionnaire survey of 778 pre-service teachers, Partial Least Squares Structural Equation Modeling (PLS-SEM) and fuzzy-set Qualitative Comparative Analysis (fsQCA) were employed for sequential empirical analysis. The PLS-SEM results reveal that II and SE were significantly and positively associated with AI literacy through the serial mediation of PU, PEOU, and BI. The fsQCA further identified four distinct equifinal configurations associated with high AI literacy: "High-efficacy Practice-Oriented", "High-Behavioral-Intention-Oriented", "High-Innovativeness-Oriented", and "Long-Term-Development-Oriented". The findings demonstrate that the improvement of pre-service teachers' AI literacy follows multiple equifinal mechanisms, necessitating a shift beyond the single-training mindset. Accordingly, this study proposes differentiated cultivation pathways, providing theoretical foundations and practical references for normal universities to deliver targeted and sustainable AI literacy training. It also offers empirical evidence and strategic support for the sub-goals of SDG 4 concerning teacher capacity-building and the digital transformation of education, which aim to ensure inclusive and equitable quality education and promote lifelong learning opportunities for all.

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Keywords: pre-service teachers; AI literacy; Technology Acceptance Model (TAM); Innovation Diffusion Theory (IDT); fuzzy-set Qualitative Comparative Analysis (fsQCA); Sustainable Development Goal 4 (SDG 4)

1. Introduction

1.1. AI Literacy and Sustainable Development in Education

In recent years, a new generation of information technologies represented by ChatGPT has penetrated the education sector with unprecedented depth and breadth. AI technology, by reshaping the patterns and ecological landscapes of education [1], is advancing toward a sustainable, multifaceted revolution [Error! Reference source not found.,Error! Reference source not found.]. Against this background, AI literacy has evolved from an additional skill into an essential core competency for pre-service teachers to navigate the future of sustainable education [Error! Reference source not found.]Error! Reference source not found.. Pre-service teachers hold a dual identity: they are both current learners and future educators. Their AI literacy concerns are not only critical to their professional development, but also determine the future empowerment of technology in education [5]Error! Reference source not found.. The United Nations' 2030 Agenda for Sustainable Development established 17 global Sustainable Development Goals (SDGs). Among them, SDG 4 explicitly calls for ensuring inclusive and equitable quality education and promoting lifelong learning opportunities for all. Teachers with high AI literacy will be better equipped to use AI to narrow the educational resource gap, which aligns closely with the equity principle embedded in SDG 4. Furthermore, the cultivation of pre-service teachers' AI literacy can also generate synergistic effects with innovation infrastructure (SDG 9) and reduced inequality (SDG 10). The cultivation of pre-service teachers' AI literacy can not only enhance future teachers' individual AI application proficiency but also potentially promote future educational equity and technological innovation. Therefore, constructing a paradigm for cultivating pre-service teachers' AI literacy in the digital age and clarifying the pathways for developing teachers with high AI literacy are core tasks for advancing the digital transformation of education and addressing the educational challenges of sustainable development in the intelligent era. Positioning AI literacy cultivation within the global sustainable development agenda, particularly under the SDG 4 framework, cultivating teachers with AI literacy represents a key human capital investment for achieving educational equity, quality, and innovation.

AI literacy is the deepening and extension of digital literacy in the intelligent era, encompassing the ability to understand, apply, and critically evaluate AI technology. As core actors in educational transformation, teachers' AI literacy levels directly influence teaching quality and the advancement of educational equity. SDG 4.3 specifically targets equal access for all women and men to affordable and quality technical, vocational, and tertiary education. SDG 4.4 specifically targets substantially increasing the number of youth and adults who have relevant skills, including technical and vocational skills, for employment, decent work, and entrepreneurship. SDG 4.c proposes substantially increasing the supply of qualified teachers, including through international cooperation for teacher training in developing countries, especially less-developed countries and small island developing states. These specific sub-targets of SDG 4 directly point to teacher digital competency-building and professional development [6,7]. Therefore, revealing the influencing factors and formation mechanisms of pre-service teachers' AI literacy holds significant importance for the sustainable development of education. This study provides micro-level empirical evidence and pathway references for teacher capacity-building within the SDG 4 framework.

1.2. Current Status and Challenges of Pre-Service Teachers' AI Literacy

Recently, AI-powered intelligent education has developed rapidly, with research focusing primarily on three areas. First, theoretical exploration and construction of the con-

notation of teachers' AI literacy. Efforts to define AI literacy have proposed various competency sets—ranging from a set of 17 specific abilities [Error! Reference source not found.] to broader international frameworks for teachers [Error! Reference source not found.] and students [7]—alongside systematic reviews that synthesize existing knowledge on the concept. Second, research focuses on the current status and effectiveness of AI training for in-service teachers. At present, teachers' acceptance of AI tools is a key factor influencing the quality of education reform [Error! Reference source not found.]. Although teachers generally recognize the great potential of AI in education, they still encounter difficulties and resistance in practical application [Error! Reference source not found.]. Third, research centers on AI applications in specific subject teaching. Such studies present practical cases, including AI learning companions, intelligent assessment, and virtual experiments, verifying AI's effects on improving teaching and learning outcomes [Error! Reference source not found., Error! Reference source not found.]

However, existing theories and practices pay insufficient attention to pre-service teachers as a distinct group, and the cultivation of their AI literacy still faces multiple challenges. First, the content of AI training tends to be fragmented and technology-oriented, neglecting the holistic role of AI in the educational ecosystem and its integration with educational philosophies and pedagogical approaches [Error! Reference source not found.]. Second, the cultivation process lacks effective psychological and behavioral intervention mechanisms. Pre-service teachers generally experience “technological anxiety” and “role conflict” toward AI technologies, and existing training models fail to address deep-seated psychological cognition [Error! Reference source not found.]. Third, the assessment of AI literacy suffers from a lack of subjectivity and insufficient practical scenarios, making it impossible to accurately evaluate and promote their ability to creatively apply AI to solve teaching problems in complex contexts [Error! Reference source not found.].

To overcome the aforementioned dilemmas, it is first necessary to clarify what constitutes AI literacy. Kandlhofer et al. [Error! Reference source not found.] first proposed the concept of AI literacy (AIL) in 2016, defining it as the ability to understand the basic technologies and concepts behind different AI products and services. Long and Magerko [Error! Reference source not found.] put forward a widely cited definition of AI literacy, conceptualizing it as “a set of core competencies that enable individuals to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use AI as a tool in online, home, and workplace settings.” Ng et al. applied Bloom's Taxonomy to structurally categorize AI literacy into four hierarchical dimensions: (1) Know and understand AI; (2) Use and apply AI; (3) Evaluate and create AI; (4) AI ethics [Error! Reference source not found.] Drawing on relevant standards and frameworks, the present study operationalizes the construct of AIL as encompassing five dimensions: use and apply AI, know and understand AI, create and evaluate AI, detect AI, and AI ethics. However, existing research has paid insufficient attention to the formation mechanisms of pre-service teachers' AI literacy. In particular, a systematic exploration of how psychological traits (e.g., II, SE) and technology cognition (e.g., PU, PEOU) interact in shaping literacy formation remains lacking.

1.3. Integration of the Technology Acceptance Model and Innovation Diffusion Theory

1.3.1. Theoretical Foundations and Integration Logic of TAM and IDT

To systematically investigate the formation and enhancement mechanisms of pre-service teachers' AI literacy, this study introduces and integrates two classical theoretical

frameworks: the Technology Acceptance Model (TAM) and the Innovation Diffusion Theory (IDT).

The TAM, proposed by Davis, is one of the most influential theoretical models in the field of information systems research. The model posits that an individual's actual use of a new technology is directly determined by their Behavioral Intention (BI), which is primarily influenced by Perceived Usefulness (PU, the degree to which one believes that using the technology can enhance their work or learning performance) and Perceived Ease of Use (PEOU, the degree to which one believes that learning and using the technology requires effort) [Error! Reference source not found.]. The TAM has been widely applied in the field of educational technology, confirming its good explanatory power for individual technology acceptance behavior [Error! Reference source not found.].

The IDT, proposed by Rogers, examines the adoption of innovation (including new technologies) from a macro-level perspective of social system diffusion process. The theory conceptualizes adoption as a dynamic process in which an innovation spreads over time through specific communication channels among members of a social system [Error! Reference source not found.]. IDT identifies five key attributes influencing the speed of innovation adoption: relative advantage, compatibility, complexity, trialability, and observability. Among these, relative advantage closely aligns with PU in TAM studies [Error! Reference source not found.], while complexity exhibits a reciprocal relationship with PEOU. In research on educational technology adoption, relative advantage, compatibility, and observability have been confirmed to significantly influence users' PU and PEOU; in the context of teachers' AI tool adoption, compatibility is regarded as a more influential predictor than PU [21]. More critically, IDT identifies II as an enduring personality trait—individuals with high innovativeness exhibit a propensity to adopt new ideas and new things earlier than others [Error! Reference source not found.,21]. Existing research has confirmed that II, as a personality trait, influences technology adoption intention primarily through altering individuals' perceptions of technology usefulness, ease of use, and compatibility, achieving full mediation [22]. Pre-service teachers with an innovative mindset are more inclined to proactively identify the potential advantages of AI technologies, thereby enhancing PU, and are also more willing to overcome initial usage difficulties, thus reducing expectations regarding PEOU [21]. This finding also provides theoretical grounding for positioning innovativeness as an antecedent variable (influencing AIL through PU/PEOU/BI) in this study.

TAM and IDT exhibit significant complementarity at the theoretical level. TAM excels in elucidating the psychological mechanisms underlying individual adoption decisions (PU, PEOU → BI), yet lacks sufficient attention to group differences in technology adoption and subsequent diffusion processes [Error! Reference source not found.]. Conversely, IDT specializes in describing the macro-level trajectories of individual innovation across user categories and technology diffusion, but fails to provide detailed analysis of the deep psychological mechanisms driving adoption decisions among different user groups [Error! Reference source not found.]. Thus, their integration represents not mere variable addition but a complementary framework based on explanatory depth: TAM reveals the cognitive mechanisms preceding the “cognition → intention” pathway, while IDT supplements this with trait-level explanations involving “individual differences → adoption propensity.” However, the TAM-IDT framework primarily addresses the relationship between traits and cognition, without fully addressing the motivational drivers spanning from “willingness to try” to “ability to implement”—a critical area where self-efficacy (SE) enters the integrated framework. Therefore, our proposed integrated model incorporates both II from IDT and SE from social cognitive theory, collectively forming the intrinsic psychological drivers of technological exploration, though each contributes distinctively in terms of theoretical basis and operational mechanisms. II, as a relatively

stable personality trait, describes one's inherent tendency to proactively explore and adopt new technologies. This trait is independent of immediate perceptions of specific technologies (e.g., PU or PEOU) and reflects enduring behavioral tendencies across diverse contexts and technological domains [24]. SE serves as the key psychological driver that propels individuals from the cognitive stage of innovation adoption to the practical action stage. Its theoretical foundation stems from social cognition theory, which posits that an individual's belief in their own capabilities constitutes the central psychological mechanism influencing behavioral choices and levels of effort [25]. In the context of technology adoption, SE has been demonstrated to enhance individuals' perception of technology usefulness [26], reduce apprehension about technical complexity, and facilitate skill acquisition [27]. Thus, integrating SE into the TAM-IDT integration model helps elucidate the complete psychological pathway from "ability beliefs" to "technology cognition" and ultimately to "competency development".

In the technology acceptance context, individuals with high self-efficacy are more confident in overcoming difficulties when using new technologies; this belief directly influences their assessment of a technology's usefulness and ease of use [24]. While innovativeness determines one's willingness to try, self-efficacy provides the confidence foundation for daring to attempt it. Together, these factors offer an antecedent explanation for the core cognitive constructs of TAM (PU/PEOU), forming a complete chain of "psychological traits → cognitive beliefs → behavioral intentions".

1.3.2. Development of an Integrated Framework: The Path from Technical Understanding to AI Literacy

Building on the complementary relationship between TAM and IDT, this study develops an integrated TAM-IDT model—a conceptual framework spanning from technological cognition to literacy development (Figure 1). The core pathway can be summarized as: psychological traits (II, SE) → technological cognition (PU, PEOU) → behavioral intention (BI) → actual usage behavior → repeated practice (e.g., mastery experiences) → enhancement of AI literacy. This framework is further extended across three dimensions. First, at the explanatory level, it establishes a fundamental chain of "traits → cognition → intention" centered on TAM's cognitive mediation pathway and informed by IDT's II; second, at the motivational level, it incorporates SE as the confidence foundation enabling individuals to bridge the gap between intention and action; third, across temporal dimensions, it extends the analysis from "adoption intention" to "ability formation," reflecting the dynamic nature of literacy development. These aspects are elaborated below.

The logic of this chain lies in the following. The TAM explains the transformation from "cognition" (PU/PEOU) to "intention" (BI)—whether individuals are willing to use AI; however, "willingness to use" does not equate to "effective use," let alone "AI literacy." A critical gap exists between "intention" and "literacy," which requires psychological motivation at two levels. First, II provides a tendency toward "willingness to try," enabling individuals to accumulate technical knowledge through active exploration even before forming clear usage intentions; SE provides the confidence foundation for "daring to attempt," empowering individuals to persevere when facing uncertainties and complexities of new technologies. Second, BI drives actual usage behavior, while sustained, deep engagement—such as applying AI to solve problems in real teaching scenarios, reflecting on technological outcomes, and adjusting usage strategies—ultimately fosters AI literacy. Social cognitive theory supports this process: mastery experience (personal successful task completion) serves as the strongest source of capability development, while vicarious experiences, social persuasion, and physiological-emotional states also play significant roles. II provides context-independent exploratory motivation, while self-efficacy offers perseverance in overcoming challenges—these jointly explain the "psychological

drivers that propel individuals to actively engage, persistently explore, and ultimately develop capabilities,” a dimension beyond TAM’s focus on cognitive judgment alone.

This logic aligns with experiential learning theory [**Error! Reference source not found.**] and the critical reflections on TAM [**Error! Reference source not found.**]. Learning is a process of knowledge creation through experiential transformation, emphasizing the mechanisms of “learning by doing” and “cognitive deepening through reflection.” It has been argued that TAM overemphasizes behavioral intention and initial adoption, neglecting the feedback effects of actual post-implementation usage behaviors on capability development [**Error! Reference source not found.**]. A related call has been made to extend research to longitudinal usage patterns. The integrated framework of this study addresses precisely this gap: research on technology acceptance should not stop at intention or initial use but should extend to examine the feedback effects of sustained usage on capability development, where persistent, in-depth usage practices ultimately evolve into AI literacy.

In this study, IDT’s “classification of technology adopter groups” provides a theoretical foundation for user stratification analysis, facilitating the development of tailored AI literacy cultivation strategies and enhancing the precision of technology diffusion [**Error! Reference source not found.**]. The “diffusion pathways” proposed by IDT address gaps in the TAM regarding adoption progression, offering a clear pathway for pre-service teachers to progress from initial exposure to sustained AI use. By integrating individual cognitive factors with IDT, this study establishes a conceptual framework that balances macro and micro perspectives. This approach not only addresses the TAM’s limited adaptability to complex external environments but also overcomes IDT’s insufficient focus on individual psychological decision-making processes, thereby improving the flexibility and applicability of the integrated TAM-IDT model in sustainable teacher education practices.

From the perspective of SDG 4, the aforementioned transformation pathways correspond to two critical aspects of teacher capacity-building. First, the predictive role of psychological traits (II and SE) in AI literacy aligns with SDG 4.4 (Technological and Digital Skills), highlighting that teacher education should not only address external technological conditions but also focus on identifying and nurturing pre-service teachers’ innovative tendencies and efficacy beliefs, thereby extending digital skills development beyond mere technical proficiency to encompass psychological preparedness. Second, the pathway from BI to AI literacy corresponds to SDG 4.c (Teacher Professional Development), emphasizing that professional development programs should establish a cyclical mechanism of “use → reflection → capability enhancement” rather than relying solely on one-off training sessions. Together, these two dimensions form this study’s response to SDG 4: the former addresses “what kind of educators we aim to cultivate” (teachers with AI literacy), while the latter focuses on “how to cultivate them” (through sustained practice-driven skill development).

It should be noted that the aforementioned integration framework serves multiple functional purposes in this study. The theoretical constructs examined—including II, SE, PU, PEOU, BI, and AIL—are all defined based on the existing theoretical literature, with their operational measurement methods detailed in Section 2.2 (e.g., AI literacy as a second-order reflective construct measured across five dimensions: knowledge, usage, creativity, evaluation, and ethics; AI usage duration as a self-reported single-item indicator). Subsequent research hypotheses will be formulated in Section 1.5, derived from the logical relationships among these theoretical constructs into testable predictive propositions (e.g., “II and SE mediate effects on BI through PU/PEOU”). These propositions constitute theoretical hypotheses that require validation or refinement through subsequent empirical analyses (PLS-SEM and fsQCA in Section 3).

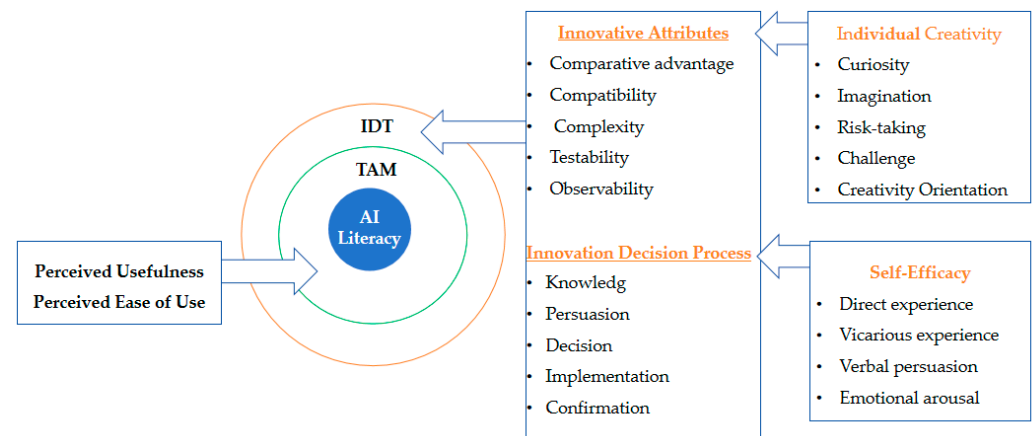


Figure 1. Theoretical Framework of the Integrated TAM-IDT Model. Note: The blue circle at the center represents AI literacy, the inner green ring represents the TAM constructs (PU and PEOU), and the outer orange ring represents the IDT constructs (Innovative Attributes and the Innovation Decision Process). Arrows flowing from right to left indicate the proposed influence of individual psychological traits (Individual Creativity, Self-Efficacy) and innovation attributes toward technological cognition and, ultimately, AI literacy.

