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Research on Sustainable Pathways for Pre-service Teachers' AI Literacy Based on the TAM-IDT Integrated Model

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Abstract

With the deep integration of artificial intelligence (AI) into education, AI literacy has emerged as a core competency indispensable for pre-service teachers. However, the formation mechanisms and sustainable cultivation pathways remain underexplored. This study integrates the Technology Acceptance Model (TAM) and the Innovation Diffusion Theory (IDT) to construct a theoretical model where Individual Innovations (II) and Self-Efficacy (SE) serve as antecedents, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) as mediators, Behavior Intention (BI) as a proximal variable, and AI literacy (AIL) as the outcome variable. Through a questionnaire survey of 778 pre-service teachers, mixed empirical tests were conducted using Structural Equation Modeling (SEM) and fuzzy-set Qualitative Comparative Analysis (fsQCA). SEM results indicate that II and SE significantly and positively influence AIL through a chain mediation involving PE, PEOU, and BI. fsQCA further identifies four convergent high-AIL configurational pathways: "High-efficacy-practice-oriented" "High-adoption-intention-oriented" "High-innovative-qualities-oriented" and "Balanced-development-oriented". The study reveals that enhancing pre-service teachers' AIL involves diverse yet equivalent mechanisms, necessitating a shift beyond singular training paradigms. Based on these findings, the research proposes differentiated cultivation pathways, providing both theoretical foundations and practical references for teacher-training institutions to implement precise and sustainable AIL development.

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

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1. Introduction

In recent years, new generation information technologies represented by ChatGPT have penetrated education with unprecedented depth and breadth. AI technology is fundamentally reshaping the form, structure, and environment of education[1], moving towards a sustainable multidimensional revolution[2], and building the future of a sustainable education system[3]. Against this rapidly evolving landscape, AI literacy (AIL) has risen from an additional skill to a core key competency essential for pre-service teachers. In June 2024, Digital Promise (U.S.) released a comprehensive AIL Framework, while UNESCO concurrently published domain-specific AI competency frameworks for both students and educators [4,5]. This makes the cultivation of AIL for teachers, especially future pre-service teachers, increasingly important and urgent[6]. Pre-service teachers have a dual identity, being both learners of current education and the main force of future education. Their AIL is not only related to personal career development, but also affects the application of technology empowerment in future education[7]. Rather than awaiting passive adaptation to AI-driven change, proactive capacity-building is imperative. Therefore, building a paradigm for cultivating AIL among pre-service teachers in the digital age and cultivating future teachers with high-level AIL has become the core task of promoting the digital transformation of education and addressing the challenges of education in the intelligent age.

Currently, AI-driven intelligent education has entered a fast track, with research primarily focusing on three key areas. First, there is theoretical exploration and construction regarding the connotation, framework, and evaluation criteria of teachers' AIL. For instance, Long et al. (2023) proposed 17 AIL competencies[8], while UNESCO suggested a teacher AI capability framework encompassing five core competencies: humanistic AI concepts, AI ethical awareness, AI foundational knowledge, AI instructional capabilities, and AI professional development[5]. From an educational ecology perspective; Di Wu et al. (2024) identified core elements across three dimensions—technology, pedagogy, and culture—that influence teachers' behavioral intentions in using AI within AI-enabled environments[9]. Second, attention is directed toward the current status, challenges, and strategies of AI training for in-service teachers. Presently, teachers' acceptance of AI tools remains a critical factor affecting the quality of educational reform[10]. Although educators widely recognize AI's transformative potential in education, practical implementation still faces certain difficulties and obstacles[11]. Third, research examines application models and effectiveness of AI technologies in specific subject teaching. Such studies primarily showcase practical cases in scenarios like AI buddy support, AI intelligent assessment, and AI virtual experiments[12], validating AI's role in enhancing teaching or learning efficiency and outcomes[13].

However, existing theories and practices have shown insufficient attention to the special group of pre-service teachers, and the cultivation of AIL among pre-service teachers still faces many challenges. Firstly, AI training content tends to be fragmented and technological. Current teacher AI training often focuses on introducing individual AI tools or specific technologies, such as how to use an AI writing assistant, how to operate a learning platform, etc., while ignoring the overall role of AI technology in the education ecosystem and its integration with other educational concepts and teaching methods[14]. Secondly, the cultivation process lacks effective psychological and behavioral intervention mechanisms. Research has shown that pre-service teachers generally have "skill anxiety" and "role conflict" towards AI technology, fearing that the technology is too complex to master and that excessive application of technology will weaken the educational value of teachers[15]. The existing training models often adopt "knowledge imparting" and "skill training", which fail to effectively address and reverse these deep psychological cognition, resulting in superficial cultivation effects. Finally, there are issues with the lack of subjectivity, insufficient practical fields, and tool barriers in the evaluation of cultivation[16]. The evaluation of pre-service teachers' AIL has not been embedded into their practical activities such as educational internships, internships, or micro teaching, resulting in a "two skin" relationship between literacy cultivation and teaching practice, which cannot accurately assess and promote their ability to creatively use AI to solve teaching problems in complex situations.

In this context, to systematically explore the formation and improvement mechanism of AIL among pre-service teachers, this study introduces and integrates two classic theoretical frameworks: the Technology Acceptance Model (TAM) and the Innovation Diffusion Theory (IDT). The TAM model focuses on individuals' perceived usefulness (PU) and perceived ease of use (PEOU) of technology, and is the core cognitive model that explains their intention to adopt technology. The Innovation Diffusion Theory (IDT) reveals the pattern of new technologies spreading in communities over time, and emphasizes individual innovation (II) as a stable personality trait that is key to distinguishing different categories of adopters (such as innovators, early adopters). Highly innovative individuals are more inclined to become early adopters of innovation, willing to explore new things and have a lower threshold for perceiving technological complexity[17]. At the same time, self-efficacy (SE), as an individual's subjective judgment of whether they can successfully complete a task, is the "psychological engine" that drives the innovation decision-making process[18]. The initial experience of successful adoption can positively enhance SE, and the high SE will further stimulate continuous exploration and deep use of new technologies. At present, research has defined the connotation of AIL from the dimensions of knowledge, skills, ethics, etc. However, the acceptance of these AI by pre-service teachers and how they effectively transform them into observable AIL still need to be further explored from the perspective of internal psychological mechanisms. Beyond simply defining the components of AIL, it is equally critical to unpack the formative pathways that enable teachers to integrate these competencies into their pedagogical practices.

Therefore, this study aims to integrate the micro cognition of TAM with the macro diffusion perspective of IDT, with pre-service teachers as the research object, focusing on how II and SE affect PU and PEOU, thereby influencing individuals' BI to adopt AI, and ultimately affecting their AIL level. By combining the linear influence mechanism of SEM with the configuration path analysis of fsQCA, a theoretical model of the formation mechanism of AIL among pre-service teachers is constructed using a combination of quantitative and qualitative methods. The multiple antecedent conditions that contribute to the formation of AIL are explored, providing empirical evidence for constructing pre-service teachers' AIL cultivation path.