1.4. Objectives and Core Research Questions

The TAM focuses on individuals' PU and PEOU of technology, serving as the core cognitive model explaining technology adoption intention. The IDT reveals the patterns through which new technologies spread within communities, with particular emphasis on II as a stable personality trait that serves as the key differentiator among distinct adopter categories (e.g., innovators, early adopters). Individuals with higher innovativeness are more inclined to be early adopters of innovation; they are disposed to explore novel things and exhibit a lower perceptual threshold for technological complexity [Error! Reference source not found.]. Meanwhile, SE, as an individual's subjective judgment of whether one can successfully accomplish a given task, functions as the "psychological engine" driving the innovation decision-making process [Error! Reference source not found.]. Successful initial adoption experiences can positively enhance SE, and heightened SE in turn further motivates sustained exploration and in-depth use of new technologies. Accordingly, to investigate how II, SE, PU, PEOU, and BI affect AI literacy, this study constructs an integrated TAM-IDT model. Furthermore, to examine whether II, SE, PU, PEOU, BI, and individual characteristic information exert conjunctive effects on AI literacy, this study employs a fuzzy-set Qualitative Comparative Analysis (fsQCA) model. In other words, it is not only necessary to identify what influences AI literacy, but also to understand how high AI literacy is formed.

Therefore, this study focuses on how II and SE influence PU and PEOU, which in turn affect individuals' BI to use AI, ultimately impacting their AI literacy level. To achieve this objective, the study proposes three core research questions: RQ 1 and RQ 2 focus on the empirical relationships among the core variables, while RQ 3 explores how the differentiated pathways identified in this study can provide references for teacher capacity-building aligned with SDG 4. The three specific research questions are as follows:

RQ1: How do individual innovativeness and self-efficacy influence pre-service teachers' AI literacy? Do perceived usefulness, perceived ease of use, and behavioral intention play mediating roles? Do gender and academic discipline moderate pre-service teachers' AI literacy? Are grade level and AI usage time included in the model as control variables to exclude potential confounding effects?

RQ2: What are the multiple antecedent condition configurations that influence the formation of high AI literacy among pre-service teachers?

RQ3: Based on the empirically identified multiple influencing mechanisms, how can differentiated cultivation pathways for pre-service teachers' AI literacy be constructed? Under the framework of SDG 4 (Quality Education), what implications do such cultivation pathways hold for teacher workforce capacity-building?

1.5. Research Hypotheses

1.5.1. Hypotheses on the Relationship Between II and AIL

Individual Innovativeness (II) is a core concept of IDT, referring to the intrinsic innovative tendency to proactively explore AI technology and willingly adopt it.

II refers to an individual's tendency to adopt new ideas, new practices, or new things earlier than other members within their social system. IDT regards high-innovativeness individuals as "innovators" and "early adopters," who generally hold more open attitudes toward new technologies or new things and are willing to take risks to explore [Error! Reference source not found.]. Therefore, for AI as an emerging technology, pre-service teachers with high innovativeness are more likely to proactively discover its potential instructional value, enhance PEOU, and are more inclined to develop and demonstrate higher AI literacy through in-depth exploration [Error! Reference source not found.]. Relevant empirical studies also support that II, as an important intrinsic stimulus, has a significant effect on technology perception beliefs [Error! Reference source not found.]. Therefore, this study proposes the following hypothesis:

H1. *Individual innovativeness has a significant positive predictive effect on the following factors: (a) perceived ease of use, (b) perceived usefulness, (c) behavioral intention, and (d) AI literacy.*

1.5.2. Hypotheses on the Relationship Between SE and AIL

SE is a core concept of Social Cognitive Theory, referring to the confidence and belief in one's ability to successfully learn, master, and apply AI technology in educational and teaching contexts.

SE is the central construct of Bandura's social cognitive theory, referring to an individual's belief in their capability to organize and implement specific action plans to achieve certain accomplishments. Regulated through four sources (mastery experience, vicarious learning, social persuasion, and physiological states), pre-service teachers with high SE are better able to enhance their perception of technology's usefulness and reduce barriers to technology use [Error! Reference source not found.], holding stronger confidence in mastering AI and applying it to instruction. This confidence directly shapes their cognitive appraisal of AI; they are more likely to believe that AI tools are controllable and can be effectively utilized. At the same time, high SE itself serves as a key internal driver that motivates individuals to face challenges, engage in sustained learning, and ultimately achieve AI literacy. Research indicates that SE is an important psychological resource for overcoming barriers to technology adoption and fostering skill acquisition. Therefore, this study proposes the following hypothesis:

H2. *Self-efficacy has a positive predictive effect on the following factors: (a) perceived ease of use, (b) perceived usefulness, (c) behavioral intention, and (d) AI literacy.*

1.5.3. Hypothesized Relationships Between the Technology Acceptance Model and AIL

PEOU, PU, and BI are the core constructs of the TAM. Specifically, PEOU refers to the degree to which an individual perceives that learning and using AI technology re-

quires minimal effort and involves a relatively effortless process. PU denotes an individual's subjective judgment that a given technology is beneficial for enhancing their learning, work efficiency, or professional development when adopting a new technology. BI refers to an individual's subjective inclination to use AI technology in future teaching practices. Existing studies have indicated that PU and PEOU substantially influence users' learning motivation and the pathways through which their literacy is enhanced [Error! Reference source not found.]. AI literacy not only encompasses the ability to understand AI technologies but also covers the capacity to apply them in practical tasks [Error! Reference source not found.]. In other words, when individuals perceive AI tools as easy to use and valuable for their current learning or work, their literacy in knowing and understanding AI, detecting AI, and using and applying AI will be reinforced. Critical reviews of decades of TAM development, pointed out that treating BI as the endpoint of technology acceptance research overlooks the feedback effect of actual usage behavior after technology adoption on competence development [Error! Reference source not found.]. AI literacy is a multidimensional competency structure that not only includes the identification and judgment of AI technologies, cognition and understanding, use and evaluation, but also emphasizes critical and creative application in real teaching contexts under the premise of adhering to AI ethics [Error! Reference source not found.]. A qualitative study on pre-service teachers' AI literacy also found that genuine improvement in AI Literacy stems from "learning by doing". This involves understanding technology, reflecting on applications, and iterating improvements through actual teaching attempts. Based on the above, this study treats AI literacy as the ultimate outcome variable and proposes that BI not only directly drives usage behavior but also feeds back into literacy formation through continuous practice. Accordingly, the following hypotheses are proposed:

H3. *Perceived Ease of Use has a significant positive predictive effect on: (a) perceived usefulness, (b) behavioral intention, and (c) AI literacy.*

H4. *Perceived Usefulness has a significant positive predictive effect on: (a) behavioral intention, and (b) AI literacy.*

H5. *Behavioral Intention has a significant positive predictive effect on AI Literacy.*

1.5.4. Hypotheses on the Mediating Role of the Technology Acceptance Model

According to the TAM, PEOU and PU are core cognitive beliefs that explain individuals' technology adoption behavior, both of which indirectly influence actual usage through BI [Error! Reference source not found.]. It reflects a stable tendency of individuals to proactively try new information technologies, and has been empirically confirmed to affect technology adoption intention and actual usage through the mediating effects of PEOU and PU [Error! Reference source not found., Error! Reference source not found.]. SE, as an individual's belief in their own capability to accomplish specific tasks, has likewise been confirmed as an important antecedent of PEOU and PU [Error! Reference source not found., Error! Reference source not found.], and significantly predicts BI through these cognitive appraisals. In the classic TAM pathway, PEOU not only directly determines BI but also indirectly strengthens it by enhancing PU, constituting a serial mediation effect [Error! Reference source not found.]. BI is the most direct predictor of individuals' actual technology usage behavior, and the formation of AI literacy precisely depends on sustained, in-depth AI tool usage and reflective practice [Error! Reference source not found., Error! Reference source not found.]. Therefore, as relatively distal personality and psychological traits, II and SE can achieve an indirect promoting effect on AI

literacy through the chain of cognitive and motivational mediation: “PEOU → PU → BI.” Based on the above theoretical logic, this study proposes the following mediation effect hypotheses:

H6. *Perceived ease of use mediates the relationships of (a) individual innovativeness with AI literacy, and (b) self-efficacy with AI literacy.*

H7. *Perceived usefulness mediates the relationships of (a) individual innovativeness with AI literacy, (b) self-efficacy with AI literacy, and (c) perceived ease of use with behavioral intention.*

H8. *Behavioral intention mediates the relationships of (a) individual innovativeness with AI literacy, and (b) self-efficacy with AI literacy.*

1.5.5. Moderating Role Hypotheses

While the transformation from BI to literacy indeed constitutes the core pathway for AI literacy, the ultimate formation of literacy is also influenced by more proximal personality and psychological traits (II, SE). The effects of these traits may vary in strength depending on the social categories and experiential backgrounds of individuals. Therefore, the present study further treats gender and disciplinary background as moderating variables to examine how they function in the predictive strength of II and SE on AIL. Previous research has found that male pre-service teachers scored significantly higher than females on the overall AI literacy scale, suggesting that gender role socialization and stereotypes in the technology domain may reduce the efficiency with which females translate their innovative tendencies and efficacy beliefs into actual literacy. Thus, gender may exert a moderating effect on the AIL pathway [Error! Reference source not found.]. Previous research has shown that pre-service teachers from STEM disciplines exhibited significantly higher AI literacy and readiness than their humanities and social science counterparts, indicating that disciplinary knowledge structures, curriculum technology integration, and professional identity can provide more ample cognitive resources and institutional support for the translation of II or SE into literacy [Error! Reference source not found.]. Hence, discipline may play a moderating role in the AIL pathway. Accordingly, the present study proposes the following moderating effect hypotheses:

H9. *Gender plays a moderating role in the following relationships: (a) between individual innovativeness and AI literacy, (b) between self-efficacy and AI literacy.*

H10. *Disciplinary background plays a moderating role in the following relationships: (a) between individual innovativeness and AI literacy, (b) between self-efficacy and AI literacy.*

1.5.6. Control Variable Settings

Regarding grade level, prior research has pointed out that there are structural differences in AI learning objectives and knowledge emphases across different educational stages, indicating that individuals at different educational stages vary in cognitive maturity and accessible learning ecosystems [Error! Reference source not found.]. These factors can enhance or constrain the room for II and SE to exert influence on AIL. Intervention studies have confirmed that individuals with prior AI tool experience exhibit significant improvements in knowledge, perceptions, and behavioral intentions, suggesting that AI exposure time serves as a source of technological familiarity for individuals and may amplify the promoting effects of II and SE on AI literacy [Error! Reference source not found.]. Therefore, in addition to the aforementioned theoretical hypotheses, this study also incorporates grade level (freshman to senior) and AI exposure time (from less than 1 month to

over 1 year) as control variables into the structural model. Following methodological recommendations [Error! Reference source not found., Error! Reference source not found.], control variables are constructed as single-indicator latent variables, each pointing to all endogenous latent variables (PEOU, PU, BI, AIL). Since grade differences may reflect varying curriculum exposure and cognitive development stages, and AI exposure time is directly related to technical proficiency and internalization degree, both may independently affect technological cognition and literacy levels apart from the core independent variables. The purpose of including control variables is to exclude the potential confounding effects of grade level and usage experience on the relationships among core variables, thereby more accurately estimating the net effects of core antecedents such as II and SE on AI literacy. Control variables do not involve theoretical hypotheses; their path coefficients are used solely for statistical control and are not subject to hypothesis testing.

Furthermore, the above hypotheses (particularly H1(d), H2(d), and H5) correspond directly to specific sub-targets of SDG 4. Specifically, H1(d) and H2(d) test the predictive effects of pre-service teachers' psychological traits (innovativeness and self-efficacy) on AI literacy—AI literacy, as the core technical skill of teachers in the digital era, has its formation mechanism revealed in direct response to the implementation pathway of SDG 4.4 (enhancing relevant skills, including technical skills and digital literacy) at the teacher education level. H5 tests the transformation from behavioral intention to AI literacy—this 'intention → use → competence' logical chain provides a micro-level mechanism explanation for SDG 4.c (enhancing education quality and increasing the supply of qualified teachers through teacher training); namely, that teacher training should transcend short-term technical operation training toward sustainable, competence-oriented cultivation. The above hypotheses jointly constitute the core framework of this study, while the remaining hypotheses (H1(a)–H1(b), H2(a)–H2(b), H3–H4, H6–H10) elucidate the mediating mechanisms and boundary conditions of this core transformation chain.

Finally, based on an integrative perspective, this study constructs a hypothesized model (Figure 2) with II and SE as antecedent variables, PU and PEOU as mediating variables, BI as a proximal outcome variable, gender and major as moderating variables, grade and AI exposure time as control variables, and AI literacy as the ultimate outcome variable.

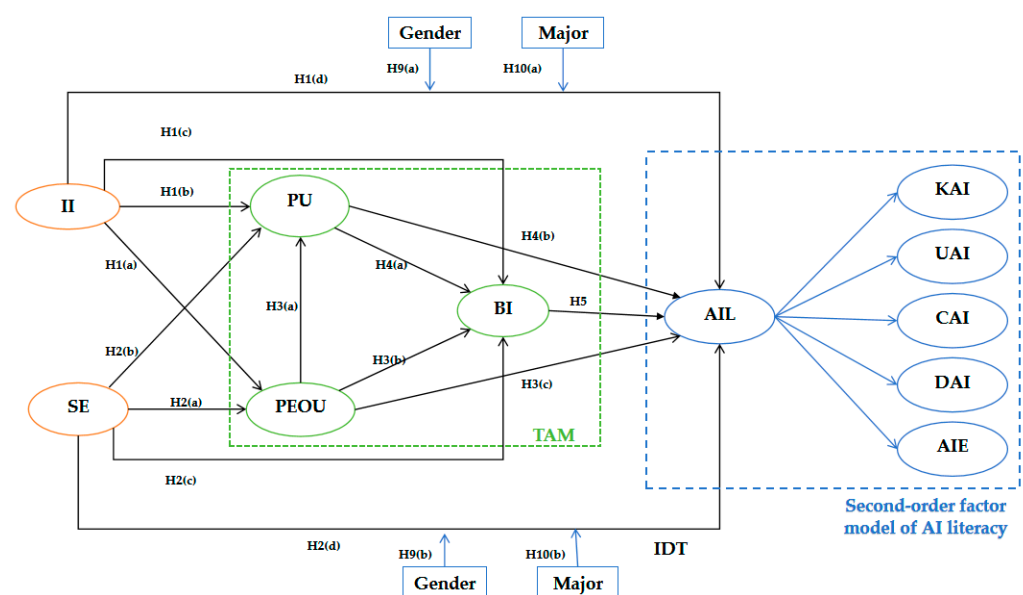


Figure 2. Research hypothesis model. Note: The green dashed box encloses the TAM constructs (PU, PEOU, BI); the blue dashed box on the right encloses the second-order factor model of AI literacy,

with AIL loading onto five dimensions: KAI, UAI, CAI, DAI, and AIE. Black solid arrows represent the hypothesized paths (H1–H10), and the top/bottom arrows from Gender and Major represent the moderating effects (H9–H10).

Furthermore, to further verify the configurational effects on AI literacy when II, SE, TAM, and individual characteristics information are combined in relation to AI literacy, we subsequently employed fsQCA analysis, incorporating PEOU, PU, BI, II, SE, and individual characteristic information as antecedent variables for the fsQCA. A research model (Figure 3) examining the configurational effects influencing pre-service teachers' AI literacy is thus constructed.

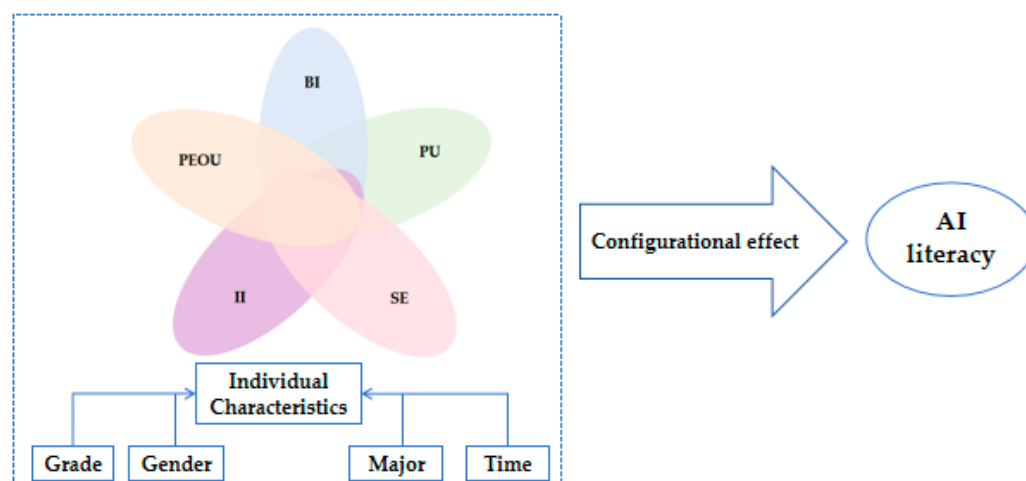


Figure 3. fsQCA research model. Note: The overlapping colored ellipses (BI, PEOU, PU, II, SE) represent the five antecedent conditions in the fsQCA analysis. The blue dashed box encloses all antecedent conditions, with individual characteristics (Grade, Gender, Major, and AI exposure time) feeding into the configuration from below. The rightward arrow labeled “Configurational effect” indicates that combinations of these conditions jointly produce the outcome—AI literacy.