The main contributions of this paper can be summarized as follows:

• The TAM-IDT integration model was constructed and verified, which deepened the understanding of the formation mechanism of AI literacy;

•The hybrid research method of SEM and fsQCA is used to realize the complementary analysis of linear effect and configuration effect;

• It proposes differentiated cultivation path and system guarantee mechanism to provide an operable action framework for precision cultivation.

This article is structured as follows: Section **Error! Reference source not found.** expounds the theoretical basis and construction logic of TAM-IDT integration model and puts forward research hypotheses; Section **Error! Reference source not found.** introduces the research design of this study, including the questionnaire design and data collection process; Section **Error! Reference source not found.** presents the data analysis results of SEM and fsQCA, including the result equation model test and fuzzy set qualitative analysis; Section **Error! Reference source not found.** interprets the empirical results, derives research implications, and proposes four differentiated pathways tailored to pre-service teachers' AIL cultivation; Sections **Error! Reference source not found.** discusses the theoretical implications and thepractical implications for education; Section **Error! Reference source not found.** explores the study limitations and future research.

2. Theoretical Basis and Research Hypothesis

2.1. Theoretical Basis and Model Construction

2.1.1. Technology Acceptance Model (TAM) and Innovation Diffusion Theory (IDT)

Technology Acceptance Model (TAM), proposed by Davis, is one of the most influential theoretical models in the field of information system research. The model proposes that an individual's actual use of a new technology is directly determined by his BI, which is mainly affected by PU (the degree to which he believes that using the technology can improve his work or learning performance) and PEOU(the degree to which he believes that learning and using the technology requires effort)[19]. TAM model is widely used in the field of educational technology, which proves its good explanatory power for individual technology acceptance behavior.

Innovation diffusion theory (IDT) was proposed by Rogers. It examines the adoption of innovation (including new technology) from a macro social system communication process. The theory regards adoption as a dynamic process that spreads among members of the social system through specific communication channels over time [20]. IDT not only emphasizes that the five attributes of innovation itself, such as comparative advantage, compatibility, complexity, testability and observability, will affect the speed of its adoption, but more importantly, it identifies the persistent personality trait of II (the tendency of individuals to adopt new ideas and things earlier than others in their social system).

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This integration of TAM and IDT effectively compensates for the limitations of each single theoretical framework, forming a more systematic analysis system for technology adoption behavior. TAM's focus on individual psychological perceptions such as PU and PEOU addresses IDT's lack of in-depth exploration of the micro-level psychological mechanisms that drive adoption decisions. Meanwhile, IDT's emphasis on macro-level diffusion trajectories and user classification (innovators, early adopters, etc.) supplements TAM's neglect of group differences and dynamic diffusion processes. Together, they bridge the gap between individual adoption intention and collective diffusion patterns, enabling researchers to analyze technology adoption from both micro and macro perspectives.

2.1.2. Construction Logic of TAM-IDT Integration Model

Based on the theoretical consistency and complementarity of TAM and IDT, the study selected the core elements of the two as the basis to build the tam-idt integration model to analyze the AIL of pre-service teachers. From the perspective of TAM, whether pre-service teachers adopt AI and improve AIL is mainly affected by subjective cognitive factors such as PU, PEOUand behavior attitude; From the perspective of IDT, whether technology can achieve effective diffusion depends on its diffusion path in different social systems, audience characteristics and the perception characteristics of technology itself. Therefore, the external variables of the model are based on the elements and stages of innovation diffusion of IDT, and II, as the core of innovation diffusion elements, has become the antecedent variable affecting PU and PEOU in TAM. Research shows that pre-service teachers with innovative spirit are more likely to actively discover the potential advantages of AI technology to improve PU, and are more willing to overcome the difficulties in the initial use to reduce the requirements for PEOU [21]. In addition, SE, as another antecedent variable, is also included in this model because it is the key psychological motivation driving individual learning and action. Research shows that SE directly affects individuals' confidence in "Mastering AI", and then affects the diffusion process of innovative technology and individuals' judgment on the usefulness and ease of use of technology perception [22].

Based on the differences and correlations between TAM and IDT at the application level, the study selected the advantages of the two theoriesas the path framework for analyzing the cultivation of pre-service teachers' AIL. Although Tam can reveal the formation mechanism of individual adoption intention, it ignores the phased transformation process of technology adoption behavior and the characteristics of group differences, and it is difficult to explain the extended logic of technology from "accepted" to "continuously used [23]. Although IDT emphasizes the diffusion path and group classification, it lacks the description of the internal mechanism of individual psychological perception and behavior attitude [24]. Therefore, the research combines the advantages of the two, and constructs the analysis framework of pre-service teachers' AIL based on TAM-IDT integration model, aiming to realize the dynamic modeling of the whole process of diffusion from "cognition willingness adoption promotion". In this study, IDT's "technology adoption population classification" provides a theoretical basis for user hierarchical analysis, helps to build differentiated AIL cultivation strategies, and improves the accuracy of technology diffusion [25]; The diffusion path of IDT complements the blank of TAM model in the logic of adoption behavior promotion, provides a phased behavior explanation for pre-service teachers from awareness to continuous use of AI technology, and provides a time sequence clue for the strategy design of this study. Therefore, this study integrates individual cognitive factors and innovation technology diffusion theory, and constructs a path analysis framework that pays equal attention to both macro and micro aspects, which not only makes up for the lack of adaptability of TAM model to external complex environment, but also overcomes the limitation of IDT theory that does not pay enough attention to individual psychological decision-making process. Through the introduction of dynamic diffusion dimension and group heterogeneity analysis logic in the cultivation of pre-service teachers' AIL, the flexibility and adaptability of the integration model in practical application are enhanced.

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2.2. Research Hypothesis

2.2.1. Definition of Core Variables

Based on the perspective of integration, this study constructed a theoretical model with "II" and "SE" as the antecedents, with "PU" and "PEOU" as the mediators, with "Ai adoption intention" as the near end outcome variable, and "AIL" as the final outcome variable. The core variables are defined as follows:

(1) PU: refers to the extent to which pre-service teachers believe that the use of AI technology can improve their teaching effect, learning efficiency or professional development.

(2) PEOU: refers to the fact that pre-service teachers believe that learning and using AI technology requires less effort and the process is easier.

(3) BI: refers to the subjective tendency and behavioral intention of pre-service teachers to try to use AI technology in future teaching practice.

(4) II: refers to the intrinsic innovation characteristics that pre-service teachers tend to actively explore AI technology through individuals and are willing to adopt.

(5) SE: refers to the pre-service teachers' confidence and belief that they can successfully learn, master and apply AI technology in the teaching scene.

(6) AIL: it was first proposed by Kandlhofer, and it is believed to be the ability to understand the basic technologies and concepts behind different AI products and services [26]. Referring to relevant standards and frameworks, this study added AI ethics to the AI framework issued by the American Association for higher education informatization, including the use and application of AI, understanding and understanding of AI, creating AI, identifying AI and AI ethics.

2.2.2. Research Hypothesis

Supported by the above theoretical basis and literature review, this section builds a research model based on TAM and IDT, and accordingly puts forward the following assumptions, as shown in **Figure 1**. The research focuses on the relationship between II, SE, PU, PEOU, BI, AIL and other core variables.

1. Hypothesis of the impact of PU and PEOU on BI.

PU is the subjective judgment of individuals when accepting new technology that the technology will help to improve their learning, work efficiency or effect. PEOU is the degree to which individuals think it is easy to use new technologies. Previous studies have shown that PU and PEOU largely affect users' learning motivation and literacy improvement path for technology [19]. AIL includes not only the ability to understand AI technology, but also the ability to apply it in practical tasks [8]. In other words, when individuals think that AI tools are easy to use and valuable for their current learning or work, their literacy in understanding and understanding AI, identifying AI, and using and applying AI will be strengthened. Therefore, this study puts forward the following assumptions.

H1: PEOU has a positive impact on PU

H2: PU has a positive impact on the BI

H3: PEOU has a positive impact on the BI

2. Hypothesis of the impact of PU, PEOU and BI on AIL.

AIL is a multi-dimensional ability structure, which not only includes the identification and judgment, cognition and understanding, use and evaluation of AI technology, but also emphasizes the critical and creative application in the real teaching situation under the premise of AI ethics[27]. Tam theory usually takes "behavioral intention" as the end point of adoption, but the formation of literacy requires that behavioral intention must be transformed into continuous, in-depth and reflective practice [28]. Therefore, this study regards AIL as the final outcome variable, and believes that core cognitive beliefs (PU, PEOU) and behavioral intentions will directly or indirectly shape literacy. On the one hand, strong will to act is the premise of driving practice and exploration; On the other hand, positive practice can reverse consolidate individuals' perception and control of

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technological value, and continuously improve their literacy in this cycle. Based on this, this study puts forward the following assumptions.

H4: BI has a positive impact on AIL

H5: PU has a positive impact on AIL

H6: PEOU has a positive impact on AIL

3. Hypothesis of the impact of II on BI and AIL.

II refers to the tendency of individuals to accept new ideas, new practices or new things earlier than other members of their social system. IDT theory regards highly innovative individuals as "innovators" and "early adopters". They usually have a more open attitude towards new technologies or new things and are willing to take risks to explore [29]. Therefore, for the emerging technology of AI, highly innovative pre-service teachers are more likely to actively explore its potential teaching value, improve PEOU, and are more inclined to form and show higher AIL in the process of in-depth exploration [30]. Relevant empirical studies also support that II, as an important internal stimulus, has a significant impact on technology perception beliefs [31]. Therefore, the following assumptions are made.

H7: II has a positive impact on PU

H8: II has a positive impact on PEOU

H9: II has a positive impact on AIL

4. Hypothesis of the influence of SE on BI and AIL.

Self efficacy is the core concept of Bandura's social cognition theory, which refers to the individual's belief in their ability to organize and implement specific action plans to achieve certain achievements. By mastering experience, alternative learning, social persuasion and physiological state, pre-service teachers with high SE can strengthen the usefulness of perceived technology and reduce the barriers to technology use [32], and have greater confidence in mastering AI and applying it to teaching. This confidence will directly affect their cognitive assessment of AI, and they are more likely to believe that AI tools can be controlled and play a role by themselves. At the same time, high SE itself is the key internal driving force to drive individuals to face challenges, continue to learn and finally master AIL. Research shows that SE is an important psychological resource to adjust the barriers of technology adoption and promote skill mastery. Therefore, the following assumptions are made.

H10: SE has a positive impact on PU

H11: SE has a positive impact on PEOU

H12: SE has a positive impact on AIL

Based on the above research hypothesis, in order to further explore whether there is a combined effect of variables, individual signs and other information on AIL, the study also designed to include PEOU, PU, BI, II, SE and individual characteristics into the antecedent variables for fsQCA, and built a research model of influencing factors of pre-service teachers' BI and AIL, as shown in **Figure 1**.

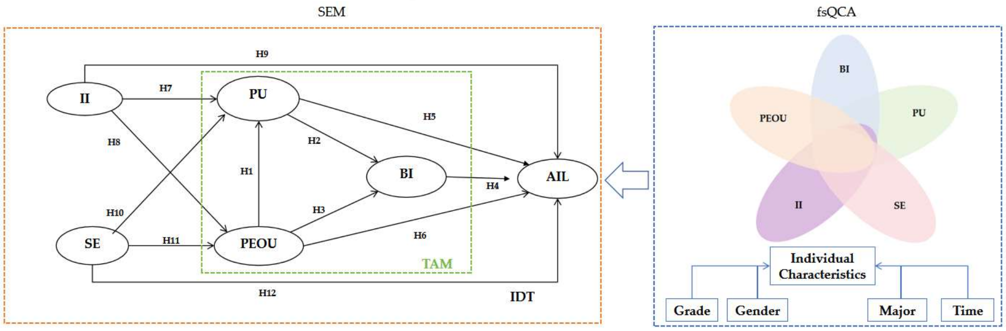

Figure 1. A hypothesized research model.

3. Materials and Methods

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3.1. Research Design

In this study, the hierarchical verification method is adopted, and the SEM and fsQCA are comprehensively used to explore the complementary mechanism of the formation of pre-service teachers' AIL. The specific research process is as follows:

1. The structural equation model is used to test the linear path and hypothesis relationship of the theoretical model. Based on Amos 24.0 software, the structural relationship among potential variables (II, SE, PU, PEOU, BI, AIL) in the TAM-IDT integration theoretical model was verified. The reliability and validity of the scale were tested by measuring the model, and the path significance and influence coefficient of the research hypothesis (H1-H12) were tested by structural model to reveal the linear influence mechanism between variables.
2. SPSS 27.0 was used for descriptive statistics, correlation analysis and mediation effect test. On the basis of SEM analysis, SPSS 27.0 was used to test the normality and common method deviation of the sample data, and the bootstrap method with deviation correction (repeated sampling for 5000 times) was used to further verify the mediating effect and confidence interval of PU, PEOU and BI behavior between II, SE and AIL, so as to lay the foundation for subsequent configuration analysis.
3. Qualitative comparative analysis of fuzzy sets is used to explore the multiple antecedents of high AIL. In view of the fact that SEM mainly tests the net effect and symmetric relationship between variables, and it is difficult to reveal the complex interaction and the same result effect between multiple antecedents, fsQCA 3.0 software is introduced in this study. On the basis of necessity analysis, the combination of sufficient conditions for high AIL of production students was identified by constructing a truth table and setting the consistency threshold (0.85) and frequency threshold (8). This method can reveal different causal paths leading to the same result, and provide an empirical basis for the formulation of differentiation cultivation strategies.