The structure of this paper is organized as follows. The first section elaborates on the theoretical foundation and construction logic of the TAM-IDT integrated model and proposes the research hypotheses. Section 2 introduces the research design, including questionnaire development and data collection procedures. Section 3 presents the data analysis results from both PLS-SEM and fsQCA, including model validation, path analysis, mediation analysis, moderation analysis, and fsQCA. Section 4 discusses the empirical findings and research implications, and proposes four differentiated pathways for cultivating pre-service teachers' AI literacy. Section 5 explores the theoretical and practical significance of the study. Section 6 summarizes the research limitations and future research directions.

2. Materials and Methods

2.1. Research Design

2.1.1. Research Procedure

Based on the foregoing research hypotheses, this study adopted a staged empirical research approach, integrating PLS-SEM and fsQCA, to investigate the influencing factors and configuration mechanisms of pre-service teachers' AI literacy. The combined use of both methods enables a multi-faceted examination of the research questions. PLS-SEM is suitable for exploratory studies with complex structural models, as it prioritizes prediction and theory development over model fit. This study employed SmartPLS 4.0 (v.4.1.0.9)

for data analysis. fsQCA (v 3.0) was utilized to explore complex configurational conditions of multiple influencing factors and identify asymmetric mechanisms regarding which combinations of conditions lead to the same outcome. This study used fsQCA (v 3.0) software for the analysis.

2.1.2. Data Analysis Procedures and Methods

Data analysis was conducted in three sequential stages, with the following methods employed.

1. The online statistical platform SPSSAU (Version 26.0) [4545] and SmartPLS 4.0 (v.4.1.0.9) were used to verify the validity of the measurement model, assess common method bias, and conduct reliability and validity tests.
2. Model evaluation and hypothesis testing. Partial least squares structural equation modeling (PLS-SEM) was adopted to evaluate the research model, and SmartPLS 4.0 (v.4.1.0.9) was used to validate the structural model. Owing to its strengths in predicting dependent variables and explaining relationships among independent variables, PLS-SEM has gained increasing attention in research on AI user experience and behavioral intention [46–48]. Additionally, the PLS method exhibits robustness and accuracy with non-normal data, making it suitable for the dataset collected in this study [49]. A bootstrapping procedure with 5000 resamples was performed to obtain bias-corrected confidence intervals for direct and indirect effects, thereby testing the research hypotheses.
3. Configurational Analysis. fsQCA (v 3.0) software was employed to identify the combinations of necessary and sufficient conditions for high AI literacy. Calibration was performed using the percentiles of 95%, 50%, and 5%, with a consistency threshold set at 0.85 and a frequency threshold at 8. Both parsimonious and intermediate solutions were generated, based on which core and peripheral conditions were identified.

2.2. Questionnaire Development

The questionnaire consisted of three main sections: demographic information, an AI behavioral intention scale, and an AI literacy scale. The full list of questionnaire items corresponding to all potential variables is provided in Table S1.

2.2.1. Demographic Characteristic Information

The first part of the questionnaire collected respondents' demographic characteristic information, including grade level, academic discipline, gender, and AI exposure time.

This study adopted a broad operational definition of 'AI exposure time', referring to the cumulative time since participants first encountered technological tools with intelligent interactive features, without requiring sustained or professional use. Specifically, three categories of technology were covered: (1) everyday applications embedded with recommendation algorithms and personalized content delivery (e.g., short video recommendations, intelligent search, personalized content distribution); (2) voice interaction and intelligent assistants (e.g., smartphone voice assistants, smart speakers, intelligent customer service); (3) generative AI tools (e.g., ChatGPT (GPT-3.5 Turbo), Doubao AI, AI writing assistants, and AI drawing tools). This definition was designed to capture the various forms of AI technology that pre-service teachers may encounter in their daily lives, rather than being limited to AI applications in educational settings. Based on this definition, AI exposure time was segmented into four intervals—ten years or more, five to ten years, one to five years, and less than one year—aiming to approximate the distinction between 'early adopters' and 'late majority' among pre-service teachers through temporal categories, consistent with the adopter classification logic of Rogers' IDT [50].

Regarding the ‘ten years or more’ AI exposure time category, it should be noted that between 2013 and 2015, smartphone recommendation algorithms (e.g., Toutiao, YouTube recommendation systems) and voice assistants (e.g., Siri, Google Now) had already become widely prevalent in Chinese society. For the pre-service teacher population aged 18–25 in this study, ‘ten years or more’ implies that their initial AI exposure began during junior or senior high school, which broadly aligns with the timeline of widespread AI technology exposure in everyday life. Therefore, the reference point for this category has a reasonable socio-technological developmental background.

2.2.2. AI Behavioral Intention Scale

The second section comprised a scale measuring respondents’ behavioral intention to use AI. Drawing on TAM and IDT, five key constructs were extracted: II (5 items), SE (4 items), PU (5 items), PEOU (3 items), and BI (3 items). This section contained 20 items across five dimensions (see Table 1).

Table 1. Sources of Scale Items.

Questionnaire Structure	Research Variables	Number of Items	Reference Source
AI Literacy	Perceived Usefulness (PU)	5	Davis (1985) [51]
	Perceived Ease of Use (PEOU)	3	Davis (1985) [51]
	Behavioral Intention (BI)	3	Venkatesh et al. (2003) [Error! Reference source not found.]
	Individual Innovativeness (II)	5	Williams (1979) [52]
	Self-Efficacy (SE)	4	Schwarzer (1995) [53]
	Know and understand AI (KAI)	4	Ng et al. (2023) [Error! Reference source not found.]
	Use and apply AI (UAI)	3	Ng et al. (2023) [Error! Reference source not found.]
	Create AI (CAI)	3	Ng et al. (2023) [Error! Reference source not found.]
	Detect AI (DAI)	4	Long and Magerko (2020) [Error! Reference source not found.]
	AI ethics (AIE)	3	Ng et al. (2023) [Error! Reference source not found.]

The dimensions of PU and PEOU are derived from Davis’s TAM scale, retaining the original item content [51]**Error! Reference source not found.**. The BI follows the original definitions of “use intention” and “use behavior” provided by Davis. In this study, this intention is consolidated into a proximal outcome variable that also serves as a mediating variable influencing final AI literacy. II is measured using Williams’ Cognitive–Affective Interaction Theory-based Creativity–Affection Scale [52]**Error! Reference source not found.**, comprising five items. These include questions such as “I enjoy experimenting with various AI technologies during teaching and training,” each representing curiosity, risk-taking, challenge-seeking, and imagination, as well as one item reflecting innovative tendencies: “I like to befriend individuals exploring new AI technologies.” SE adheres to Schwarzer and Jerusalem’s original definition [53]**Error! Reference source not found.**, with the term “system” replaced with “AI technology” in this study.

2.2.3. AI Literacy Scale

To comprehensively and accurately assess the AI literacy level of pre-service teachers, this study systematically adapted established scales into a Chinese version based on the integration of existing theoretical frameworks.

1. **Theoretical Dimension Construction.** This study combined an established four-dimensional AI literacy framework—comprising Know and Understand AI, Use and Apply AI, Evaluate and Create AI, and AI Ethics [Error! Reference source not found.]—with the “Detect AI” capability identified in the literature [Error! Reference source not found.], ultimately forming a five-dimensional AIL assessment framework: Know and Understand AI (KAI), Use and Apply AI (UAI), Evaluate and Create AI (CAI), Detect AI (DAI), and AI Ethics (AIE). A measurement scale based on these five dimensions has been developed and validated in prior research, with satisfactory psychometric properties. [54]Error! Reference source not found..

2. **Scale Parallel Back-Translation.** This study strictly followed the parallel back-translation procedure to ensure cross-cultural equivalence. The procedure included the following steps.

Forward Translation. Two independent bilingual researchers (both familiar with the source language cultural context) separately translated the original English items into Chinese.

Synthesis. The two forward translation results were compared and discussed, and a consensus Chinese version was ultimately formed.

Backward Translation. Another bilingual expert who had not independently reviewed the original English version back-translated the consensus Chinese version into English.

Comparison and Revision. An expert panel compared the back-translated version with the original English scale to evaluate its conceptual equivalence, semantic equivalence, and operational equivalence. Based on the comparison results, the Chinese version was revised accordingly.

Finalization. Based on the pre-test feedback, the Chinese version of the scale was finalized for formal implementation.

3. **Expert Review.** After completing the back-translation process, the items were further optimized through a “pedagogical contextualization” approach to align with the characteristics of the pre-service teacher population. For example, the generic expression “using AI” was specified as “applying AI in lesson preparation or simulated teaching”. After three domain experts reviewed the content validity, the final scale comprised 17 items.

The data collection for the second and third parts adopted a 5-point Likert scale, with scores ranging from 1 to 5 representing strongly disagree, somewhat disagree, neutral, somewhat agree, and strongly agree, respectively.

2.2.4. Ethical Considerations

To ensure that the questionnaire survey complied with ethical standards, all participants were fully informed of the purpose of this study prior to completing the questionnaire and provided informed consent. The confidentiality of participant information was strictly maintained, and the voluntary nature of participation was emphasized, with participants retaining the right to withdraw from the study at any time. In accordance with Article 32 of the Ethical Review Measures for Life Science and Medical Research Involving Human Subjects (Order No. 4 of 2023), jointly issued by the National Health Commission, the Ministry of Education, the Ministry of Science and Technology, and the National Administration of Traditional Chinese Medicine of the People’s Republic of China, research

employing anonymous data, causing no harm to subjects, and involving no sensitive personal information or commercial interests is exempt from ethical review.

2.3. Questionnaire Distribution and Collection

This study employed a convenience sampling method to collect data from the pre-service teacher population. All participants were students enrolled in teacher education programs, with efforts made to cover a diversity of grade levels and disciplinary backgrounds as comprehensively as possible.

The survey was conducted in October 2025, with 845 questionnaires collected. After screening the returned questionnaires, 67 invalid responses were excluded—those with excessively short completion times (<120 s), patterned responses (e.g., consecutively selecting the same option), or evident logical contradictions—resulting in 778 valid questionnaires.

Demographic analysis of the 778 valid responses showed that females accounted for 57.33% of the sample, broadly consistent with the overall characteristic of a higher proportion of females in China’s teacher education programs. The distribution across grade levels from freshman to senior was relatively balanced (21.47–26.61%), with graduate students comprising 5.66%. Disciplinary backgrounds spanned liberal arts, sciences, arts, and physical education, among others, with liberal arts and science students together accounting for 61.95%, broadly consistent with the student composition of teacher education institutions. The distribution of AI exposure time showed that 50.51% of participants had five or more years of AI exposure, reflecting the generational characteristic of contemporary pre-service teachers as ‘digital natives’ who have generally encountered AI technology early. Overall, the demographic composition of the sample broadly matched the characteristics reported in studies of Chinese pre-service teachers, indicating that the sample encompassed a reasonable range of diversity within the target population. (see Table 2).

Table 2. Demographic Information of Participants.

Variable		<i>n</i>	Percentage (%)
Grade	Freshman	167	21.47%
	Sophomore	182	23.39%
	Junior	207	26.61%
	Senior	178	22.88%
	Postgraduate Student	44	5.66%
Gender	Male	332	42.67%
	Female	446	57.33%
	Humanities	266	34.19%
	Science	216	27.76%
	Art	152	19.54%
	Physical	115	14.78%
AI exposure time	Other	29	3.73%
	Within one year	105	13.50%
	One to five years	280	35.99%
	Five to ten years	321	41.26%
	Ten years or more	72	9.25%

Note: The AI exposure time refers to the cumulative period since the initial contact with AI technologies (e.g., AI-driven applications, intelligent assistants, and generative AI tools), not continuous professional use. For pre-service teachers aged 18–25, the “five to ten years” period corresponds to their first exposure during junior high or high school.

2.4. Adaptability Analysis of Research Instruments

The adaptability of research instruments refers to the alignment between measurement tools and research purposes at the levels of theoretical dimensions, target populations, cultural contexts, and statistical structures. This reflects the core consensus in scale development and validation research: scale development must be grounded in clearly defined theoretical constructs [55]**Error! Reference source not found.**, must ensure comprehensibility for the target population [56**Error! Reference source not found.**]**Error! Reference source not found.**, must undergo rigorous back-translation and adaptation procedures to ensure conceptual, semantic, and operational equivalence [57]**Error! Reference source not found.**, and must demonstrate consistency between factorial structure and theoretical expectations through reliability and validity analyses [58]**Error! Reference source not found.**.

2.4.1. Adaptability Analysis of the AI Behavior Scale

The AI Behavior Intention Scale is developed based on the core constructs of the TAM and IDT, encompassing five dimensions: PU, PEOU, BI, IL, and SE. In this study, TAM and IDT serve as classical theoretical frameworks for explaining technology adoption behaviors that have been widely applied in educational technology acceptance research. The five selected constructs—PU, PEOU, BI, IL, and SE—correspond to key elements of both TAM, IDT, and social cognitive theory, aligning closely with the theoretical model investigating the formation mechanisms of AI literacy among pre-service teachers. The operational definitions and measurement items of each construct are rigorously derived from established theoretical sources, ensuring alignment between the scale content and theoretical constructs. To accommodate the characteristics of pre-service teachers, the scale items have been adapted for the instructional context. For example, the original TAM construct “using the system” has been specified as “using AI technology in teaching practice”.

2.4.2. Adaptability Analysis of the AIL Scale

The AIL scale proposed in this study demonstrates methodological adaptability to the research purposes, target population, and research context. At the theoretical level, this study integrated an existing four-dimensional AI literacy framework—comprising Know and Understand, Use and Apply, Evaluate and Create, and AI Ethics—with the “Detect AI” capability proposed in the literature, thereby constructing a five-dimensional integrated framework. This framework is highly congruent with the study’s conceptualization of AI literacy, thereby ensuring that the scale content can effectively reflect the theoretical constructs. Regarding context, the study performed “pedagogical contextualization” of items tailored to the pre-service teacher population (e.g., specifying “using AI” as “using AI in lesson preparation or simulated teaching”). Furthermore, the study strictly followed a well-established parallel back-translation procedure for the Chinese adaptation [57], ensuring sound conceptual, semantic, and operational equivalence between the Chinese version and the original scale.

In this study, AIL was modeled as a reflective second-order construct. The choice of measurement specification for the second-order construct followed the criteria proposed by Jarvis et al. [**Error! Reference source not found.**]. According to these criteria, the applicability of a reflective specification requires the following conditions: (1) the causal direction should flow from the construct to the indicators; (2) the indicators should be interchangeable; (3) the indicators should be highly correlated; and (4) the nomological network of the indicators should be consistent. In this study, the five dimensions of AIL—KAI, UAI, CAI, DAI, and AIE—serve as reflective indicators for the following reasons.

First, from the perspective of causal direction, this study conceives AIL as a latent, comprehensive competence trait that causes variation in individual performance across

the five dimensions, rather than the five dimensions ‘defining’ or ‘constituting’ AIL. Specifically, individuals exhibit stronger AI knowledge, application ability, creativity, detection ability, and ethical awareness because they possess higher AI literacy—the five dimensions are reflections of the latent trait, not its causes.

Second, the five dimensions exhibited moderate-to-high inter-dimension correlations (Pearson correlation coefficients ranging from 0.61 to 0.75), satisfying the requirement that reflective indicators should be highly correlated. Furthermore, the second-order confirmatory factor analysis results showed that the standardized loadings of each dimension on AIL ranged from 0.611 to 0.755 ($p < 0.001$), with good second-order model fit (SRMR = 0.045, CFI = 0.962), indicating that the five dimensions shared a common core construct.

Third, from the perspective of indicator interchangeability, removing any single dimension would not fundamentally alter the theoretical connotation of AIL—regardless of whether ‘knowledge and understanding’ or ‘application ability’ is removed, the remaining dimensions still jointly point to the higher-order construct of ‘AI literacy’. This is consistent with the reflective indicator characteristic that ‘removing an indicator should not change the domain of the construct’.

Furthermore, regarding the nature of the construct, AIL refers to the fundamental literacy of an individual in applying AI, a comprehensive psychological construct encompassing dimensions of knowing, understanding, detecting, and using. Psychological constructs are generally measured through reflective indicators because they are the underlying factors that produce the observed indicators [60]. In other words, AI literacy, as a latent psychological trait, ‘causes’ the performance differences of individuals across the five dimensions, rather than the five dimensions ‘defining’ AI literacy. Therefore, a reflective measurement model aligns more closely with the theoretical essence of AIL. Moreover, the five-dimensional structure has been empirically validated, and treating AI literacy as a reflective second-order construct has been shown to be a viable approach [54]. Consequently, this study follows this established measurement strategy, ensuring comparability and replicability of the scale structure. Modeling AIL as a reflective second-order construct is supported by clear theoretical and methodological rationales.

3. Data Analysis Results

The entire data analysis process was divided into three steps. First, the quality of the measurement instruments used was evaluated by estimating the relationships between the latent constructs and their corresponding indicators, which constituted the assessment of the measurement model [61]. These specific settings were discussed separately for the lower-order constructs (LOCs) and the higher-order construct (HOC), clarifying the associations between the LOCs and the HOC. Subsequently, the explanatory and predictive power of the model was examined by assessing the inter-construct relationships, which included the estimation of the structural model. On this basis, mediation effect analysis and moderation effect analysis were conducted. Finally, to further reveal the synergistic and substitutive relationships among the antecedent conditions and identify multiple equifinal paths to achieving high AI literacy, fsQCA analysis was performed.

3.1. Measurement Model

3.1.1. Common Method Bias (CMB) Test

Given that all variables in this study were collected at a single time point through self-report scales, the potential influence of Common Method Bias (CMB) needed to be evaluated. To assess its severity, this study employed multiple methods for CMB testing.

First, a preliminary test was conducted using the Harman single-factor analysis method. Principal component analysis without rotation was employed to identify factors

for all items. The results revealed 11 factors with eigenvalues greater than 1; the first factor accounted for only 30.018% of the total variance, below the critical threshold of 50% [62], indicating no single factor dominates data interpretation. The cumulative variance explained by the first two factors was 36.317%, and that by the first three factors was 42.022%, demonstrating a relatively even distribution of variance explanation power. The cumulative variance explained by the first ten factors reached 71.687%. Thus, it can be preliminarily concluded that this study does not exhibit significant common method bias. It should be noted that the Harman single-factor test, as a preliminary screening tool for CMB, has certain limitations in sensitivity; therefore, this study further employed more rigorous testing methods for validation.

Second, the Common Latent Factor (CLF) method was applied. A common factor pointing to all observed variables was introduced into the measurement model to control for systematic variation attributable to the measurement method [63,64]. The results showed that the squared loadings of the common method factor (R^2) for all items were below the 50% threshold, and the squared loadings of the substantive factors (R^2) exceeded R^2 , indicating that item variance was predominantly explained by the substantive constructs (see Table S2). Although this method remains controversial in the methodological literature, it is widely adopted as supplementary evidence for CMB assessment. Combined with the results of the other three tests in this study, common method bias does not pose a significant threat.

Third, to further assess the potential impact of CMB, a full collinearity test was conducted. Unlike the collinearity test conducted at the conventional indicator level, the full collinearity test calculates VIF values at the latent variable level by using the inverse matrix of the correlation coefficient matrix among latent variables. The results show that the full collinearity VIF values for all latent variables are below the strict threshold of 3.3 recommended by Kock (2015), further indicating that common method bias does not pose a significant threat in this study according to the test criteria [65].

In addition, the HTMT ratio results further supported discriminant validity. The HTMT values for all constructs were below the stringent threshold of 0.85 (detailed in Sections 3.1.2 and 3.1.3), indicating sufficient differentiation among constructs, which to some extent ruled out CMB interference attributable to high construct overlap.

Based on the comprehensive analysis of these four tests, although no single test can definitively determine the presence of bias, their results collectively corroborate that common method bias hardly significantly interferes with the structural relationships between variables, indicating robustness in the structural relationship estimates.

3.1.2. Measurement Model Assessment of LOCs

To validate the first-order reflective measurement model employed in this study, we followed specific empirical rules regarding reliability and validity [**Error! Reference source not found.**]. Indicator reliability was verified through factor loadings, all of which exceeded the recommended threshold of 0.7 [**Error! Reference source not found.**], indicating acceptable item reliability. At the construct level, internal consistency reliability was assessed through composite reliability (ρ_c), reliability coefficient (ρ_a), and Cronbach's alpha (α). Following the latest guidelines, this study prioritized the use of the ρ_a scale, which has demonstrated its superiority [**Error! Reference source not found.**]. The ρ_a values for all LOCs (Table 3) ranged from 0.779 to 0.912, indicating that the measurement instruments used are reliable while effectively avoiding item redundancy [**Error! Reference source not found.**]. Next, convergent validity of the reflective constructs was evaluated through the average variance extracted (AVE). The AVE values for all first-order constructs reached acceptable levels (>0.5), confirming the convergent validity of the latent

variables [Error! Reference source not found.,Error! Reference source not found.]. Finally, to verify discriminant validity at the first-order level, we employed the Fornell–Larcker criterion and the heterotrait–monotrait (HTMT) ratio analysis. The Fornell–Larcker criterion was used to examine the congruence between the scale results and the research design. Using the square root of AVE approach, the square root of AVE for each factor was greater than “the maximum correlation coefficient between that factor and other factors”, indicating that the scale design is reasonable, valid, and possesses good discriminant validity. The HTMT ratio is a more stringent method for assessing discriminant validity, judging the discriminability between variables by comparing the average of the heterotrait–heteromethod correlations with the average of the monotrait–heteromethod correlations. Generally, HTMT values below 0.85 indicate good discriminant validity [Error! Reference source not found.,Error! Reference source not found.]. The Fornell–Larcker criterion and HTMT results for the first-order measurement scales are shown in Table 4, indicating that each LOC is empirically distinct from the others, thus confirming the discriminant validity of the first-order model.

Table 3. First-order measurement model summary.

LOC	Indicator	Indicator Reliability	Internal Consistency Reliability			Convergent Validity
		Loading	α	ρ_a	ρ_c	AVE
II			0.912	0.912	0.934	0.74
	II1	0.869				
	II2	0.838				
	II3	0.849				
	II4	0.86				
	II5	0.883				
SE			0.886	0.889	0.921	0.745
	SE1	0.874				
	SE2	0.87				
	SE3	0.849				
	SE4	0.86				
PEOU			0.813	0.819	0.889	0.728
	PEOU1	0.853				
	PEOU2	0.871				
	PEOU3	0.835				
PU			0.882	0.884	0.914	0.679
	PU1	0.812				
	PU2	0.8				
	PU3	0.846				
	PU4	0.835				
	PU5	0.826				
BI			0.773	0.781	0.868	0.686
	BI1	0.805				
	BI2	0.848				
	BI3	0.832				
KAI			0.847	0.849	0.897	0.686
	KAI1	0.815				
	KAI2	0.834				
	KAI3	0.842				
	KAI4	0.82				
UAI			0.82	0.823	0.892	0.735
	UAI1	0.865				

	UAI2	0.864				
	UAI3	0.842				
CAI			0.777	0.779	0.871	0.692
	CAI1	0.825				
	CAI2	0.826				
	CAI3	0.843				
DAI			0.869	0.87	0.911	0.718
	DAI1	0.848				
	DAI2	0.842				
	DAI3	0.86				
	DAI4	0.84				
AIE			0.785	0.786	0.875	0.699
	AIE1	0.819				
	AIE2	0.833				
	AIE3	0.856				

Note: II = Individual Innovativeness; SE = Self-Efficacy; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; BI = Behavioral Intention; KAI = Knowledge and Understanding AI; UAI = Using and Applying AI; CAI = Creating and Evaluating AI; DAI = Detecting AI; AIE = AI Ethics; α = Cronbach's Alpha, ρ_a = reliability coefficient a, ρ_c = Composite Reliability; AVE = Average Variance Extracted.

Table 4. Fornell–Larcker Criterion/HTMT.

Variable	II	SE	PEOU	PU	BI	KAI	UAI	CAI	DAI	AIE
II	0.86	0.423	0.391	0.477	0.313	0.386	0.425	0.367	0.458	0.351
SE	0.381	0.863	0.338	0.522	0.412	0.399	0.419	0.346	0.486	0.326
PEOU	0.337	0.289	0.853	0.4	0.369	0.41	0.362	0.306	0.423	0.339
PU	0.43	0.464	0.341	0.824	0.439	0.446	0.406	0.428	0.512	0.387
BI	0.264	0.343	0.298	0.366	0.829	0.462	0.35	0.351	0.406	0.367
KAI	0.34	0.349	0.344	0.388	0.375	0.828	0.415	0.331	0.455	0.44
UAI	0.369	0.36	0.299	0.346	0.281	0.35	0.857	0.407	0.493	0.447
CAI	0.31	0.29	0.246	0.357	0.276	0.27	0.326	0.832	0.376	0.372
DAI	0.409	0.429	0.358	0.449	0.335	0.391	0.418	0.31	0.847	0.452
AIE	0.297	0.273	0.273	0.323	0.289	0.361	0.361	0.29	0.375	0.836

Note: (1) Fornell and Larcker criterion: diagonal elements (shown in bold) represent the square root of the Average Variance Extracted (AVE), while off-diagonal elements below the diagonal represent the inter-construct correlations. (2) Heterotrait–Monotrait (HTMT) ratio values are shown above the diagonal.

3.1.3. Measurement Model Assessment of HOCs

We employed a Type I reflective–reflective, second-order CFA approach, loading the LOCs of AIL onto the corresponding HOCs. As shown in Table 5, the five first-order factors of the second-order AIL scale are KAI, UAI, CAI, DAI, and AIE. According to the SmartPLS results, for the second-order factor AIL, the path coefficients from AIL to KAI, UAI, CAI, DAI, and AIE were 0.702, 0.711, 0.611, 0.755, and 0.667, respectively, and were significant at the 0.001 level. Although only three path coefficients exceeded 0.7 [Error! Reference source not found.], the remaining path coefficients were still above 0.6. Moreover, the overall Cronbach's alpha coefficient of the second-order AIL scale was 0.878, and the composite reliability was 0.734, both exceeding the recommended thresholds, indicating that the measurement model is reliable [Error! Reference source not found.]. Furthermore, the first-order factors exhibited moderate Pearson correlations with each other, ranging from 0.61 to 0.75. The positive correlations among the first-order factors can be explained by the underlying second-order factor “AIL” [Error! Reference source not found.].

found.]. The correlations between the path coefficients from the first-order factors to AIL indicate that these first-order factors are strongly influenced by AIL. According to the theory of reflective measurement models, latent constructs are viewed as common causes of their observed indicators **[Error! Reference source not found.]**. The methodological literature further distinguished between reflective and formative models, noting that in reflective models, the construct causes variation in the indicators **[Error! Reference source not found.]**. The principles for judging the direction of relationships between constructs and their measures have been systematically articulated in the measurement literature. **[Error! Reference source not found.]**. Based on the above theories, AIL, as a comprehensive psychological construct, treats its five first-order factors (KAI, UAI, CAI, DAI, AIE) as reflective dimensions of AIL. The path coefficients from AIL to each first-order factor were significant (0.611–0.755, $p < 0.001$), indicating that these first-order factors are strongly influenced by AIL, consistent with the expectations of a reflective measurement model.

To verify the rationality of constructing the second-order model, it should be noted that a loading greater than 0.7 is a rule-of-thumb recommendation to ensure AVE exceeds 0.5. In this study, deleting AIE and CAI would increase the AVE of AIL to 0.591 but decrease Cronbach's alpha to 0.655 and composite reliability to 0.66. As Hair et al. **[Error! Reference source not found.]** suggest, an item should be retained if its removal does not significantly improve composite reliability or AVE, and its loading falls between 0.4 and 0.7. **[Error! Reference source not found.]**. For second-order models, the dilution effect on indicators is expected due to the higher abstraction of the higher-order construct. Furthermore, the AVE of all constructs except AIL was greater than 0.5; the AVE of AIL was 0.477, slightly below 0.50, but its CR was 0.781, exceeding 0.70. Prior guidelines in the literature indicate that convergent validity remains acceptable when AVE is below 0.50 but CR is above 0.60 **[58]Error! Reference source not found..** This result indicates that the scale has good internal consistency and convergent validity.

Table 5. Second-order measurement model summary.

Variable	Indicator	Indicator Reliability loading	Internal Consistency Reliability			Convergent Validity AVE
			α	qa	qc	
AIL			0.725	0.734	0.819	0.477
	AIE	0.667				
	CAI	0.611				
	DAI	0.755				
	KAI	0.702				
	UAI	0.711				

Note: α = Cronbach's Alpha, qa = reliability coefficient a, qc = Composite Reliability; AVE = Average Variance Extracted. Reliability and validity statistics for the first-order constructs (II, SE, PEOU, PU, BI) are reported in Table 3.

Similarly, at the construct level, internal consistency reliability was assessed using composite reliability (qc), reliability coefficient (qa), and Cronbach's alpha (α). The qa value for the second-order construct AIL (see Table 5) is 0.734 and the qa values for the first-order constructs (see Table 3) range from 0.779 to 0.912, indicating that the measurement instruments are reliable while effectively avoiding item redundancy [Error! Reference source not found.]. The HTMT correlation coefficients (see Table 6) are all below 0.85. Consequently, all necessary reliability and validity criteria have been satisfied, and our second-order measurement model is confirmed.

Table 6. Fornell–Larcker Criterion/HTMT ratio at second-order.

Variable	II	SE	PEOU	PU	BI	AIL
II	0.86	0.423	0.391	0.477	0.313	0.613
SE	0.381	0.863	0.338	0.522	0.412	0.612
PEOU	0.337	0.289	0.853	0.4	0.369	0.569
PU	0.429	0.464	0.34	0.824	0.439	0.673
BI	0.264	0.343	0.298	0.366	0.828	0.597
AIL	0.503	0.5	0.444	0.543	0.453	0.691

Notes: (1) Fornell and Larcker criterion: diagonal elements (shown in bold) represent the square root of the Average Variance Extracted (AVE), while off-diagonal elements below the diagonal represent the inter-construct correlations. (2) Heterotrait–Monotrait (HTMT) ratio values are shown above the diagonal.

Furthermore, this study compared the goodness-of-fit between the first-order and second-order models. SRMR is used to measure the discrepancy between the model-predicted values and the actual observed values. An SRMR value below 0.1 is generally considered to indicate acceptable model fit [Error! Reference source not found.]. This means that the discrepancy between the model-predicted values and the actual observed values is within an acceptable range. For more stringent model evaluation, an SRMR value below 0.08 is required; this criterion is typically applied in research contexts demanding higher standards to ensure superior model fit, with lower SRMR values indicating better fit. The Normed Fit Index (NFI) is one of the important indicators for evaluating the overall goodness-of-fit of structural equation models in SmartPLS. Its value ranges between 0 and 1, with values closer to 1 indicating better model fit [Error! Reference source not found.]. As shown in Table 7, the second-order model exhibits a lower SRMR value and a higher NFI value compared to the first-order model, indicating that the overall goodness-of-fit of the second-order model is superior to that of the first-order model. In other words, after

introducing the second-order factor, the model demonstrates stronger explanatory power for the data, smaller residuals, and a more reasonable structure.

Table 7. Comparison between the First-Order Model and the Second-Order Model.

Index	First-Order Model		Second-Order Model	
	Saturated Model	Estimated Model	Saturated Model	Estimated Model
SRMR	0.040	0.052	0.044	0.045
d_ULS	1.134	1.898	0.718	0.778
d_G	0.509	0.543	0.270	0.276
Chi-square	2436.728	2565.751	1258.310	1278.303
NFI	0.841	0.833	0.873	0.871

To test the robustness of the AIL measurement specification, this study supplemented the reflective second-order model with an alternative formative second-order model for AIL. In the formative model, the five first-order dimensions (KAI, UAI, CAI, DAI, AIE) served as formative indicators pointing to the second-order construct AIL, with the remaining structural model specifications held constant. As shown in Table 8, the core path coefficients and significance levels under the two models were essentially identical (maximum difference < 0.01), including the non-significant II → BI relationship, which remained consistent across both models. The above results indicated that the choice of AIL measurement specification did not affect the substantive conclusions of this study, and the results exhibited satisfactory robustness.

Table 8. Comparison between reflective and formative second-order models.

Path	Reflective Model (AIL)		Formative Model (AIL)	
	β	<i>p</i> Values	β	<i>p</i> Values
II → PEOU	0.265	0	0.266	0
II → PU	0.252	0	0.252	0
II → BI	0.054	0.167	0.053	0.167
II → AIL	0.22	0	0.218	0
SE → PEOU	0.188	0	0.187	0
SE → PU	0.321	0	0.32	0
SE → BI	0.182	0	0.178	0
SE → AIL	0.192	0	0.198	0
PEOU → PU	0.163	0	0.162	0
PEOU → BI	0.158	0	0.154	0
PEOU → AIL	0.18	0	0.181	0
PU → BI	0.205	0	0.201	0
PU → AIL	0.231	0	0.232	0
BI → AIL	0.191	0	0.19	0

The logic underlying path coefficient estimation differs between reflective and formative models. The reflective model first fits the second-order factor and then estimates path coefficients, whereas the formative model first synthesizes the second-order factor as a weighted composite of the first-order dimensions and then estimates path coefficients. As shown in the table, the two approaches yielded nearly identical results. Based on theoretical considerations, this study adopted the reflective model for the AIL second-order construct. The study conceptualizes AIL as a latent, comprehensive competency trait, not mechanically assembled from its dimensions. That is, individuals exhibit competence

across various domains because they possess AI literacy, and the five dimensions are manifestations of AIL rather than its constituent components. This theoretical premise aligns with the logic of the reflective model. Although the formative model also fitted the data well, it did not align with the theoretical underpinnings of this study and was therefore used only as a robustness check.

3.2. Structural Equation Model

3.2.1. Multicollinearity (VIF)

First, a multicollinearity test was conducted on the model [Error! Reference source not found.]. We calculated the variance inflation factor (VIF) values for the independent variables, all of which ranged from 1.043 to 1.547, well below the more conservative threshold of 3 [Error! Reference source not found.], indicating the absence of multicollinearity issues [Error! Reference source not found., Error! Reference source not found., Error! Reference source not found.]. Therefore, the structural model estimation results are not affected by collinearity issues, and the data are suitable for further analysis.

In addition, to further assess the potential impact of common method bias (CMB), this study adopted the full collinearity test. By calculating the inverse of the correlation coefficient matrix among the latent variables, the full collinearity VIF value for each latent variable was extracted. The results show that the full collinearity VIF values for all latent variables are below the stringent threshold of 3.3 recommended by Kock [Error! Reference source not found.]. According to the criteria of this test, it is concluded that common method bias does not pose a serious threat in this study, and the estimated structural relationships have good robustness.

3.2.2. Model Evaluation Results and Importance-Performance Analysis

1. Model Explanatory Power and Predictive Relevance

Table 9 presents the R^2 , adjusted R^2 , and Q^2 values for each latent variable in the model. The R^2 value reflects the explanatory power of the independent variables on the latent variables. Among them, the R^2 of AIL (0.498) reaches a moderate level, indicating that these independent variables have a certain degree of explanatory power for AIL [Error! Reference source not found.]. Although the R^2 value of PEOU is relatively low (0.144), it still falls within a reasonable range for exploratory research. The adjusted R^2 values are close to the original R^2 values, indicating that the model has no significant noise effects and exhibits good explanatory stability. Furthermore, the Q^2 values for all latent variables are greater than zero, indicating that the model has effective predictive relevance. These results suggest that although individual indicators are not high in magnitude, the overall model demonstrates moderate explanatory power and predictive ability, supporting its applicability in both the measurement model and the structural model.