3.2. Questionnaire Design

The questionnaire is mainly composed of three parts: the first part is the demographic characteristics of respondents, including grade, major, gender and AI exposure time; The second part is the survey scale of respondents' BI, including five dimensions of II, SE, PU, PEOU and BI, with a total of 40 questions (as shown in **Table 1**); The third part is the survey scale of AIL of respondents, including 5 dimensions and 17 questions, including knowing and understanding AI, using and applying AI, creating AI, identifying AI and AI ethics. The second and third parts of the survey were measured by the Likert five scale, and 1-5 respectively indicated very inconformity, relatively inconformity, general compliance, relatively compliance and complete compliance.The specific scale items are shown in Table S1.

Table 1. Sources of Scale Items.

Questionnaire structure	Research variables	Number of items	Reference source
Behavioral intention to use AI	Self efficacy (SE)	4	Schwarzer (1995)[35]
	Perceived usefulness (PU)	5	Davis (1986,1989)[19,33]
	Perceived ease of use (PEOU)	3	Davis (1986,1989)[19,33]
	Behavior intention(BI)	3	Venkatesh et al (2003)[34]
	Individual innovation (II)	5	Williams (1979)[36]
AI literacy	Know and Understand AI (KAI)	4	Ng et al (2021)[6]
	Use and application AI (UAI)	3	Ng et al (2021)[6]
	Creating AI (CAI)	3	Ng et al (2021)[6]

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Detect AI (DAI)	4	Long & Magerkja (2020)[8]
AI ethics (AIE)	3	Ng et al (2021)[6]

1. AI behavioral intention scale

PU and PEOU refer to the TAM scale of Davis (1986, 1989) and retain the content of the original item [33]. The BI refers to the original definition of "intention to use" and "behavior to use" in Davis (1986, 1989)[19]. In this study, the BI is combined into a proximal outcome variable, which is also used as an intermediary variable to affect the final AIL. II refers to Williams' cognitive affective interaction theory's creativity emotion measurement scale [22] and sets four items, such as "in the process of teaching and training, I like to try various AI technologies", which respectively point to curiosity, adventure, challenge and imagination, and one item with innovative tendency, "I like and explore the use of new AI technologies to become friends", a total of five items. Self efficacy refers to the original definition content of schwarzer&jerusalem (1995) [37], and changes the "system" in the original item as the AI technology in this study.

2. AI Literacy Scale

The artificial intelligence Literacy Scale [38] compiled by astridcarolu et al. Is widely used in AIL research. It defines five dimensions of AIL, including knowing and undstandingAI, using and applying AI, detecting AI, creating AI, and AI ethics, with a total of 17 items. In the later study, in order to further analyze the impact of AI behavior intention on AIL, multiple secondary indicators of AIL were combined into a variable "AIL".

3.3. Reliability and Validity Test

The study used spss27.0 software for data analysis, and obtained the Cronbach 'alpha coefficient and combination reliability of 11 potential variables. According to the reliability test results, the overall Cronbach' alpha coefficient of the scale was 0.836 (greater than 0.8), indicating that the scale has good reliability. Meanwhile, the Cronbach's alpha coefficients of PU, PEOU, BI, II, SE and AIL dimensions were 0.882, 0.813, 0.773, 0.912, 0.886 and 0.819, respectively (as show in Table S2). The reliability coefficients of each sub dimension were greater than 0.7, indicating that the measurement indicators had good internal consistency and the reliability of each dimension was good. In addition, the CITC values of all items also show that each item has a good correlation with its own dimension, which further proves the validity of the scale.

And KMO value is 0.914 (greater than 0.8), Bartlett sphericity test is significant (approximate chi square value is 15106.869, degree of freedom is 666, P value is 0, significantly lower than 0.05), which further verifies that the data has sufficient correlation and is suitable for factor analysis (as shown in Table S3). These results provide a solid data foundation for the subsequent factor analysis and ensure the reliability and effectiveness of the analysis results.

3.4. Questionnaire Distribution and Recovery

This study was carried out in October 2025 in Northeast, South and Northwest China. Using purposive sampling method, pre-service teachers from various types of normal universities were invited to participate. Before the questionnaire was issued, the researchers explained the purpose of the study to the participants and collected informed consent to ensure compliance with ethical norms. Then the questionnaire was sent to the pre-service teachers who volunteered to participate in the study online.

A total of 1000 questionnaires were distributed, 815 valid questionnaires were recovered (effective rate=92.07%), and 778 valid questionnaires were recovered. See **Table 2** for the demographic data of the subjects.

Table 2. Demographic information of participants.

Variable	N	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%
AI experience (Time)	Within one year	105	13.50%
	Two years	280	35.99%
	Five years	321	41.26%
	Ten years or more	72	9.25%

4. Results

4.1. Measurement Model Inspection

4.1.1. Confirmatory Factor Analysis of mMeasurement Model

Further factor analysis found that the items of each subscale in the scale were in their components, the corresponding mean variance extraction ave values were greater than 0.5, the combined reliability CR values were greater than 0.7, and the CR values were greater than the ave values (as shown in **Table 3**), indicating that the internal consistency of the scale was stable, and the convergence validity value indicated that the items were well focused on the target construct, and the overall structure of the questionnaire was good.

Table 3. Confirmatory factor analysis results of measurement model.

variable	Number of items	Mean variance extraction ave value	Combined reliability CR value
PE	5	0.599	0.882
PEOU	3	0.592	0.813
BI	3	0.531	0.772
II	4	0.675	0.912
SE	5	0.662	0.887
AIL	5	0.579	0.82

4.1.2. Discrimination Validity of mMeasurement Model

In order to further analyze the consistency between the scale results and the research design, the study used the ave square root judgment method. As shown in **Table 4**, the ave square root value of each factor is greater than the "maximum value of the correlation coefficient between this factor and other factors", indicating that the scale design is reasonable and effective, and has good discriminant validity.

Table 4. Discriminant validity of measurement model (Pearson correlation and ave square root value).

variable	PE	PEOU	BI	II	SE	AIL
PE	0.774					
PEOU	0.338	0.77				
BI	0.362	0.292	0.728			

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II	0.428	0.336	0.263	0.822		
SE	0.46	0.286	0.34	0.38	0.814	
AIL	0.538	0.437	0.447	0.498	0.489	0.588

Note: diagonal numbers are ave square root values.

4.2. Measurement Model Inspection

4.2.1. Normality Test

The K-S test is used to test the normality of PU, PUE, BI, SE, II and AIL. From **Table 5**, it can be seen that PU, PUE, BI, SE, II and AIL are all significant ($p<0.05$), which means rejecting the original hypothesis (original hypothesis: normal distribution of data), and Pu, pue, Bi, Se, II and AIL are not normal. Combined with the fact that the absolute value of kurtosis is less than 10 and the absolute value of skewness is less than 3, it shows that although the data is not absolutely normal, it is basically acceptable for normal distribution, so the maximum likelihood method can be used for structural equation model test.