Table 9. Values of R^2 and Q^2 .

Variable	R^2	R^2 Adjusted	Q^2
AIL	0.498	0.491	0.231
BI	0.199	0.194	0.13
PEOU	0.144	0.142	0.103
PU	0.313	0.31	0.209

2. Importance–Performance Map Analysis of the Model

Furthermore, this study further conducted an Importance–Performance Map Analysis (IPMA) to identify the key leverage points for improving AI literacy (AIL) [84]. This method plots the total effects (importance) of antecedent variables against the mean latent

variable scores (performance) in a single coordinate system, helping to identify key drivers that exhibit high importance but currently low performance [Error! Reference source not found.]. The IPMA results are shown in Figure 4. Overall, II and SE demonstrate the highest importance, but their current performance is at a medium-to-low level (approximately 58–60). This reveals a clear “high importance, medium-to-low performance” characteristic, representing the most urgent strategic priority for improving AI literacy. In contrast, although BI exhibits the highest performance, its importance is the lowest, indicating that merely increasing usage intention has limited driving power for literacy transformation.

Regarding the selection of the importance-axis threshold, this study adopted a data-driven approach. Given that there is no universally mandatory standard for classifying ‘importance’—it is generally accepted that values above 0.2 represent a ‘relevant impact’ [Error! Reference source not found.]—this study set the threshold at 0.3 based on the actual distribution of the sample data. This choice was informed by the following considerations: the aim of this study was to identify key factors exerting substantive driving effects on AI literacy, rather than all statistically significant variables. As shown in Table 10, the importance values for II (0.366) and SE (0.360) were notably higher than those for the other variables, while the importance values for PU (0.267), PEOU (0.253), and BI (0.192) were relatively lower. The importance values of all antecedent variables formed two distinct ‘clusters’: II = 0.366 and SE = 0.360 constituted the high-value group; PU = 0.267, PEOU = 0.253, and BI = 0.192 constituted the low-value group. A clear gap existed between the two clusters; accordingly, this study selected 0.3 as the dividing threshold for the importance axis to accurately reflect this natural data structure. Had a threshold of 0.2 been adopted, four variables other than BI would have been classified as ‘high importance’, making it difficult to differentiate the degree of influence; by adopting the 0.3 threshold, II and SE could be clearly identified as the key leverage points for priority intervention. This more stringent threshold selection facilitated a focus on the small number of critical driving factors with substantive impact on AI literacy, providing more targeted decision-making guidance for teacher education practice.

Table 10. Importance and performance values of antecedent variables.

Variable	Importance	Performance
BI	0.192	65.427
II	0.366	58.159
PEOU	0.253	63.347
PU	0.267	62.227
SE	0.360	59.516

In terms of setting the dividing point on the performance axis, two general approaches exist: one based on the data mean (data rating) and the other based on the scale mean (scale mean) [Error! Reference source not found., Error! Reference source not found.]. This study adopted the latter, using the midpoint of the percentage scale, 50, as the dividing threshold for the performance axis. This choice followed the scale-midpoint tradition in the IPA literature [Error! Reference source not found.], using the midpoint of the percentage scale (50) as the dividing line between high and low performance. Specifically, variables with performance scores above 50 were classified as ‘high performance’ and those below 50 as ‘low performance’. This approach is not dependent on sample distribution, possesses good interpretability and cross-study comparability, and can be traced back to the classic work of Martilla and James [Error! Reference source not found.].

Thus, four quadrants were formed: upper right (high importance–high performance), upper left (high importance–low performance), lower right (low importance–high performance), and lower left (low importance–low performance). Based on this classification, priority improvement areas could be identified where current performance levels fell below importance levels. The IPMA results are presented in Figure 4. The total effect of II was 0.366, and that of SE was 0.360, ranking first and second among all antecedent variables. The third-ranked variable, PU, had a total effect of 0.267; the importance values of II and SE exceeded it by 37.1% and 34.8%, respectively. Taken together, individual innovativeness and self-efficacy exhibited the highest importance but currently medium-to-low performance levels (approximately 58–60), demonstrating a clear ‘high importance, medium-to-low performance’ profile. These two variables constitute the strategic priorities most urgently requiring intervention for enhancing AI literacy. In contrast, although BI exhibited the highest performance, its importance was the lowest, indicating that merely enhancing usage intention had limited driving force for literacy transformation.

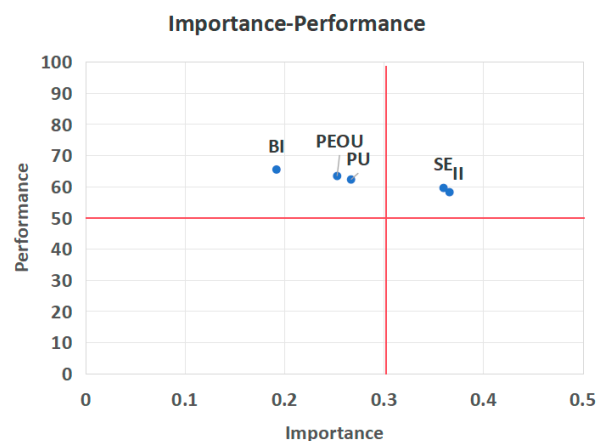


Figure 4. Importance–Performance Map. Note: The red horizontal line ($y = 50$) marks the performance-axis threshold (midpoint of the 0–100 scale), and the red vertical line ($x = 0.3$) marks the importance-axis threshold adopted in this study. The four resulting quadrants classify each antecedent variable: upper-left (high importance, low performance) indicates priority improvement areas; upper-right (high importance, high performance) indicates strengths to maintain; lower-left and lower-right indicate low-priority areas.

3.2.3. Path Analysis Results

To verify the significance of various factors influencing the enhancement of pre-service teachers' AI literacy, this study conducted a path analysis on the constructed structural equation model. The path coefficients among variables are shown in Table 11 and Figure 5. Regarding the relationships among II, SE, PEOU, PU, BI, and AI literacy, this study found that II had a direct positive effect on PEOU ($\beta = 0.265, p < 0.001$), PU ($\beta = 0.252, p < 0.001$), and AIL ($\beta = 0.22, p < 0.001$), but had no significant effect on BI ($\beta = 0.054, p = 0.165$). Regarding the relationship between SE and AI literacy, SE had a direct positive effect on PEOU ($\beta = 0.188, p < 0.001$), PU ($\beta = 0.321, p < 0.001$), BI ($\beta = 0.182, p < 0.001$), and AIL ($\beta = 0.192, p < 0.001$). Regarding the relationships among TAM core variables and AIL, PEOU had a direct positive effect on PU ($\beta = 0.163, p < 0.001$), BI ($\beta = 0.158, p < 0.001$), and AIL ($\beta = 0.18, p < 0.001$); PU had a direct positive effect on BI ($\beta = 0.205, p < 0.001$) and AIL ($\beta = 0.231, p < 0.001$); BI had a direct positive effect on AIL ($\beta = 0.191, p < 0.001$).

The path testing results showed that, among the direct effect hypotheses (H1–H5), all were supported with the exception of H1(c). Furthermore, all path effect sizes (f^2) were

relatively small (0.003–0.124), but remain meaningful in social science research [Error! Reference source not found.,Error! Reference source not found.].

Table 11. Path Coefficient Analysis Results.

Hypothesis	Path	β	p	SE	z (CR)	Conclusion	f^2	Effect Size
H1(a)	II $\rightarrow$ PEOU	0.265	0	0.035	7.61	Supported	0.07	small
H1(b)	II $\rightarrow$ PU	0.252	0	0.031	8.13	Supported	0.074	small
H1(c)	II $\rightarrow$ BI	0.054	0.165	0.039	1.39	Not supported	0.003	no
H1(d)	II $\rightarrow$ AIL	0.22	0	0.03	7.439	Supported	0.071	small
H2(a)	SE $\rightarrow$ PEOU	0.188	0	0.036	5.237	Supported	0.035	small
H2(b)	SE $\rightarrow$ PU	0.321	0	0.03	10.731	Supported	0.124	small
H2(c)	SE $\rightarrow$ BI	0.182	0	0.039	4.68	Supported	0.03	small
H2(d)	SE $\rightarrow$ AIL	0.192	0	0.032	6.064	Supported	0.052	small
H3(a)	PEOU $\rightarrow$ PU	0.163	0	0.031	5.174	Supported	0.033	small
H3(b)	PEOU $\rightarrow$ BI	0.158	0	0.037	4.294	Supported	0.026	small
H3(c)	PEOU $\rightarrow$ AIL	0.18	0	0.03	5.995	Supported	0.052	small
H4(a)	PU $\rightarrow$ BI	0.205	0	0.039	5.277	Supported	0.036	small
H4(b)	PU $\rightarrow$ AIL	0.231	0	0.034	6.82	Supported	0.069	small
H5	BI $\rightarrow$ AIL	0.191	0	0.03	6.304	Supported	0.056	small

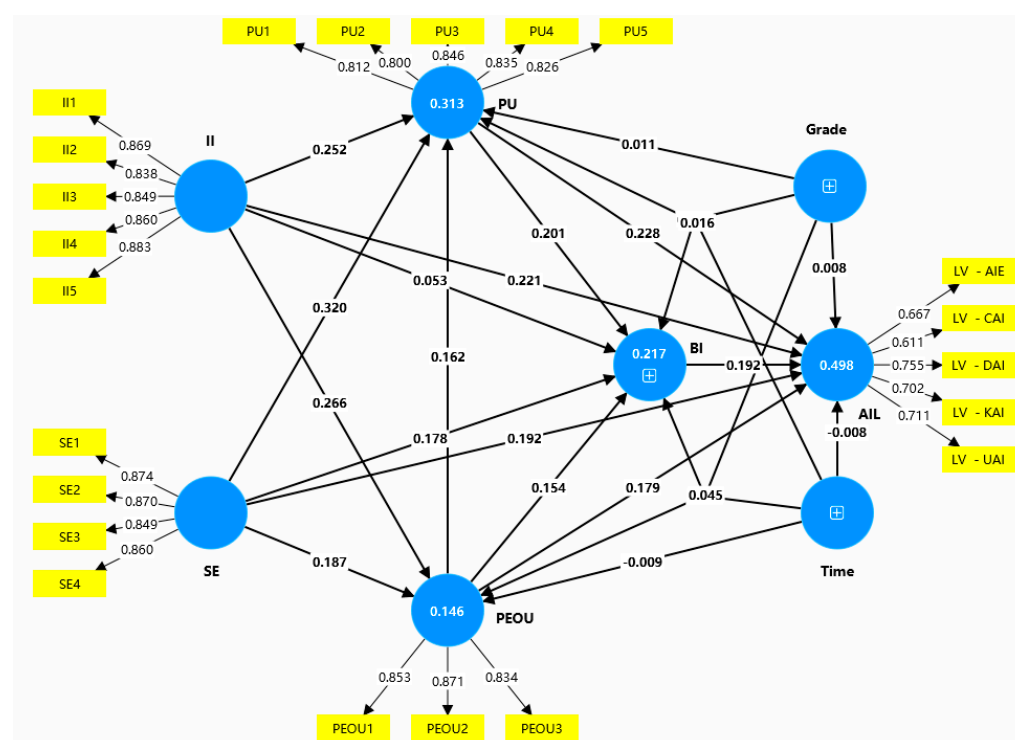


Figure 5. Result for the structural model. Note: Blue ellipses represent latent constructs (II, SE, PU, PEOU, BI, AIL) and control variables (Grade, AI exposure time); yellow rectangles represent observed indicators (e.g., II1–II5, SE1–SE4, PU1–PU5, PEOU1–PEOU3, and the AIL second-order indicators LV-AIE/CAI/DAI/KAI/UAI). Values inside the ellipses (e.g., 0.313, 0.217, 0.498, 0.146) denote the R² of the endogenous constructs. The numbers on the arrows represent path coefficients: arrows from indicators to latent variables denote loadings, while arrows between latent variables denote structural path coefficients.

3.2.4. Model Comparison

This study found that the II $\rightarrow$ BI path was non-significant ($p = 0.165$), and the non-linear effect of BI $\rightarrow$ AIL was only marginally significant ($p = 0.054$), suggesting that the

mediating role of BI may not be indispensable. This finding echoes the critical perspective put forward by existing researchers on TAM, who pointed out that TAM's treatment of BI as the endpoint of technology acceptance research overlooks the feedback effect of actual usage behavior on competency development following technology adoption [**Error! Reference source not found.**]. Consequently, the formation of competency literacy may bypass the explicit intention stage, being achieved directly through cognitive evaluation and practical iteration. It is worth noting that, given the cross-sectional nature of the data, the non-significant statistical result can only be interpreted at a theoretical level. Whether this genuinely reflects a “bypassing of the intention stage” would require longitudinal observation of the same cohort for further confirmation.

Therefore, to validate the effectiveness of the present model, this study constructed an alternative model (Model 2) and systematically compared it with the originally hypothesized model (Model 1). Model 2 omitted the BI construct, retaining only the paths through which II and SE influence AIL via PEOU and PU. Model comparison was conducted using the model comparison function in SmartPLS 4.0, evaluating predictive performance (RMSE) based on PLSpredict (10-fold cross-validation, repeated 10 times), with BIC and Akaike weights serving as model selection criteria. The comparison results are presented in Table 12.

Table 12. Model Comparison Results.

Target Construct	Index	Model 1 (Original Model)	Model 2 (Model Without BI)	Difference	Conclusion
AIL	BIC	−483.342	−447.439	$\Delta\text{BIC} = -35.90$	Model 1 is significantly better
	Akaike weight	1	0	–	Probability that Model 1 is the best model is 100%
	PLSpredict (Avg loss diff)	–	–	$0.000 (p = 0.126)$	No significant difference
PEOU	BIC	−90.26	−90.345	$\Delta\text{BIC} = +0.085$	No significant difference
PU	BIC	−253.476	−253.551	$\Delta\text{BIC} = +0.075$	No significant difference

For the core construct of AI literacy (AIL), Model 1 had a significantly lower BIC than Model 2 (difference of 35.9), with an Akaike weight of 1.00, indicating that the original model achieved a better balance between fit and parsimony. Although PLSpredict indicated no statistically significant difference in predictive power between the two models, Model 1 did not exhibit worse performance ($p > 0.05$, loss difference = 0). Taken together, these results provide empirical support for retaining the original model with BI as a mediator. For PEOU and PU, the two models performed comparably, as expected (since BI does not directly affect these two constructs). Overall, the model comparison supports the theoretical model construction of this study.

3.2.5. Mediation Effect Analysis

To thoroughly evaluate the indirect effects of the TAM on pre-service teachers' AI literacy, this study employed a bias-corrected Bootstrap method (5000 resamples) to test mediation effects, with a 95% confidence interval [**Error! Reference source not found.**]. A mediation effect was considered significant if the Bootstrap confidence interval did not contain zero. Table 13 presents the mediation analysis results in detail, revealing the mediating roles of PEOU, PU, and BI in the relationships between II, SE, and AIL. PEOU had

a significant indirect effect on the relationship between II and AIL ($\beta = 0.048$, 95% CI [0.029, 0.069], $p < 0.001$), as well as on the relationship between SE and AIL ($\beta = 0.034$, 95% CI [0.018, 0.053], $p < 0.001$). Thus, Hypothesis H6 was supported. PU had a significant indirect effect on the relationship between II and AIL ($\beta = 0.058$, 95% CI [0.037, 0.083], $p < 0.001$), on the relationship between SE and AIL ($\beta = 0.035$, 95% CI [0.018, 0.055], $p < 0.001$), and on the relationship between PEOU and BI ($\beta = 0.033$, 95% CI [0.018, 0.053], $p < 0.001$). Thus, Hypothesis H7 was supported. BI did not have a significant indirect effect on the relationship between II and AIL ($\beta = 0.010$, 95% CI [−0.004, 0.026], $p < 0.001$), but it did have a significant indirect effect on the relationship between SE and AIL ($\beta = 0.035$, 95% CI [0.018, 0.055], $p < 0.001$). Accordingly, Hypothesis H8(a) was not supported, while Hypothesis H8(b) was supported.

Furthermore, in terms of serial mediation effects, the study also found that for II, the chain paths via PEOU $\rightarrow$ PU $\rightarrow$ AIL, PEOU $\rightarrow$ BI $\rightarrow$ AIL, PU $\rightarrow$ BI $\rightarrow$ AIL, and PEOU $\rightarrow$ PU $\rightarrow$ BI $\rightarrow$ AIL were all significant (95% CI not containing zero, $p < 0.05$). For SE, the chain paths via PEOU $\rightarrow$ PU $\rightarrow$ AIL, PEOU $\rightarrow$ BI $\rightarrow$ AIL, and PU $\rightarrow$ BI $\rightarrow$ AIL were all significant (95% CI not containing zero, $p < 0.05$), but the path via PEOU $\rightarrow$ PU $\rightarrow$ BI $\rightarrow$ AIL did not reach significance (effect value = 0.001, 95% CI containing zero, $p = 0.006$). The above results indicate that II and SE not only indirectly influence AIL through the parallel mediation of PEOU and PU, but also exert indirect effects on AIL through the sequential chain path of “PEOU $\rightarrow$ PU $\rightarrow$ BI.” Moreover, the longest chain path was non-significant for SE but significant for II. This may be because individuals with high SE tend to engage in more direct action (from PEOU directly to BI or AIL) rather than going through an extended cognitive evaluation chain. These findings confirm the key mediating role of TAM core constructs between individual traits and literacy outcomes, revealing a complete transmission mechanism from psychological traits to technology cognition, to behavioral intention, and ultimately to the formation of literacy capabilities.

Table 13. Mediation Analysis Results.

Indirect Path	β	SD	T-Value	p-Value	CI (95%)	Results
Indirect effect via PEOU						
II $\rightarrow$ PEOU $\rightarrow$ AIL	0.048	0.01	4.617	0	(0.029, 0.069)	Significant mediation
SE $\rightarrow$ PEOU $\rightarrow$ AIL	0.034	0.009	3.863	0	(0.018, 0.053)	Significant mediation
Indirect effect via PU						
II $\rightarrow$ PU $\rightarrow$ AIL	0.058	0.012	5.014	0	(0.037, 0.083)	Significant mediation
SE $\rightarrow$ PU $\rightarrow$ AIL	0.074	0.013	5.845	0	(0.05, 0.1)	Significant mediation
PEOU $\rightarrow$ PU $\rightarrow$ BI	0.033	0.009	3.648	0	(0.018, 0.053)	Significant mediation
Indirect effect via BI						
II $\rightarrow$ BI $\rightarrow$ AIL	0.01	0.008	1.362	0.173	(−0.004, 0.026)	Non-significant mediation
SE $\rightarrow$ BI $\rightarrow$ AIL	0.035	0.01	3.585	0	(0.018, 0.055)	Significant mediation
Serial mediation effect						
II $\rightarrow$ PU $\rightarrow$ BI $\rightarrow$ AIL	0.01	0.003	3.686	0	(0.005, 0.016)	Significant mediation
II $\rightarrow$ PEOU $\rightarrow$ BI $\rightarrow$ AIL	0.008	0.003	3.086	0.002	(0.004, 0.014)	Significant mediation
II $\rightarrow$ PEOU $\rightarrow$ PU $\rightarrow$ AIL	0.01	0.003	3.63	0	(0.005, 0.016)	Significant mediation
II $\rightarrow$ PEOU $\rightarrow$ PU $\rightarrow$ BI $\rightarrow$ AIL	0.002	0.001	2.956	0.003	(0.001, 0.003)	Significant mediation
SE $\rightarrow$ PU $\rightarrow$ BI $\rightarrow$ AIL	0.013	0.003	3.805	0	(0.007, 0.02)	Significant mediation
SE $\rightarrow$ PEOU $\rightarrow$ BI $\rightarrow$ AIL	0.006	0.002	2.966	0.003	(0.002, 0.01)	Significant mediation
SE $\rightarrow$ PEOU $\rightarrow$ PU $\rightarrow$ AIL	0.007	0.002	3.323	0.001	(0.003, 0.012)	Significant mediation
SE $\rightarrow$ PEOU $\rightarrow$ PU $\rightarrow$ BI $\rightarrow$ AIL	0.001	0	2.758	0.006	(0, 0.002)	Non-significant mediation

Total indirect effect						
II → AIL	0.366	0.029	12.736	0	(0.311, 0.423)	Significant mediation
SE → AIL	0.360	0.023	11.321	0	(0.298, 0.415)	Significant mediation

3.2.6. Moderation Effect Testing and Control Variable Analysis

1. Moderation Effect Testing

This study tested the moderating effects of gender and major on the influence of II and SE on AIL (H9–H10). Since gender is a dichotomous categorical variable and major is a multi-categorical variable, the moderation effect test for both was conducted using multi-group analysis (MGA). Before conducting multi-group analysis (MGA) to test the moderating effects of gender and major (H9–H10), this study followed the three-step MICOM (Measurement Invariance of Composite Models) procedure to assess cross-group measurement invariance. This approach includes configural invariance, compositional invariance, and equality of means and variances. Configural invariance was confirmed by using identical model specifications, data processing, and algorithm settings (PLS-SEM, path weighting scheme, maximum iterations of 300) across groups [Error! Reference source not found.]. Compositional invariance was assessed using a permutation test (5000 random permutations). As shown in Table S3, for all constructs in the gender grouping, the original correlations (c) between the construct scores of the first and second groups were not significantly lower than 1 (i.e., the 5% quantile of the empirical distribution was below c , and the permutation test p -value > 0.05). Therefore, compositional invariance was established for all constructs. The results of the equality of means and variances test showed that for most constructs, there were no significant differences in means and variances across gender groups. However, significant differences were found for BI and Time (AI exposure time) ($p < 0.05$). According to established guidelines in measurement invariance testing, partial measurement invariance (i.e., configural and compositional invariance) is sufficient to support meaningful cross-group comparisons of path coefficients. The same analysis was conducted for the major grouping (Arts vs. Sciences); compositional invariance was established for all constructs, with similar results. Therefore, conducting MGA is appropriate.

Based on the partial measurement invariance confirmed by MICOM, this study employed the PLS-MGA method to test the moderating effects of gender and major on each core path. In SmartPLS, the total sample was divided into a male group ($n = 332$) and a female group ($n = 446$) by gender, and into an arts group ($n = 266$) and a sciences group ($n = 216$) by major. The measurement model and structural model with identical specifications were run in each group to obtain path coefficients, and PLS-MGA was used to test whether the differences in path coefficients between groups were statistically significant (a PLS-MGA p -value < 0.05 was considered significant).

As shown in Table S4(1) and S4(2), gender and major did not show significant differences between groups for any core paths (e.g., $II \rightarrow AIL$, $SE \rightarrow AIL$, $PEOU \rightarrow AIL$, $PU \rightarrow AIL$, $BI \rightarrow AIL$) (PLS-MGA $p > 0.05$). Therefore, gender and major do not play moderating roles in the model of this study, and hypotheses H9(a)(b) and H10(a)(b) are not supported.

2. Control Variable Analysis

Grade and AI exposure time were included as control variables, each pointing as a single-indicator latent variable to all endogenous latent variables (PEOU, PU, BI, AIL). The path analysis results for the control variables are shown in Table S5. Grade had a significant positive effect on BI ($\beta = 0.085$, $p = 0.009$), and AI exposure time also had a significant positive effect on BI ($\beta = 0.092$, $p = 0.005$). This means that pre-service teachers in higher grades and those with longer AI exposure time had significantly higher BI. However, the direct effects of grade and AI exposure time on PEOU, PU, and AIL were not significant ($p > 0.05$). Overall, the two control variables mainly influence BI, rather than directly affecting technology cognition or ultimate literacy. This result supports the necessity of including them as control variables in the model, while indicating that the net effects of the core independent variables on AIL are not significantly disturbed by grade or AI exposure time.

3.2.7. Nonlinearity Check

To assess the functional form of the relationships among key variables in the model, this study conducted a nonlinearity test using the quadratic term (QE) of each latent variable as the predictor and the target endogenous variable as the outcome. The test was implemented by calculating $QE(X) = X^2$ (where X is the standardized latent variable score). A significant path coefficient indicates a nonlinear effect of X on Y . The nonlinearity test results are presented in Table S6. The quadratic term path coefficient of PEOU on AIL was significantly negative ($\beta = -0.046, p = 0.045$), indicating an inverted U-shaped relationship between the two: when PEOU is low, its increase has a positive effect on AIL; however, beyond a certain threshold, further increasing PEOU may reduce AIL. In addition, the quadratic effect of Behavioral Intention (BI) on AIL approached significance ($\beta = -0.043, p = 0.054$), suggesting a similar marginally decreasing trend. The nonlinear effects for the remaining variable pairs were all non-significant ($p > 0.05$), supporting the appropriateness of the linear assumption for these relationships.

The above results indicate that, overall, the model is predominantly linear, but the relationship between PEOU and AIL exhibits nonlinear characteristics. The presence of partial nonlinearity does not undermine the credibility of the model; rather, it provides new insights into the formation mechanism of AI literacy. Specifically, a moderate level of technological challenge facilitates literacy development, whereas excessive simplification or excessive complexity may have detrimental effects. Furthermore, given the cross-sectional, self-report nature of the data, this finding suggests, from a theoretical perspective, that a moderate level of technological challenge may facilitate deeper learning, whereas excessive simplification may fail to sufficiently stimulate users' cognitive engagement. However, it should be noted that, due to the cross-sectional design, the present study cannot establish whether changes in PEOU precede changes in AIL. The exact mechanism underlying this inverted U-shaped relationship thus awaits further validation through longitudinal research.

3.3. Fuzzy-Set Qualitative Comparative Analysis

3.3.1. Theoretical Foundations of fsQCA

The PLS-SEM analysis presented above revealed the linear influence pathways of each variable on AI literacy, confirming the theoretical hypotheses proposed by this study. However, social phenomena often follow a logic of 'multiple conjunctural causation'—that is, different combinations of antecedent conditions may lead to the same outcome [Error! Reference source not found.]. This understanding has become a consensus in the methodology field. In research contexts of technology acceptance and literacy formation, an individual's behavioral intention or competence level is rarely determined by a single factor; rather, it is jointly shaped by different combinations of multiple factors.

The theoretical foundation of fsQCA lies in the principle of equifinality, which holds that the same outcome can be achieved through multiple different combinations of antecedent conditions. This principle differs fundamentally from the 'net effect' logic underlying SEM: SEM focuses on the independent contribution of a given independent variable to the dependent variable (i.e., after controlling for other variables, whether the average effect of X on Y is significant), whereas fsQCA focuses on the sufficiency of condition configurations (i.e., which combinations of conditions are sufficient to produce Y). SEM answers 'whether X affects Y ', while fsQCA answers 'which combinations of conditions can produce Y '. The former is suitable for testing linear hypotheses, while the latter is suitable for exploring multiple pathways. The two approaches address research questions at different levels and constitute complementary, rather than substitutive, relationships. In technology acceptance research, an individual's behavioral intention is not determined by

a single factor but jointly shaped by different combinations of multiple factors. For example, some teachers may adopt new technology due to high self-efficacy, while others may exhibit the same behavior due to favorable facilitating conditions and social support. Such phenomena of ‘different routes to the same destination’ cannot be captured by linear symmetric methods such as SEM, because SEM focuses on the ‘net effect’ of a single independent variable on the dependent variable, rather than how multiple condition combinations jointly produce an outcome.

In this study, the formation of AI literacy likewise follows the principle of equifinality. Pre-service teachers with different backgrounds and different traits may attain high AI literacy through different psychological pathways—some relying on high self-efficacy, some depending on high perceived usefulness and ease of use, and others benefiting from prolonged AI exposure experience. fsQCA is an effective tool for identifying these equifinal pathways, capable of revealing ‘which condition combinations’ can lead to high AI literacy, rather than merely answering ‘whether a particular factor is significant’.

In recent years, fsQCA has become an important method in the field of educational technology for exploring the influencing mechanisms of teachers’ technology adoption behavior. Existing research has employed fsQCA to identify multiple configurational pathways for science teachers’ use of virtual experiments [Error! Reference source not found.], revealed the equifinal configurations of preschool teachers’ continuous intention to use AIGC [Error! Reference source not found.], and discovered multiple antecedent configurations in the study of STEM teachers’ AI teaching innovation intentions [Error! Reference source not found.]. These studies indicate that the induction of teachers’ technology adoption intentions is a process of multi-factor configurational coupling, where a single factor generally does not possess the necessary explanatory power for the outcome. The equifinality principle is the core theoretical assumption distinguishing fsQCA from traditional linear methods.

Based on this, the present study further adopted the fsQCA method to investigate the configurational effects among variables such as IL, SE, PU, and individual characteristic information (grade level, AI exposure time), identifying multiple equifinal pathways to achieving high AI literacy. The study also examined the correlations of grade level, discipline, gender, and AI exposure and usage time with behavioral intention and AI literacy. Pearson correlation analysis showed that none of these four variables were significantly correlated with AI literacy, but all exhibited varying degrees of correlation with behavioral intention, as shown in Table 14, with grade level and AI exposure time showing more significant correlations with behavioral intention. Therefore, grade level and AI exposure time were included as antecedent variables in the subsequent fsQCA analysis [Error! Reference source not found.].

Table 14. Pearson correlation—standard format.

Variable	Grade	Major Direction	Gender	AI Exposure Time
BI	0.119 **	−0.084 *	0.085 *	0.130 **
AIL	0.055	−0.065	−0.005	0.055

Note: * $p < 0.05$, ** $p < 0.01$.

3.3.2. Selection and Calibration of Variables

First, the mean of the measurement items for each variable is calculated as the raw data for that variable [Error! Reference source not found.]. Before conducting fsQCA, raw data need to be calibrated to transform them into interpretable set concepts suitable for fsQCA analysis. Calibrated set membership scores should range between 0 and 1 [Error! Reference source not found.]. Specifically, to address the issues associated with the traditional Likert 5-point scale calibration method (using thresholds of 5, 3, and 1), which

often results in fuzzy-set membership scores of 0.5 and a concentrated distribution of raw data, we follow the standards proposed by C. C. Ragin [Error! Reference source not found.]: 5% (fully out of the set), 95% (fully in the set), and 50% (crossover point). The calibrate function in fsQCA 3.0 software was used to perform the calibration, thereby obtaining the set membership of the calibrated variables (see Table 15).

Table 15. Calibration Anchor Points for Variables.

Variable	Full Membership	Crossover Point	Full Non-Membership
PU	5	3.6	2
PEOU	5	3.667	2
BI	5	3.667	2
II	5	3	2
SE	5	3.5	1.75
AIL	4.474	3.588	2.471
Grade	5	3	1
Time	4	3	1

3.3.3. Necessity Analysis

Before constructing the truth table, it is necessary to test whether single antecedent variables constitute necessary conditions for AI literacy. According to established criteria in the fsQCA methodology [Error! Reference source not found.], antecedent variables with consistency levels above 0.9 are considered necessary conditions for the outcome variable, while coverage below 0.8 indicates weak explanatory power of a single antecedent variable for the outcome variable [Error! Reference source not found.]. In this study, to address cases where fuzzy-set membership scores equal 0.5, the method proposed by P. C. Fiss is applied, in which membership scores of 0.5 are adjusted by adding 0.001 to become 0.501 [Error! Reference source not found.].

As shown in Table 16, the consistency levels of all antecedent variables are below 0.9, and the coverage levels are below 0.8. This indicates that none of the selected variables in this study constitute a single necessary condition for AI literacy. Therefore, it is necessary to combine these antecedent variables for configuration analysis to explore their joint effects.

Table 16. Necessity Analysis of Individual Elements.

Variable	AI literacy		~AI literacy	
	Consistency	Coverage	Consistency	Coverage
PU	0.75	0.78	0.48	0.50
~PU	0.52	0.50	0.79	0.76
PEOU	0.73	0.74	0.52	0.52
~PEOU	0.54	0.53	0.75	0.73
BI	0.76	0.73	0.54	0.52
~BI	0.51	0.53	0.72	0.75
II	0.81	0.73	0.58	0.52
~II	0.47	0.52	0.70	0.78
SE	0.74	0.77	0.50	0.52
~SE	0.54	0.52	0.77	0.75
GRADE	0.56	0.66	0.54	0.63
~GRADE	0.68	0.60	0.71	0.62
TIME	0.53	0.72	0.49	0.67
~TIME	0.76	0.60	0.79	0.62

3.3.4. Analysis of Configuration Results

This study uses fsQCA 3.0 software for analysis. First, a truth table of 2^k rows is constructed, where k is the number of antecedent conditions, and each row represents a possible combination of conditions [Error! Reference source not found.]. During the fsQCA process, when the sample size is relatively large, the frequency threshold should be set above 1. In this study, the frequency threshold is set to 8, and the number of cases meeting the outcome condition should account for at least 70% [Error! Reference source not found.]. At the same time, to ensure the accuracy of the analysis results, the consistency threshold is set to 0.85. Through configuration analysis, 11 configuration results contributing to AIL are obtained, as shown in Table 17.

As shown in the table, the consistency and solution consistency of all configurations are higher than 0.8, meeting the 0.75 threshold recommended by C. C. Ragin [Error! Reference source not found.], indicating that the 11 configurations are sufficient conditions for promoting the formation of AIL. The solution coverage reaches 0.642, meaning that these 11 configurations collectively account for 64.2% of cases that contribute to AIL formation, reflecting a high degree of explanatory power. Configurations sharing the same core conditions are grouped together, resulting in the identification of four distinct training patterns that facilitate the development of AIL.

Table 17. Results of fsQCA Configuration Path Analysis.

Antecedent Conditions	AI literacy										
	High-Efficiency Practice-Oriented				High-Behavioral-Intention-Oriented			High-Innovative-Business-Oriented		Long-Term-Development-Oriented	
	S1a	S1b	S1c	S1d	S2a	S2b	S2c	S3a	S3b	S4a	S4b
PU	●	●	⊗	⊗	●		●	⊗	⊗		
PEOU			⊗	⊗	●	●	●	⊗	⊗	⊗	●
BI	●		●	⊗	●	●	●	●	●	●	●
II	●	●	⊗	●	●	●	●	●	●	●	●
SE	●	●	●	●				⊗		●	●
GRADE		⊗	●	●		●	●		●	●	⊗
TIME		⊗	⊗	●	⊗	⊗		●	●	●	●
Consistency	0.929	0.907	0.852	0.921	0.941	0.912	0.943	0.852	0.878	0.920	0.963
Original coverage	0.492	0.389	0.192	0.171	0.416	0.326	0.345	0.207	0.198	0.223	0.283
Unique coverage	0.027	0.030	0.023	0.006	0.013	0.008	0.006	0.005	0.000	0.001	0.006
Overall consistency	0.843										
Overall coverage	0.642										

Note: ⊗ indicates the absence of core conditions; • indicates that core conditions exist; ⊗ indicates that the edge condition is missing; • indicates that edge conditions exist; Blank indicates whether the condition is missing or not.

1. Mode 1: High-efficiency Practice-Oriented type. This mode includes four configurations: S1a, S1b, S1c, and S1d. SE serves as the core condition, with varying auxiliary conditions. Among them, S1a (PU * BI * II * SE) is the configuration with the largest coverage among all paths. Within this mode, regardless of the levels of PU and II, irrespective of grade or AI exposure time, and even in the absence of PEOU, high SE alone can promote the formation of AI literacy. This finding validates that SE, identified in this study as a critical factor influencing AI literacy at the theoretical level, plays an essential role in the innovation diffusion process. This path shows that for pre-service teachers who are confident in their abilities and perceive AI tools as easy to use (high PEOU) and are willing to

try them, even if their II is not high, they can effectively enhance AI literacy through active practice. This highlights the pivotal role of confidence and ease-of-use experience for the general population.