Table 5. Analysis results of normality test.

variable	sample size	average value	Standard deviation	Skewness	Kurtosis	Kolmogorov Smirnov test	Shapiro Wilk tes
PU	778	3.488	0.9	-0.161	-0.799	0.092**	0.972**
PEOU	778	3.533	0.966	-0.326	-0.723	0.134**	0.955**
BI	778	3.62	0.908	-0.406	-0.491	0.14**	0.956**
SE	778	3.382	0.952	-0.188	-0.687	0.101**	0.97**
II	778	3.327	0.906	-0.026	-0.604	0.143**	0.963**
AIL	778	3.533	0.648	-0.172	-0.909	0.068**	0.976**

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

4.2.2. Model Fitness Test

The goodness of structural equation fitting mainly includes three types of indicators, namely, absolute fitting indicators （CMIN/DF、GFI、RMR、RMSEA）, value-added fitting indicators (NFI, CFI, IFI) and reduced fitting indicators（PGFI、PNFI）. The test results show that the absolute fitting index, value-added and simple fitting index of the model have reached the excellent standard level (as shown in **Table 6**), and the model and data fit well as a whole, which can be further analyzed.

Table 6. Model fitting index.

Common indicators	χ2	df	p	χ^2/df	GFI	RMSEA	RMR	CFI	NFI
Judgment criteria	-	-	>0.05	<3	>0.9	<0.10	<0.05	>0.9	>0.9
Value	550.18	263	0	2.092	0.947	0.037	0.041	0.97	0.944
Other indicators	**NNFI**	**TLI**	**AGFI**	**IFI**	**PGFI**	**PNFI**	**PCFI**	**SRMR**	**RMSEA 90% CI**
Judgment criteria	>0.9	>0.9	>0.9	>0.9	>0.5	>0.5	>0.5	<0.1	-

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Value	0.966	0.966	0.934	0.97	0.766	0.828	0.85	0.037	0.033 ~ 0.042

Note: for defaultmodel, χ^2 (300)=9867.091, P=1.000 , AIC=122.586, BIC=411.303 .

In addition, the standardized regression coefficients between the measured variables and potential variables are greater than 0.5 except CAI (as shown in **Table 7**), indicating that the observed variables have strong explanatory power on potential variables. The CAI factor load coefficient was 0.499, although it did not reach 0.5, but $p<0.05$, and the overall model fitness index was judged comprehensively. The model fitness was good and statistically acceptable, which also showed that each variable had sufficient variance interpretation rate to show that each variable could be displayed on the same factor.

Table 7. Load factors of structural equation model.

X	→	Y	Non standardized regression coefficient	SE	Z (CR value)	p	Standardized regression coefficient
PEOU	→	PUE1	1	-	-	-	0.769
PEOU	→	PUE2	1.045	0.053	19.586	0	0.798
PEOU	→	PUE3	0.961	0.051	18.664	0	0.735
PU	→	PU1	1	-	-	-	0.757
PU	→	PU2	0.965	0.047	20.491	0	0.738
PU	→	PU3	1.042	0.046	22.535	0	0.806
PU	→	PU4	0.998	0.045	22.018	0	0.788
PU	→	PU5	1.019	0.047	21.563	0	0.773
BI	→	BI1	1	-	-	-	0.704
BI	→	BI2	1.065	0.066	16.097	0	0.755
BI	→	BI3	1.03	0.065	15.883	0	0.725
II	→	II1	1	-	-	-	0.839
II	→	II2	0.871	0.034	25.719	0	0.788
II	→	II3	0.919	0.035	26.536	0	0.804
II	→	II4	0.901	0.033	27.278	0	0.819
II	→	II5	0.951	0.033	29.21	0	0.857
SE	→	SE1	1	-	-	-	0.84
SE	→	SE2	0.925	0.035	26.274	0	0.82
SE	→	SE3	0.894	0.036	24.741	0	0.785
SE	→	SE4	0.905	0.035	25.753	0	0.808
AIL	→	AIE	0.92	0.076	12.124	0	0.543
AIL	→	CAI	0.816	0.072	11.336	0	0.499
AIL	→	DAI	1.139	0.08	14.313	0	0.685
AIL	→	KAI	0.964	0.074	12.98	0	0.595
AIL	→	UAI	1	-	-	-	0.602

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Note: → indicates regression influence relationship or measurement relationship The horizontal bar '-' indicates that this item is a reference item.

4.2.3. Research Hypothesis Test

The path test results show that most of the hypotheses proposed in the study have been verified. The standardized path coefficient and the corresponding significance level between the potential variables are shown in **Figure 2** (summary of regression coefficients for the model is shown in Table S4). The hypothesis test results are shown in Table S4. The path analysis results show that the path coefficients of all 12 research hypotheses (H1-H12) are positive and reach the significance level of 0.001, which are all supported. PEOU significantly positively affected PU (β=0.163, p<0.001). PU (β=0.297, p<0.001) and PEOU (β=0.192, p<0.001) significantly positively affected BI. BI (β=0.196, p<0.001), PU (β=0.233, p<0.001) and PEOU (β=0.182, p<0.001) significantly positively affected AIL. II significantly positively affected PU (β=0.252), PEOU (β=0.266) and AIL (β=0.221), all p<0.001. SE significantly positively affected PU (β=0.318), PEOU (β=0.185) and AIL (β=0.189), all p<0.001.

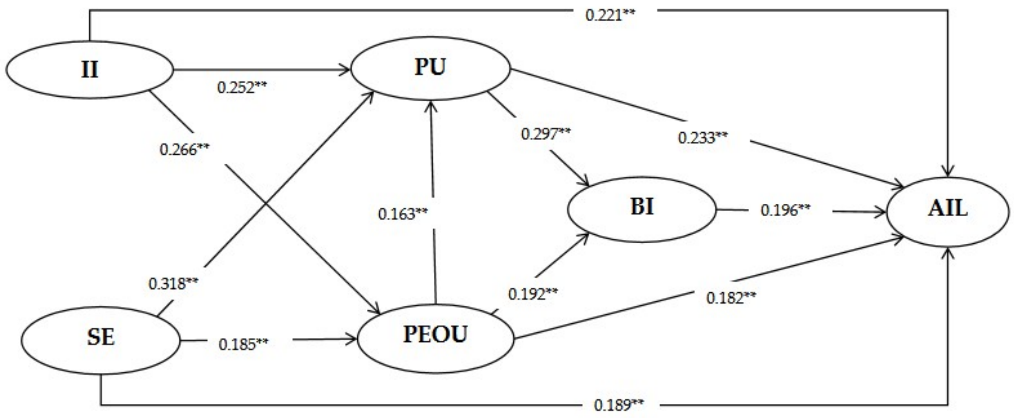

Figure 2. This is a figure. Schemes follow the same formatting.

4.2.3. Intermediary Effect Analysist

In order to further verify the mechanism of PEOU, PU, and BI in II, SE, and AIL, it is necessary to test the mediating effect of TAM. By using bias corrected bootstrap method to repeatedly sample 5000 times to test the mediating effect, the confidence is 95% [39]. It can be seen from

Table 8 that PU and PEOU play a significant parallel intermediary role between II and AIL, and between SE and AIL. BI behavior plays a significant mediating role between SE and AIL, but the mediating role between II and AIL is not significant. There is a chain mediation path from II/SE →PEOU → PU → BI → AIL.

Table 8. Indirect effect analysis.

Mediation type	Path	Effect	Boot SE	BootLL CI	BootUL CI	*z*	*p*	mediation
Parallel intermediary	**II⇒PEOU⇒AIL**	0.034	0.011	0.029	0.07	3.253	0.001	exist
	II⇒PU⇒AIL	0.042	0.011	0.037	0.083	3.72	0	exist
	II⇒BI⇒AIL	0.008	0.008	-0.004	0.028	0.999	0.318	no exist
	SE⇒PEOU⇒AIL	0.023	0.009	0.017	0.052	2.565	0.01	exist
	SE⇒PU⇒AIL	0.05	0.012	0.051	0.1	4.068	0	exist
	SE⇒BI⇒AIL	0.024	0.01	0.018	0.056	2.481	0.013	exist
	II⇒PEOU⇒PU⇒AIL	0.007	0.003	0.005	0.016	2.634	0.008	exist
	II⇒PEOU⇒BI⇒AIL	0.006	0.003	0.004	0.014	2.247	0.025	exist

	II⇒PU⇒BI⇒AIL	0.007	0.003	0.005	0.016	2.606	0.009	exist
	II⇒PEOU⇒PU⇒BI⇒AIL	0.001	0.001	0.001	0.003	2.107	0.035	exist
Chain intermediary	**SE⇒PEOU⇒PU⇒AIL**	0.005	0.002	0.003	0.011	2.281	0.023	exist
	SE⇒PEOU⇒BI⇒AIL	0.004	0.002	0.002	0.01	1.995	0.046	exist
	SE⇒PU⇒BI⇒AIL	0.009	0.003	0.007	0.02	2.586	0.01	exist
	SE⇒PEOU⇒PU⇒BI⇒AIL	0.001	0	0.001	0.002	1.871	0.061	exist
	II⇒PEOU⇒BI⇒AIL	0.006	0.003	0.004	0.014	2.247	0.025	exist
	II⇒PU⇒BI⇒AIL	0.007	0.003	0.005	0.016	2.606	0.009	exist
	II⇒PEOU⇒PU⇒BI⇒AIL	0.001	0.001	0.001	0.003	2.107	0.035	exist

4.3. Qualitative Analysis of Fuzzy Sets

The above SEM analysis results show that pre-service teachers' AIL and BI are affected by many common factors. According to the standardization coefficient between each factor is less than 0.4, indicating that the linear relationship between factors is weak. Therefore, this study uses fsQCA method to further analyze the data to explore the combination effect between variables. In addition, the study also examined the correlation between grade, major, gender, AI exposure and use time on the BI and AIL. Pearson correlation analysis showed that these four variables had no correlation on AIL, but they had different degrees of correlation on the BI, as shown in the

Table 9, and grade, AI exposure and use time had more significant correlation on the BI. Therefore, in the subsequent qualitative comparative analysis of fuzzy sets, grade, AI exposure and use time were included in the antecedent variables [40].

Table 9. Pearson correlation - standard format.

Variable	grade	major direction	gender	AI contact 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.

4.3.1. Selection and Calibration of Variables

First, take the mean value of each measurement item under each variable as the original data of each variable [41]. Before the qualitative comparative analysis of fuzzy sets, the original data should be calibrated to be converted into an interpretable set concept, so that the original data can be converted into a format suitable for fsQCA analysis. The membership of the calibrated set should be between 0-1 [42]. Specifically, in order to overcome the problem that the traditional calibration method (5, 3, 1) of likert5 scale is prone to 0.5 fuzzy set membership score and centralized distribution of original data, the calibration function of fsQCA 3.0 software is used to calibrate with reference to the standards of 5% (no membership), 95% (full membership) and 50% (intersection) proposed by C. C. ragin[43], so as to obtain the set membership of variables after calibration ,as shown in **Table 10**.

Table 10. Calibration anchor points for variables.

Variable	Full subordination	Intersection	Completely unsubordinated
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

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Grade	5	3	1
Time	4	3	1

4.3.2. Necessity Analysis

Before constructing the truth table, it is necessary to test whether a single antecedent variable constitutes a necessary condition for AIL. According to the standard of c.q.schneider[44], the consistency level of the antecedent variable higher than 0.9 is considered as a necessary condition for the result variable, while the coverage rate lower than 0.8 indicates that the explanatory power of a single antecedent variable for the result variable is weak [40]. In this study, when the membership score of a fuzzy set is 0.5, P. C. fiss' method is used to increase the membership score of 0.5 by 0.001 to 0.501[41].

As shown in **Table 11**, the consistency level of each antecedent variable is lower than 0.9 and the coverage rate is lower than 0.8, which means that the variables selected in this study do not constitute a single necessary condition for AIL. It is necessary to combine the antecedent variables for configuration analysis to explore their linkage effects.

Table 11. 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
PUE	0.73	0.74	0.52	0.52
~PUE	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

4.3.3. Analysis of Configuration Results

This study uses fsQCA 3.0 software for analysis. First, a truth table of 2K rows is constructed, where k is the number of antecedent conditions, and each row represents a possible combination of conditions [45]. In the process of fsQCA analysis, if the sample size of the study is large, the frequency threshold should be greater than 1. In this study, the frequency threshold is set to 8, and the number of cases that meet the result conditions reaches 70% [46]. At the same time, in order 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 can be obtained, as shown in

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Table 12.

It can be seen from the table that the consistency and reconciliation consistency of all configurations are higher than 0.8, meeting the 0.75 threshold recommended by C. C. Ragin[43], indicating that 11 configurations are sufficient conditions to promote the formation of AIL. The coverage rate of the solution reaches 0.642, indicating that 11 configurations can cover 64.2% of the cases that promote the formation of AIL, indicating that the interpretation degree of the combination path is high. The antecedent variable configurations with the same core conditions are classified into one category, and finally four types of training modes to promote the formation of AIL are obtained.

Table 12. fsQCA configuration path analysis results.