2. Mode 2: High-Behavioral-Intention-Oriented type. This mode includes three configurations: S2a, S2b, and S2c. In this mode, PEOU and BI are the core conditions, while II is a peripheral condition. In this mode, regardless of whether PU and AI exposure time are present or absent, high levels of PEOU, BI, and II can promote AI literacy. This path suggests that for pre-service teachers who will inevitably engage in the teaching profession, even if they lack confidence temporarily, maintaining a high adoption intention toward new technologies and perceiving the technology as easy to use can still lead to achieving high AI literacy.

3. Mode 3: High-Innovativeness-Oriented type. This mode includes two configurations: S3a and S3b. In this mode, II, BI, and AI exposure times are the core conditions, while PEOU and PU are absent conditions. In this mode, regardless of whether SE and grade are present or absent, as long as individuals possess high innovation quality, even if they do not perceive ease of use or usefulness, after prolonged exposure to AI, they will develop BI, thereby promoting AI literacy. According to previous findings, PLS-SEM showed that II does not directly influence AIL through BI, but fsQCA shows that II can combine with other conditions (such as long-term AI exposure) to bypass BI and influence AIL directly or through other paths. This mode addresses the verification of the non-existent “II → BI → AI literacy” path in the mediation results. This path indicates that for pre-service teachers with an inherent spirit of exploration and risk-taking, as long as they deeply perceive the value of AI for teaching and develop BI, they can achieve high AI literacy even if their SE and PEOU are moderate. In other words, high innovators may directly enter the “exploration–learning” literacy improvement cycle without necessarily going through an explicit “adoption intention” stage, which is essentially consistent with the performance of “early adopters” in IDT.

4. Mode 4: Long-Term-Development-oriented type. This mode includes two configurations: S4a and S4b. In this mode, BI, II, SE, and AI exposure times are the core conditions. Within this mode, regardless of whether PEOU, PU, and grade are present or absent, as long as individuals exhibit BI, possess high II and SE, and have long-term AI exposure, they can also promote the formation of AI literacy. This path represents an ideal state in which individuals simultaneously possess intrinsic exploration motivation, strong confidence, high recognition of value, and an effortless usage experience, thereby enabling improvement in their AI literacy level.

3.4. Preliminary Implications of Research Findings for SDG 4

The above results yield preliminary implications for teacher capacity-building under the SDG 4 (Quality Education) framework. The validation of Hypothesis H2(d) reveals that self-efficacy exerts a significant direct predictive effect on AI literacy ($\beta = 0.192$). This finding furnishes micro-level empirical evidence for the implementation of SDG 4.4 (technical and vocational skills) within teacher education: boosting pre-service teachers’ self-efficacy serves as an effective entry point to cultivate the digital competencies they require for the AI era. Furthermore, the four equifinal configuration paths identified via fsQCA further demonstrate that pre-service teachers with distinct personal traits can attain high AI literacy through diverse developmental starting points, which echoes the differentiated support principle highlighted in SDG 4.c (qualified teachers and teacher professional development).

These implications will be elaborated upon, alongside the theoretical framework, in Section 4 (Discussion).

4. Discussion of Results

This study integrated PLS-SEM and fsQCA to investigate the formation mechanism of pre-service teachers' AI literacy. PLS-SEM was employed to test model paths and mediation and moderation effects, while fsQCA was used to uncover the multiple condition combinations leading to high AI literacy. The PLS-SEM analysis supported the majority of the proposed direct and mediation hypotheses. However, among the direct effect hypotheses (H1–H5), all were supported with the exception of H1(c); among the mediation hypotheses, all were supported except H8(a); and the moderation hypotheses (H9–H10) were not supported. The six unsupported hypotheses (H1(c), H8(a), H9(a), H9(b), H10(a), and H10(b)) indicated that the proposed framework generated predictions that could be empirically falsified.

It should be noted that the data for this study were derived from pre-service teachers' self-reports, measuring perceived cognitions and attitudes rather than direct observation of actual AI usage behavior in authentic teaching practice, and not longitudinal tracking of teaching effectiveness or student development. Therefore, when extending the research findings to macro-level educational transformation and SDG-related domains, this study positions them as preliminary inferences based on the theoretical framework, rather than directly tested evidence of practical effectiveness. The following sections sequentially interpret the theoretical implications of the structural equation model and fsQCA configurational results.

A potential concern is that the predominantly positive, unidirectional hypotheses make the model difficult to falsify. We acknowledge this limitation; however, three observations may alleviate this concern. First, these hypotheses are grounded in well-established theoretical frameworks (TAM, IDT) with substantial prior empirical support, making the directional predictions theoretically reasonable rather than arbitrary. Second, the six unsupported hypotheses (including direct, mediation, and moderation paths) indicate that the model is not universally confirmed. Third, the fsQCA analysis introduced configurational complexity beyond linear positive effects, testing the model under equifinality conditions, thereby further enhancing falsifiability.

4.1. Discussion of PLS-SEM Path Coefficients Results

Based on the TAM and IDT, this study revealed multiple linear pathways underlying the formation of pre-service teachers' AI literacy.

First, II was positively associated with PEOU, PU, and AIL, but its direct effect on BI was not significant (H1(c) not supported). According to the integrated expectations of TAM-IDT, highly innovative individuals should exhibit stronger technology usage intentions. However, the research findings did not support this prediction. Two possible reasons may account for this: First, innovativeness, as a stable personality trait, may influence AI literacy by directly shaping the individual's cognitive evaluations of technology (PU, PEOU) rather than through forming explicit usage intentions. This is consistent with the mediation analysis results showing that the $II \rightarrow PEOU \rightarrow AIL$ and $II \rightarrow PU \rightarrow AIL$ paths were significant, while the $II \rightarrow BI \rightarrow AIL$ path was not [Error! Reference source not found.]. Second, pre-service teachers, being in the preparation stage of professional development, may have their technology adoption behavior more strongly driven by rational judgments of technological value rather than directly activated by personality traits. This finding delineates the theoretical boundary of the innovativeness concept in IDT: innovativeness does not indiscriminately apply to the formation of all behavioral intentions, and its effect on AI literacy requires cognitive evaluation (PU/PEOU) as a necessary mediator and cannot be reduced to a direct effect.

Second, SE significantly and positively affected all core variables (PEOU, PU, BI, AIL), with relatively large effect sizes (e.g., $SE \rightarrow PU$, $\beta = 0.321$), confirming that SE is a key

psychological resource driving AI literacy [24]. Pre-service teachers with high self-efficacy were not only more likely to perceive AI as easy to use and useful but also more inclined to form usage intentions and directly translate them into literacy.

Furthermore, it should be noted that this study, through the direct path test of BI $\rightarrow$ AIL ($\beta = 0.191$, $p < 0.001$), provided empirical support for the logic that ‘usage intention translates into literacy’. This path indicates that behavioral intention does predict the level of AI literacy. However, it must be clarified that this prediction is mediated by actual usage behavior: intention drives usage behavior, and usage behavior is the prerequisite for literacy formation. Although the effect size of BI $\rightarrow$ AIL ($f^2 = 0.056$) is small, considering that AI literacy formation is a long-term process involving cognitive, affective, and behavioral dimensions, this effect carries theoretical significance in exploratory research [Error! Reference source not found., Error! Reference source not found.]. Simultaneously, the alternative model comparison showed that removing the BI path led to a significant decline in model fit ($\Delta BIC = -35.9$), further validating the indispensability of the ‘from intention to literacy’ link [Error! Reference source not found.].

In the TAM core paths, the chain mediation of PEOU $\rightarrow$ PU $\rightarrow$ BI $\rightarrow$ AIL was established, and all direct paths (PEOU $\rightarrow$ AIL, PU $\rightarrow$ AIL, BI $\rightarrow$ AIL) were significant. This is consistent with the classic TAM but extends its explanatory boundary: technology acceptance is not only a precursor to adoption behavior but also an influencing factor for literacy formation. Notably, the direct effects of PEOU and PU on AIL ($\beta = 0.180$, 0.231) were even stronger than their effects on BI ($\beta = 0.158$, 0.205), indicating that the enhancement of pre-service teachers’ AI literacy does not completely depend on behavioral intention; it may also be realized through parallel paths of cognitive internalization and skill accumulation. This finding carries implications for teacher education: even when strong usage intentions have not yet formed, providing easy-to-use and useful AI tools can still promote AI literacy enhancement.

4.2. Discussion of Mediation Effect Results

The mediation analysis further reveals the transmission mechanism from individual traits to AI literacy. The total indirect effect of II on AIL is significant ($\beta = 0.366$), primarily through the parallel mediation of PEOU and PU, while the mediation via BI is not significant. This explains why the direct effect II $\rightarrow$ BI is not supported: highly innovative individuals bypass the “intention” stage and influence literacy directly through cognitive evaluation (PEOU, PU) [Error! Reference source not found.]. This may be because innovators focus more on the characteristics of the technology itself rather than on planned behavior.

In contrast, the total indirect effect of SE on AIL is also significant ($\beta = 0.360$), and the mediating path via BI is supported. This indicates that SE is associated with literacy both through the cognitive path (PEOU, PU) and through the motivational path (BI). The serial mediation results show that most of the full chains from II or SE through “PEOU $\rightarrow$ PU $\rightarrow$ BI $\rightarrow$ AIL” are significant, except for the path SE $\rightarrow$ PEOU $\rightarrow$ PU $\rightarrow$ BI $\rightarrow$ AIL, which is not significant. This interesting finding suggests that individuals with high SE tend to adopt more direct and efficient learning paths; i.e., they may rely on trial-and-error and adaptive learning in practice rather than on prolonged stepwise reasoning. This echoes the action-oriented characteristic of SE theory.

4.3. Discussion of Individual Characteristics Results

This study found that neither gender nor discipline significantly moderated the effects of II or SE on AIL (H9–H10 not supported). This finding delineates the applicable boundary of moderation effects. In the context of this study, the transformation pathway

from psychological traits to literacy was not systematically moderated by gender and discipline. Although previous studies have reported that male pre-service teachers tend to score higher on AI literacy scales [Error! Reference source not found.], the present study did not detect significant gender moderation effects after controlling for other variables, suggesting that gender differences may manifest more at the descriptive level than the structural pathway level. Moreover, the influence of disciplinary background in teacher education may be more pronounced at the level of pedagogy and curricular content, without producing systematic moderating effects on the relationship between psychological traits and technological cognition in the process of AI literacy formation. Notably, although H9–H10 were not supported, individual characteristics such as grade level and AI exposure time in the fsQCA analysis still influenced the formation pathways of AI literacy through combinations with other conditions, suggesting that the effects of individual characteristics may be more likely to involve complex condition combinations (configurational effects) rather than simple linear moderation.

Regarding control variables, the significant positive effects of grade level and AI exposure time on behavioral intention were consistent with existing research [41,42], reflecting that as learning stages advance and experience accumulates, pre-service teachers' willingness to adopt AI naturally strengthens. However, their direct effects on AI literacy were not significant, indicating that literacy formation depends more on the complex transmission of individual intrinsic traits (innovativeness, self-efficacy) and cognitive beliefs (usefulness, ease of use) rather than simple temporal accumulation.

4.4. Discussion of fsQCA Configurational Results

While PLS-SEM reveals average effects and mediating pathways, not all individuals follow a "typical path". The four high-AIL configuration paths identified by fsQCA confirm equifinality; in other words, multiple condition combinations can lead to the same outcome.

Path 1: High-Efficacy Practice-Oriented type. The core condition is high SE. Even when PEOU is low, high SE alone can still foster high AIL. This finding goes beyond the average effect of SE in PLS-SEM and reveals a compensatory mechanism: SE can compensate for insufficient ease of use. For confident pre-service teachers, even if a tool is not particularly user-friendly, they will actively try to use it and overcome difficulties, thereby developing literacy. This implies for teacher educators that SE can be enhanced through successful experiences, role models, etc., rather than only by lowering technology thresholds.

Path 2: High-Behavioral-Intention-Oriented type. The core conditions are high PEOU and high BI, with II as a peripheral condition. These pre-service teachers are "pragmatic adopters": as long as the technology is easy to use and they are willing to use it, they can achieve high literacy even without deeply perceiving its usefulness or being highly innovative themselves. This means that providing low-threshold, fast-feedback AI tools and fostering a positive peer usage climate can effectively activate AI literacy in this group.

Path 3: High-Innovativeness-Oriented type. The most striking finding is that high II, high BI, and long-term AI exposure can produce high AIL even when both PEOU and PU are low. This reveals a mechanism where time substitutes for cognition: long-term exposure can compensate for insufficient PEOU and PU. Highly innovative individuals have an intrinsic exploratory drive; even if they initially find the technology difficult or doubt its value, continued use builds experience through "learning by doing" and ultimately enhances literacy. This complements the PLS-SEM finding that II operates through PEOU/PU mediation, whereas fsQCA shows that when time is sufficiently long, these mediators can be bypassed.

Path 4: Long-Term-Development-Oriented type. High BI, high II, high SE, and long AI exposure work together, irrespective of PEOU/PU. This is an “ideal state” where multiple positive factors reinforce each other, representing the most robust literacy development pattern.

The overall coverage of the four paths is 0.642, indicating good explanatory power. The theoretical implication is that there is no single path to high AI literacy. Educators should diagnose which type of pre-service teachers belong to (confident practice type, pragmatic intention type, innovative exploratory type, or comprehensive balanced type) and provide differentiated support: strengthen efficacy for Path 1 group, optimize ease-of-use experience for Path 2, encourage long-term immersion for Path 3, and provide challenging tasks for Path 4. This demonstrates the practical value of the equifinality principle.

Based on the above discussion, when cultivating pre-service teachers’ AI literacy, it is essential to fully recognize the differences across groups in their behavioral intention to adopt AI, and to pay close attention to the relationship between individual internal traits, psychological drivers and AI literacy, so as to form differentiated, tiered cultivation paths and support systems.

4.5. Discussion of the TAM-IDT Model

The TAM-IDT integration rests on a single complementarity: TAM explains how cognitive appraisals shape intention, whereas IDT explains why individuals differ in their readiness to engage with new technologies. Together with the experiential-learning mechanism, they form the chain: ‘psychological traits → technological cognition → behavioral intention → usage practice → literacy enhancement’. The empirical results of this study further confirm three falsification mechanisms of the model. First, the existence of unsupported theoretical paths. The II → BI path ($\beta = 0.054$, $p = 0.165$) and the indirect effect of II → BI → AIL were not significant, contradicting the TAM-IDT expectation. Second, the presence of nonlinear relationships. The inverted U-shaped relationship between PEOU and AIL ($\beta = -0.046$, $p = 0.045$) indicates that the model allows for non-monotonic relationships. Third, the comparison with alternative models. Data rejected the competing hypothesis that BI is a redundant variable. The above three lines of evidence collectively demonstrate that the model in this study possesses falsifiability and is not merely a theoretical framework that can only be confirmed.

In sum, the TAM-IDT integration, extended with SE and the experiential-learning mechanism, makes three distinct contributions to the literature on AI literacy in teacher education. First, it specifies the psychological antecedents of technology acceptance—II from IDT and SE from social cognitive theory—which TAM treats as external variables without theoretical elaboration. Second, it extends the temporal horizon of TAM from behavioral intention to sustained usage and capability formation. Third, it introduces the falsifiability criterion as a benchmark for integration models, demonstrating that the framework not only fits the data but also permits—and indeed identifies—empirical conditions that would disconfirm it. This responsiveness to disconfirmation distinguishes the present model from purely descriptive or post hoc frameworks.

The model’s applicability, however, is conditioned on several boundary assumptions. The hypothesized chain from traits to literacy presumes that (a) users have adequate access to AI tools, (b) the usage context involves sufficient complexity to elicit effortful engagement, and (c) the individual—rather than organizational or institutional—factors are the primary determinants of literacy formation. In contexts where access is restricted, where AI is used only for routine tasks, or where institutional mandates override individual choice, the predictive power of the model may be attenuated. These boundary conditions should be borne in mind when generalizing the findings to other populations or settings.

4.6. Implications for Teacher Capacity-Building Under SDG 4

The findings of this study carry three conceptual implications for teacher capacity-building within the SDG 4 framework. Because the data are cross-sectional and perceptual, these implications are theoretical inferences rather than direct evidence of policy effectiveness.

First, relevance to SDG Target 4.4 (Technical and Vocational Skills). The serial mediation path of PU and PEOU through BI influencing AI literacy formation indicates that enhancing pre-service teachers' perception of AI technology's value and usage experience is an actionable pathway for developing their digital technology competencies. SDG 4.4 requires ensuring that youth and adults acquire technical and vocational skills for employment and entrepreneurship, and the mediating mechanisms revealed by this study show that improving pre-service teachers' perceived value and ease of use of AI technology constitutes a concrete pathway for cultivating their digital technology competencies. By optimizing the AI tool application experience in teacher education curricula, future teachers' mastery of the technical capabilities required for AI-integrated teaching can be effectively promoted, providing a micro-level operationalized pathway for the implementation of SDG 4.4 at the teacher education level. This implies that cultivating pre-service teachers' AI literacy cannot rely solely on technical operation training; it also requires enhancing their perception of technological value. This finding suggests that teacher capacity-building should attend not only to the technical skills of 'learning to use' but also to the value cognition of 'understanding why to use'. The former corresponds to the technical skills requirement of SDG 4.4, while the latter points to deeper reflective capacity and critical technology literacy, providing a more operationalized refinement direction for the implementation of SDG 4.4 at the teacher education level—namely, interventions at the perceptual level are equally critical as technical training.