Antecedent conditions	AI literacy										
	High-efficiency-practice oriented				High-adoption intention-oriented			High-innovation-quality-oriented		Balanced-development -oriented	
	S1a	S1b	S1c	S1d	S2a	S2b	S2c	S3a	S3b	S4a	S4b
PU	•	•	ⓧ	ⓧ	•		•	ⓧ	ⓧ		
PUE			ⓧ	ⓧ	●	●	●	ⓧ	ⓧ	ⓧ	●
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	S1a	S1b	S1c	S1d	S2a	S2b	S2c	S3a	S3b	S4a	S4b
Overall coverage	•	•	ⓧ	ⓧ	•		•	ⓧ	ⓧ		

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", including four configurations of S1A, S1b, S1C and S1D. SE is the core condition, and its auxiliary conditions are different, and S1A (PU*BI*II*SE) is the combination with the largest coverage in all paths. In this mode, regardless of PU and II, regardless of grade and AI exposure time, even if PEOU is missing, as long as SE is high, it can promote the formation of AIL. This result confirms that the important factor affecting AIL in the theoretical level of this study is SE, which plays a vital role in the stage of innovation diffusion. This path shows that for pre-service teachers who are confident in their abilities, if they feel that AI tools are easy to use (high PEOU) and are willing to try, they can effectively improve their AIL through active practice, even if they are not innovative, which emphasizes the key role of confidence and ease of use experience for the general population.
2. Mode 2, "High-adoption intention-oriented", including three configurations S2A, S2B and S2C, in which PEOU and BI are the core conditions, and II is the marginal condition. In this mode, no matter whether the impact of PU and AI exposure time is in the missing state, as long as the PEOU, BI and II value are high, it can promote AIL. This path shows that for pre-service teachers who must engage in education in the future, even if they are not full of confidence for the time being, they can achieve high AIL as long as they maintain a high BI to adopt new technologies and perceive the ease of use of technologies.
3. Mode 3, "High-innovation-quality-oriented",including two configurations S3a and S3b, in which the II, BI and time to contact AI are the core conditions, and PEOU and PU are the missing conditions. In this mode, no matter whether the SE and grade are missing, as long as the individual has high innovation quality, even if the individual does not feel the PEOU and PU, after a long time of exposure to AI, it will also have BI to adopt AI, and thus form a role in promoting AIL. This model makes up for the verification of "PI ⟶ BI ⟶ AIL does not exist" in the mediation effect results. This path shows that for pre-service teachers who are born with the

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spirit of exploration and adventure, as long as they can deeply perceive the value of AI to teaching and have BI of adoption, they can achieve high AIL even if their SE and PEOU are average, which is basically consistent with the performance of "early adopters" in IDT.

4. Mode 4, "Balanced-development -oriented", including two configurations of s4a and s4b, in which the BI, II and SE, and the time of contacting AI are the core conditions. In this mode, no matter whether PEOU, PU and grade exist or are missing, as long as individuals show BI to adopt AI, high II and SE, and long-term exposure to AI, it can also promote AIL. This path represents an ideal state. Individuals have internal exploration motivation, strong confidence, high recognition of value and easy use experience, and their AIL level can also be improved.

5. Discussion

Through a hybrid approach combining SEM and fsQCA, this study validated the effectiveness of the TAM-IDT integrated model in elucidating the formation mechanism of AIL among pre-service teachers. The findings indicate that AI adoption serves as the pivotal behavioral mechanism for enhancing AIL. Through practical accumulation, active utilization, and cognitive deepening, individuals can translate latent technological cognition and psychological predispositions into multi-dimensional, transferable literacy competencies. During this process, II and SE emerge as the underlying psychological drivers propelling the cognitive-behavioral continuum, while PU and PEOU act as crucial technological cognitive mediators. Furthermore, BI functions as the direct conduit for translating intentions into tangible literacy behaviors. The four equivalent pathways unveiled by fsQCA underscore that the enhancement of AIL does not adhere to a "one-size-fits-all" paradigm; rather, it encompasses multiple pathways leading to a common destination. Based on these conclusions, this study proposes four differentiated cultivation pathways for fostering AIL among pre-service teachers.

5.1. Empowerment and Support Path for "High-efficiency-practice-oriented" Groups

For the broader cohort of pre-service teachers, the essence of cultivation resides in "successful experiences," while the crux of development lies in "lowering barriers to entry." Consequently, it is imperative to offer situational and low-barrier practical support to high-efficiency practice-oriented groups. Training should be grounded in authentic teaching challenges, utilizing comprehensive lists of scenario-based tool applications and exemplary case studies to aid pre-service teachers in comprehending how AI tools can specifically address issues related to teaching efficiency and effectiveness [47]. For instance, when addressing the challenge of "students' difficulties in grasping abstract knowledge," training should focus on how to employ AI to generate visual resources. Simultaneously, a school-wide digital support service system should be established to provide routine technical assistance for learning practices through effective collaboration among subject teachers, technical instructors, and intelligent agents. Furthermore, through school-based incentive mechanisms, every advancement made by teachers should be acknowledged, thereby continuously reinforcing their sense of SE.

5.2. Guidance and Training Pathways for "High-adoption-intention-oriented" Groups

This group is characterized by a strong motivation to experiment with technology (high adoption intention) and a proactive inclination towards exploration (high individual innovativeness). The crux of training lies in facilitating the transition from BI to ability while mitigating feelings of frustration. For instance, offering "toolbox-style" precise skill support, along with specific tool operation guides and teaching integration examples tailored to their interests (such as lesson planning and question setting). Establishing a "community of practice" can transform their initial enthusiasm into sustained momentum for exploration through peer sharing and achievement presentations, thereby deepening their comprehension of the value of AI in teaching (PU) through interaction.

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5.3. Stimulation and Guidance Pathways for "High-innovation-quality-oriented" Groups

For pre-service teachers possessing high innovative traits, the cultivation emphasis lies in "value deepening" and "challenge empowerment". Firstly, it is essential to reconstruct the curriculum system to underscore cutting-edge knowledge and integration. The focus should extend beyond mere tool operation, incorporating fundamental principles of artificial intelligence, educational data ethics [49], and human-computer collaborative instructional design into compulsory courses. Additionally, a "Future Learning Center" should be established, offering immersive, high-level challenge scenarios through virtual simulation teaching and AI teaching laboratories, among others. Secondly, an innovative practice platform should be constructed to foster exploration and creativity. This includes utilizing AI tools to create teaching agents that facilitate evaluation reform and developing virtual simulation experiments, thereby translating their innovative potential into the capacity to address real-world teaching challenges.

5.4. Build a Sustainable Collaborative Education Ecosystem Supporting "Balanced-development oriented"

For pre-service teachers requiring sustained long-term development, a robust ecological framework for collaborative education is also essential. Building upon the UGS (University-Government-School) multi-party collaborative education ecosystem, we should establish a collaborative education mechanism between universities and primary and secondary schools, centered on cultivating teaching practice abilities. This mechanism will foster AI technology application skills in real-world settings through dual-instructor classrooms and a seamless integration of "observation-practice-research" experiences[50]. Simultaneously, we should develop a collaborative research and development mechanism for intelligent products driven by the resolution of real teaching challenges [51], where primary and secondary school teachers identify pain points and universities provide theoretical support, thereby fostering a virtuous ecosystem.

Based on the above discussion, when cultivating AIL among pre-service teachers, it is crucial to fully acknowledge the differences in AI adoption intention among various groups. Great emphasis should be placed on understanding the correlation between individual internal traits, psychological motivations, and AIL, in order to establish differentiated and tiered training pathways and support systems.

6. Conclusions and Implications

6.1. conclusions

By integrating the TAM and IDT, this study constructed and validated a theoretical model to elucidate the formation mechanism of AIL among pre-service teachers. SEM analysis confirmed that II and SE exert a significant positive influence on AIL through the mediating effects of PU and PEOU, ultimately acting through BI. FsQCA analysis further revealed four configuration paths: "High-efficacy-practice-oriented" "High-adoption-intention-oriented" "High-innovative-qualities-oriented" and "Balanced-development-oriented". This demonstrates that the enhancement of AIL is not a singular linear process but involves multiple equivalent causal combinations, providing a direct basis for differentiated and precise training strategies.

6.2. Theoretical Implications

This study leverages the integrated TAM-IDT model to overcome the constraints of a singular theoretical lens. Prior research on teacher technology acceptance has predominantly employed the TAM model in isolation, centering on how cognitive variables such as PU and PEOU shape BI, while sidelining individual trait disparities and group heterogeneity throughout the technology diffusion lifecycle. By synergizing the micro-level TAM with the macro-level IDT, this research constructs a holistic theoretical chain spanning "individual traits → technological cognition → behavioral intention → capability outcomes". This marks the first attempt to conduct an integrated analysis of

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psychological cognitive mechanisms and innovation diffusion dynamics within the context of pre-service teacher AIL studies.

Secondly, this study introduces dual antecedent variables to advance the understanding of the underlying driving forces behind AIL development. Moving beyond the traditional TAM boundary, the model incorporates both II (derived from the adopter classification perspective in IDT) and SE (rooted in social cognitive theory) as antecedent constructs. This design not only addresses the question of group differences in "who is more inclined to adopt AI" but also unpacks the psychological motivational mechanism explaining "why these individuals can cultivate high levels of literacy", filling the gap in existing research's insufficient focus on the foundational origins of literacy formation.

Finally, this study positions AIL as the ultimate outcome variable to expand the application scope of TAM. While the classic TAM typically concludes with "behavioral intention" or "usage behavior" as the endpoint, this research adopts AIL—a multi-dimensional competency construct—as the final dependent variable. Drawing on frameworks from UNESCO, EDUCAUSE, and Ng et al., AIL is operationalized into five dimensions: “Knowing and Understanding AI”, “Using and Applying AI”, “Creating AI”, “Identifying AI” and “AI Ethics”. This design enables a theoretical shift from "technology adoption" research to "literacy cultivation" research, offering a novel analytical perspective to explore how technology acceptance translates into sustainable competencies.

6.3. Practical Implications

In this study, the mixed research method of “SEM+fsQCA" was used. SEM is well-suited for examining linear causal relationships and net effects among latent variables, illuminating the symmetric mechanism governing how antecedent factors predict literacy outcomes. In contrast, fsQCA specializes in uncovering complex equifinal and conjunctural effects of multiple preconditions, delineating asymmetric pathways through which distinct configurations of traits and cognitions converge to yield the same level of AIL. By combining these complementary approaches, this research achieves a dual-focal analysis that captures both the main effects of individual variables and the synergistic interactions between them. In addition, through the bootstrap mediation effect test, this study not only verified the parallel mediation effect of PU, PEOU and BI, but also identified the chain mediation path from "II/SE → PEOU → PU → BI → AIL". This discovery accurately depicts the micro mechanism of how psychological traits are transmitted layer by layer and ultimately shape literacy, and makes up for the deficiency of previous studies in dealing with the "black box" of mediation process.

As for the research results, this study proposes differentiated, learner-centered cultivation pathways tailored to distinct subgroups of pre-service teachers, informed by four typical profiles identified via fsQCA. For the "High-efficacy-practice-oriented" subgroup, low-threshold, high-success experiential scaffolds are designed to reinforce positive learning experiences and foster a growth mindset. For the "High-adoption-intention-oriented" subgroup, targeted support is provided to bridge the intention-behavior gap, preventing motivational attrition resulting from perceived barriers to skill development. For the "High-innovative-qualities-oriented" subgroup, advanced challenge-based learning platforms are offered to leverage their leadership potential and drive peer-to-peer knowledge exchange. For the "Balanced-development-oriented" subgroup, a collaborative education ecosystem is constructed to synergize complementary strengths, promoting holistic growth across all dimensions of AIL. This personalized framework provides actionable guidance for universities to move beyond one-size-fits-all technical training models and implement precision education strategies for AIL development.

7. Limitations and Future Research

It should be acknowledged that the cultivation of AIL constitutes a dynamic developmental continuum, which unfolds in sequential stages from cognitive arousal to behavioral engagement, and from rudimentary technology adoption to transformative pedagogical integration. By employing a cross-sectional research design with a one-time questionnaire survey, this study effectively identifies correlational relationships and path coefficients among key variables. However, this design is inherently limited by its inability to trace the longitudinal evolution of AIL constructs over time.Furthermore, this investigation prioritized individual-level psychological antecedents including II, SE, PU, and PEOU, alongside BI. Despite incorporating grade level and AI experience exposure as contextual covariates in the fsQCA analysis, macro-level environmental determinants such as institutional support frameworks, AI-integrated curriculum offerings, technological infrastructure in partner schools, peer influence dynamics, and sociocultural norms were not systematically measured. These contextual factors are posited to play critical roles in shaping pre-service teachers' AIL, either through moderating existing relationships or exerting independent effects. The exclusion of such variables consequently constrains the generalizability and explanatory scope of the proposed model.

Future research can be deepened in the following aspects: first, conducting longitudinal tracking studies to uncover the dynamic changes in causal relationships among variables. Second, exploring path differences across various types of institutions and academic disciplines, and incorporating cultural factors and organizational support into the model to expand its explanatory scope. Finally, applying research findings to specific curriculum designs and training program developments, and evaluating their effectiveness through action research. In summary, the systematic enhancement of pre-service teachers' AIL represents a foundational endeavor to address the educational challenges of the intelligent era and nurture future innovative talents. It necessitates transcending the narrow confines of mere technical training and implementing systematic design and precise interventions across multiple dimensions, including psychological cognition, behavioral shaping, and environmental support. This study offers an evidence-based theoretical framework and practical strategies, aiming to facilitate the cultivation of outstanding teachers capable of excelling in future education within the intelligent era.

Supplementary Materials: The following supporting information can be downloaded at the website of this paper posted on Preprints.org. Table S1: Questionnaire questions corresponding to potential variables; Table S2: Results of Reliability Analysis; Table S3: KMO and Bartlett's Test of Sphericity Results; Table S4: Summary of Regression Coefficients for the Model.

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