Second, relevance to SDG Target 4.c (Teacher Professional Development). The four equifinal pathways identified by fsQCA indicate that teachers with different traits can achieve high AI literacy through different starting points. This finding corresponds to the combined objectives of SDG 4.4 and SDG 4.c: pre-service teachers with different characteristics can attain high AI literacy through different condition combinations, indicating that teacher training should transcend the 'one-size-fits-all' model. The SDG 4 framework emphasizes inclusiveness and equity, and the four equifinal pathways revealed by this study suggest that AI literacy development can be achieved through multiple starting points, providing development pathways suited to the traits of pre-service teachers from diverse backgrounds, thereby helping to reduce educational inequality arising from technology anxiety, resource disparities, or cognitive gaps—consistent with the equity principle of SDG 4.

In addition, this study found that BI exerts a significant direct positive effect on AI literacy, and this effect is not entirely dependent on the mediation of PU and PEOU. This finding directly corresponds to SDG 4.c (increasing the supply of qualified teachers and teacher professional development). SDG 4.c requires enhancing education quality through teacher training, and the 'innovativeness trait → literacy formation' pathway revealed by this study suggests that teacher education institutions, in the process of AI literacy cultivation, should attend to identifying pre-service teacher cohorts with high innovativeness tendencies and provide them with differentiated expansive learning opportunities, rather than relying solely on standardized technical training courses. This finding provides micro-level empirical evidence for the SDG 4.c principle of 'providing differentiated support according to teachers' different needs and backgrounds', demonstrating that teacher professional development should match corresponding cultivation strategies to different types of teachers (innovation-driven, efficacy-driven, intention-driven, and balanced-development types).

Third, relevance to SDG Target 4.7 (Education for Sustainable Development). The ‘cognition → intention → usage → competence’ layered transformation framework revealed by the TAM-IDT integrated model explains how AI literacy gradually precipitates from the perceptual level into stable competence. This provides theoretical support for a sustainable cultivation mechanism of ‘learning for application’ in teacher education—indicating that teacher professional development should not remain at the level of one-off technical training but should construct an institutional environment of ‘sustained practice’ to enable true internalization of competencies.

It must be emphasized that the above implications are based on pre-service teachers’ self-report data and constitute theoretical inferences rather than direct measurement of teaching practice or student achievement. Future research should incorporate teaching practice records and student outcome data to further examine their actual transformation in educational effectiveness.

5. Conclusions and Implications

5.1. Conclusions

By integrating TAM and IDT, this study constructed and validated a theoretical model explaining the formation mechanism of AI literacy among pre-service teachers. The PLS-SEM analysis confirmed that II and SE exert significant positive effects on AI literacy through the mediating roles of PU and PEOU, and ultimately through BI. The model comparison results also demonstrated that the original model including BI as a mediating variable was significantly superior to the competing model that omitted BI in terms of both BIC and Akaike weights ($\Delta\text{BIC} = -35.9$), supporting the theoretical necessity of BI as a mediator. The fsQCA analysis further revealed four configuration pathways: “High-Efficacy Practice-Oriented”, “High-Behavioral-Intention-Oriented”, “High-Innovativeness-Oriented”, and “Long-Term Development-Oriented”. These findings demonstrate that the enhancement of AI literacy is not a single linear process, but involves multiple equivalent causal combinations, providing a basis for differentiated and precise cultivation strategies, and offering important implications for achieving the SDGs.

5.2. Theoretical Implications

This study transcended the limitations of a single theoretical perspective by organically integrating the micro-level TAM with the macro-level IDT, constructing a complete theoretical chain of ‘individual traits → technological cognition → behavioral intention → competence outcomes’, and achieving for the first time an integrated analysis of psychological cognitive mechanisms and innovation diffusion patterns in research on pre-service teachers’ AI literacy. The specific contributions are reflected in the following three aspects.

First, this study constructed and validated a TAM-IDT integrated “dual-pathway serial mediation” model. Previous research either adopted TAM alone, focusing on the influence of cognitive beliefs on adoption intention, or adopted IDT alone, exploring innovation attributes and adopter categories; few studies have integrated the two while simultaneously incorporating both individual traits (II) and psychological dynamics (SE) as antecedent variables. This study found that II and SE not only significantly predict AIL, but also indirectly influence AI literacy through serial mediators such as PU, PEOU, and BI. This finding reveals a complete psychological transmission chain from “individual traits” to “cognitive evaluation” and then to “behavioral intention and competence outcomes”, transcending the limitation of traditional TAM, which focuses solely on ‘belief → intention’.

In addition, the non-significance of H1(c) ($II \rightarrow BI$) indicated that the concept of innovativeness in IDT has boundary conditions for predicting behavioral intention: the effect of innovativeness on competence formation requires cognitive evaluation (PU/PEOU) as a necessary mediator, rather than directly driving intention. The non-significance of H9–H10 (moderating effects of gender and discipline) indicated that, in the context of this study, the core mechanism of transforming psychological traits into AI literacy exhibits stability across gender and discipline, with its applicable boundaries manifesting more at the level of individual psychological traits than demographic characteristics. Together, these results delineate the theoretical boundaries of the integrated model: the TAM-IDT model is applicable for explaining the pathways through which psychological traits influence literacy via technological cognition but has limitations in explaining the direct pathway from personality traits to behavioral intention and the moderating role of demographic characteristics. This boundary identification constitutes an important component of the theoretical contribution of this study.

Second, the study revealed the differentiated mechanisms through which II and SE operate in AI literacy formation. The mediation effect analysis showed that II primarily influences AIL indirectly through PEOU ($\beta = 0.266$) and PU ($\beta = 0.252$), whereas SE simultaneously operates through three pathways: PU ($\beta = 0.318$), PEOU ($\beta = 0.185$), and BI ($\beta = 0.240$). This indicates that II primarily drives the individuals' exploration and acceptance of the technology itself (high-innovation-quality orientation), while SE more comprehensively supports the entire process from cognitive evaluation to behavioral implementation (high-efficacy practice orientation). This finding provides a new theoretical explanation for understanding how different psychological traits differentially shape technology acceptance and literacy formation.

Third, the study established 'AI Literacy' as the ultimate outcome variable, extending the application boundary of TAM. Classic TAM typically takes 'behavioral intention' or 'usage behavior' as the endpoint, whereas this study positioned AI literacy—a multidimensional competence construct—as the ultimate outcome variable, drawing on established frameworks from international organizations and the prior literature. It was operationalized into five dimensions: Using and Applying AI, Knowing and Understanding AI, Detecting AI, AI Ethics, and Create AI [13,53]. This design achieved a theoretical leap from 'technology adoption' research to 'literacy formation' research. This also corroborates an important theoretical positioning of this study: TAM explains the decision-making process of 'whether one is willing to use AI', while the formation of AI literacy depends on 'sustained usage and reflection in practice'. It is worth emphasizing that the significance of the $BI \rightarrow AIL$ path indicates only a correlation between intention and literacy, not equivalence. This correlation requires actual usage practice as a necessary mediator: TAM explains the decision process of 'whether one is willing to use', and literacy formation depends on 'sustained usage and reflection in practice'. The two are connected by an indirect transformation process mediated by actual usage behavior. Behavioral intention serves to 'initiate' usage behavior, while literacy formation depends on the 'quality' and 'sustainability' of that behavior. Therefore, the PU/PEOU/BI $\rightarrow$ AIL pathways revealed by this study should be understood as an indirect association: positive attitudes contribute to promoting behavior, and behavior, when conditions are met, may precipitate into literacy.

5.3. Practical Implications

In terms of research methods, this study adopts a mixed-methods approach integrating "PLS-SEM + fsQCA". PLS-SEM excels at testing linear relationships and net effects among variables, revealing the symmetrical mechanism of "how independent variables affect dependent variables"; while fsQCA excels at exploring the complex combinatorial

effects of multiple antecedent conditions, revealing the asymmetrical mechanism of “which condition combinations can lead to the same outcome”. The two complement each other, enabling a “bifocal perspective” on the research problem. Moreover, through Bootstrap mediation effect testing, this study verifies the mediating roles of PU, PEOU, and BI. This finding accurately depicts the micro-mechanism through which psychological traits are transmitted step by step to ultimately shape literacy, addressing the limitation of previous studies that treated the mediation process as a “black box”.

In terms of research findings, this study proposes differentiated cultivation pathways for enhancing AI literacy among different groups of pre-service teachers based on the four types of typical group characteristics identified by fsQCA: for the “High-Efficacy Practice-Oriented” group, provide low-threshold, high-success-rate practical scaffolds to reinforce successful experiences; for the “High-Behavioral-Intention-Oriented” group, facilitate the transformation from “intention” to “ability” while preventing frustration; for the “High-Innovativeness-Oriented” group, offer high-level challenges and innovation platforms to leverage their leading role; for the “Long-Term Development-Oriented” group, build a collaborative education ecosystem to achieve systematic integration of multiple positive factors. This “teaching according to aptitude” cultivation framework provides practical guidance for universities to move beyond the traditional “one-size-fits-all” technical training model toward personalized and targeted AI literacy cultivation.

5.4. Implications for Teacher Capacity-Building Toward SDG 4

UNESCO [Error! Reference source not found.] has pointed out that teacher training is the critical lever for ensuring responsible, ethical, and inclusive integration of AI in education. As core actors in educational transformation, teachers’ AI literacy enhancement is directly related to the improvement of education quality and the strengthening of equity in the digital era. By revealing the formation mechanism of pre-service teachers’ AI literacy, this study provides potential cultivation pathway references for the realization of SDG 4 (Quality Education). Specifically, the findings carry implications at the level of three sub-targets.

First, correspondence with SDG Target 4.4 (Technical and Vocational Skills). This study found that PU and PEOU influence AI literacy formation through the serial mediation of BI. The psychological antecedents (innovativeness and self-efficacy) revealed by H1(d) and H2(d) provide concrete pathways for how teacher education curricula can cultivate the digital competencies required in the AI era. This finding indicates that the implementation of SDG 4.4 at the teacher education level requires not only attention to the technical skills training of ‘learning to use’ but also to the value cognition cultivation of ‘understanding why to use’. Teacher education institutions should enhance future teachers’ technological readiness by improving their perception of AI technology’s practical value and lowering usage barriers, enabling them to possess the digital competencies required in AI-integrated work environments.

Second, correspondence with SDG Target 4.c (Teacher Professional Development). This study identified four equifinal differentiated cultivation pathways, demonstrating that pre-service teachers with different traits can achieve high AI literacy through multiple starting points. The ‘intention → competence’ transformation chain verified by H5 indicates that teacher training should transcend one-off technical operation training and shift toward a cyclical cultivation model of ‘sustained use–reflection–competence enhancement’. This finding provides empirical evidence for the SDG 4.c principle of ‘providing differentiated support according to teachers’ different needs and backgrounds,’ demonstrating that teacher professional development should transcend standardized ‘one-size-fits-all’ training models and match corresponding cultivation strategies to different types of teachers.

Third, correspondence with SDG Target 4.7 (Education for Sustainable Development). The ‘cognition→intention→usage→competence’ layered transformation framework constructed by the TAM-IDT integrated model in this study provides theoretical support for a sustainable cultivation mechanism of ‘learning for application’ in teacher education, indicating that teacher professional development should construct an institutional environment of ‘sustained practice’ to enable AI literacy to gradually precipitate from the cognitive level into stable competence.

In addition, the findings of this study also carry potential reference value for SDG 9 (Industry, Innovation, and Infrastructure) and SDG 10 (Reduced Inequalities). As an important component of digital infrastructure, the effective application of AI technology depends on human capital with corresponding literacy. By enhancing pre-service teachers’ AI literacy, this study provides talent support for the construction of innovative infrastructure in the education system. Simultaneously, differentiated cultivation pathways can help pre-service teachers from different starting points (e.g., those with low confidence but high innovativeness, or those with strong intentions but weak skills) find suitable development paths, which contributes to reducing educational inequality arising from technology anxiety, resource scarcity, or cognitive disparities.

In summary, this study not only provides a theoretical foundation and a practical framework for cultivating pre-service teachers’ AI literacy, but also offers preliminary cognitive-level validation of the educational objectives outlined in the 2030 Agenda for Sustainable Development from the perspectives of educational equity, quality improvement, and innovation-driven development. Future education policy makers should integrate teacher AI literacy training into national education digitalization strategies and prioritize stratified, targeted intervention measures to ensure that technological progress benefits more teachers and students, ultimately realizing an inclusive, equitable, and sustainable educational future.

It should be noted that the aforementioned insights are based on self-reported data from pre-service teachers and represent theoretical inferences. To directly validate their practical effectiveness, longitudinal research designs incorporating objective outcome metrics are required. Future studies should integrate teaching practice records with student performance data to further assess how these findings translate into actual educational outcomes.

6. Limitations and Future Research

Although this study provides valuable findings, several limitations remain, which also point to directions for future research.

First, limitations regarding data sources. This study adopted a cross-sectional design, with all variables measured at a single time point through self-report instruments. Path coefficients represent statistical associations rather than causal effects; AI literacy formation involves multi-stage evolution, and a single survey cannot capture dynamic processes. Although using BI as a proxy for actual usage behavior has methodological precedent [Error! Reference source not found., Error! Reference source not found.], it still cannot fully test the sequential chain of ‘intention→usage→literacy’. At the same time, self-report data may be susceptible to social desirability bias, and discrepancies may exist between self-perceived AI literacy and actual competence. Future research should adopt longitudinal tracking designs and incorporate objective measurements of actual usage behavior (e.g., system logs, behavioral frequency records), and introduce multi-source data (e.g., peer evaluations, expert reviews) to reduce the limitations of self-report data.

Second, limitations regarding measurement scope. This study adopted a broad definition of AI exposure time (encompassing recommendation algorithms, voice assistants,

and generative AI), which helped capture diverse exposure experiences but may introduce subjective bias due to individual differences in understanding ‘AI’. In addition, broader contextual factors (institutional support policies, curriculum design, technological conditions of practicum schools, peer influence, and sociocultural attitudes) were not included in the measurement; these external factors may independently or synergistically influence AI literacy formation. Future research could employ more refined questionnaires (measuring exposure frequency and duration separately by technology type) or combine device log data for cross-validation; simultaneously, multilevel models (e.g., HLM, or multilevel SEM) should be constructed to incorporate both individual and contextual variables.

Third, limitations regarding sample scope. This study employed convenience sampling, with the sample primarily drawn from teacher education institutions within the researchers’ reach and from urban or suburban areas; pre-service teachers from rural or remote teacher education institutions were underrepresented. Furthermore, the sample was drawn solely from China; cross-cultural differences in technology adoption patterns, educational philosophies, and AI attitudes may influence the formation mechanisms of AI literacy (e.g., collectivist cultures may amplify peer influence, while individualist cultures may emphasize individual innovativeness to a greater extent). The generalizability of the findings should be limited to pre-service teacher populations with characteristics similar to the sample. Future research could adopt stratified random sampling or nationally representative surveys and conduct cross-cultural comparative studies to test the robustness of the model across different cultural backgrounds.

Fourth, limitations regarding the scope of conclusions. The AI literacy measurement was confined to the self-report cognitive level, and the SDG contributions were theoretical inferences. The AI literacy scale employed in this study measured participants’ perception of their own abilities rather than objective competence assessment. This implies that dimensions such as affect, behavioral tendencies, and ethical judgment were not fully covered. Consequently, the implications of this study for SDG 4 and other goals are primarily reflected in the level of theoretical framework construction and variable relationship identification rather than direct verification of practical effectiveness. Future research could adopt objective performance assessments (e.g., AI tool operational tests, teaching case reviews) or combine classroom observations, teaching portfolio analysis, and learning outcome assessments to verify the external validity of self-report conclusions and further examine the actual transformation pathways from AI literacy cultivation to educational practice.

In conclusion, enhancing pre-service teachers’ AI literacy is a foundational endeavor for addressing the educational challenges of the intelligent era and cultivating future innovative talent. This effort requires transcending the mindset of single-focus technical training and proceeding with systematic design and targeted intervention from multiple dimensions, including psychological cognition, behavioral shaping, and environmental support. This study provides an empirically grounded theoretical framework, with the aspiration of contributing to the cultivation of teachers capable of meeting the educational demands of sustainable development in the future. Future research building on these findings can further deepen our understanding and provide evidence-based practice guidance for AI literacy cultivation.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su18147206/s1>, Table S1: Questionnaire questions corresponding to potential variables; Table S2: The squares of the substantive factor loadings and the squares of the common method factor loadings for all items; Table S3(1): MICOM Results for Gender Groups (Core Constructs); Table S3(2): MICOM Results for Major Groups (Core Constructs); Table

S4(1). Multi-Group Comparison Results—Gender; Table S4(2). Multi-Group Comparison Results—Major; Table S5. Path Analysis Results of Control Variables; Table S6. Results of Nonlinearity Test.

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Institutional Review Board Statement: According to Article 32 of the “Measures for Ethical Review of Human Life Science and Medical Research” (Order No.4 of 2023) issued by the People’s Republic of China, studies utilizing anonymized data, causing no harm to subjects, and not involving sensitive personal information or commercial interests may be exempt from comprehensive ethical review. These Measures were jointly promulgated by the National Health Commission, the Ministry of Education, the Ministry of Science and Technology, and the National Administration of Traditional Chinese Medicine. Therefore, this study does not require ethical approval; relevant details are provided in Section 2.2.4 of the paper. The official policy document is available at the following link: https://www.gov.cn/zhengce/zhengceku/2023-02/28/content_5743658.htm (accessed on 15 October 2025). We sincerely appreciate your time and attention.

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Abbreviations

The following abbreviations are used in this manuscript:

TAM	Technology Acceptance Model
IDT	Innovation Diffusion Theory
AIL	AI Literacy
KAI	Know and Understand AI
UAI	Use and Apply AI
CAI	Create AI
DAI	Detect AI
AIE	AI ethics
II	Individual Innovativeness
SE	Self-Efficacy
PEOU	Perceived Ease of Use
PU	Perceived Usefulness
BI	Behavioral Intention
PLS-SEM	Partial Least Squares Structural Equation Modeling
fsQCA	Fuzzy-Set Qualitative Comparative Analysis

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