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Sustainable AI Integration in Education: Factors Influencing Pre-Service Teachers' Continuance Intention to Use Generative AI

Huazhen Li [1,2], Yadi Xu [2], Cheryl Brown [2], Billy O'Steen [3] and Zhanni Luo [1,*]

1 School of Foreign Languages and Literatures, Chongqing Normal University, Chongqing 401331, China; huazhen.li@pg.canterbury.ac.nz
2 School of Social and Cultural Studies in Education, University of Canterbury, Christchurch 8041, New Zealand; yadi.xu@pg.canterbury.ac.nz (Y.X.); cheryl.brown@canterbury.ac.nz (C.B.)
3 School of Leadership and Professional Practice, University of Canterbury, Christchurch 8041, New Zealand; billy.osteen@canterbury.ac.nz
* Correspondence: zhanni.luo@cqnu.edu.cn

Abstract

As artificial intelligence (AI) changes educational practices, understanding what sustains pre-service teachers' generative AI use beyond initial adoption becomes important. However, existing research mainly focuses on initial acceptance rather than continuance intention, which is a more realistic indicator for sustainable technology integration. This study drew on an integrated framework including psychological (GAI anxiety, GAI self-efficacy), contextual (facilitating conditions, social influence), and perceptual factors (perceived ease of use, perceived usefulness) to examine pre-service teachers' continuance intention toward GAI in future teaching. Survey data from 549 Chinese pre-service teachers were analyzed using structural equation modeling (SEM) and fuzzy-set qualitative comparative analysis (fsQCA). Results showed that GAI self-efficacy had the strongest positive associations with both perceived ease of use and perceived usefulness. GAI anxiety negatively influenced both perceptions. However, facilitating conditions did not significantly relate to perceived usefulness. The fsQCA identified six configurational pathways clustered into the following three patterns: intrinsic value driven, efficacy capability driven, and external support driven. These findings suggest that teacher education programs should prioritize building GAI self-efficacy and supportive peer environments and not focus solely on infrastructure provision.

Keywords: pre-service teachers; continuance intention; sustainable GAI integration; teacher education

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1. Introduction

1.1. Generative AI in Education

Against the backdrop of accelerating digital transformation, artificial intelligence (AI) has brought new opportunities for teaching and learning. Educational interest in AI-enabled tools has grown rapidly, driven by advances in generative AI (GAI) tools such as ChatGPT [1]. Technology has long been recognized as an enabler of enhancing teaching and learning in higher education [2]. Among recent developments, AI tools, particularly GAI, have emerged as a significant category of digital applications designed to support educational tasks through automated content creation [3]. These platforms provide accessible support for anyone with an internet connection, often at no visible cost. AI tools also incorporate features like instant feedback and personalized suggestions for an engaging teaching experience. Originating in response to the demand for efficient support, AI tools have gained prominence for reducing teacher workload and enabling personalized instruction.

GAI is already influencing pre-service teachers, who as future practitioners, are already using GAI for lesson planning, instructional design, and reflective practice [1]. According to Soutter, O'Steen, and Gilmore [4], student well-being is central to education. AI tools help achieve this by enabling more personalized and active learning and assisting in routine tasks, thereby improving efficiencies.

However, alongside their growing adoption, concerns have emerged regarding privacy risks and the digital divide [1]. The widespread availability of AI tools has transformed teacher education, creating both opportunities and challenges for educators worldwide. In this paper we explore whether pre-service teachers are willing and prepared to integrate AI tools into their professional practice [5].

1.2. Initial Acceptance and Future Intentions

While initial acceptance represents the first step in technology adoption, research attention has recently shifted toward a later and more critical phase: continuance intention after actual initial use. Initial acceptance typically refers to educators' willingness to try a new technology based on perceived usefulness and ease of use. In contrast, continuance intention refers to users' decision to continue using a technology after gaining hands-on experience, which may differ from their initial expectations [1].

A critical limitation of initial acceptance research is that users lack actual experience with the technology, which may lead to unrealistic expectations [6]. Actual use often reveals practical challenges such as technical problems, time costs, or gaps between expectations and reality. For pre-service teachers, stopping generative GAI use after initial trials affects their preparation for future teaching. For teacher education programs, low continuance rates also limit the development of AI-ready educators. Understanding the continuance intention of pre-service teachers provides a more wholistic picture of sustainable AI integration in teaching practice [7]. Existing research on pre-service teachers and GAI still focuses on initial acceptance, while continuance intention remains underexplored. This research seeks to understand what influences pre-service teachers' continuance decisions.

1.3. Factors Contributing to AI Continuous Teaching

Previous studies have identified a range of factors contributing to pre-service teachers' AI continuance intention. For example, Zhang, Schießl, Plößl, Hofmann, and Gläser-Zikuda [8] used a multigroup analysis to examine technology acceptance among pre-service teachers and identified key predictors such as perceived usefulness, perceived ease of use, and trust. Zheng, Ma, Sun, Wu, and Hu [7] examined post-acceptance factors related to continuance intention in pre-service teachers. Based on the Expectation-Confirmation Model, the study highlighted factors including confirmation, satisfaction, and perceived usefulness. Wang, Ruan, Zhang, Fu, and Duan [5] explored the structural relationships among anxiety, self-efficacy, and technological pedagogical content knowledge in the context of generative AI use.

Among the various contributing variables, psychological factors are particularly significant. Pre-service teachers with stronger GAI self-efficacy are more likely to find generative AI technologies simple to use, and confident users integrate generative AI more effortlessly into their workflows [8]. As a result, increasing confidence in GAI use can promote long-term engagement with these tools [7]. However, the specific factors that motivate pre-service teachers to maintain high self-efficacy and overcome anxiety have yet to be identified.

In addition to psychological factors, perceptual and contextual factors also play a critical role. Perceived usefulness reflects whether teachers see value in continued use of AI tools, including benefits such as time savings and improved teaching quality. For many pre-service teachers, these perceived benefits are powerful motivators for sustained use. While some studies have acknowledged facilitating conditions and policy support [9], few have treated them as central drivers of continuance. Most research treats contextual factors as background variables, rather than core factors in sustained AI integration. This oversight highlights the need for studies that explicitly examine how perceptual, psychological, and contextual factors work together in continuance decisions. Consequently, this paper asks the question "What factors influence Chinese pre-service teachers' intentions to use GAI?".

1.4. Gaps, Aims, and Research Significance

However, a critical limitation of existing research is that most studies focus on pre-service teachers' initial acceptance of generative AI, while continuance intention remains relatively underexplored. As discussed in Section 1.2, initial acceptance decisions are based on limited experience, leading to incomplete understanding of the technology [6]. For pre-service teachers, discontinuing GAI use after initial use limits their professional development and preparedness for technology-supported teaching. For teacher education programs, low continuance rates also create challenges in preparing future-ready educators who can effectively integrate generative AI into their practice. Therefore, research on GAI integration should consider factors that influence sustained use rather than focusing only on initial acceptance decisions.

Researchers have discussed factors affecting teachers' technology adoption, such as perceived usefulness, ease of use, self-efficacy, and institutional support [5,8]. However, few of them have examined how perceptual, psychological, and contextual factors work together in relation to continuance intention. Zheng, Ma, Sun, Wu, and Hu [7] suggest that when studying post-acceptance intentions, one should not only consider technology attributes but also take into account internal factors such as confidence and external factors such as institutional conditions. In the context of pre-service teachers using GAI, perceptual factors capture beliefs about technology usefulness, psychological factors describe confidence and emotional responses, and contextual factors represent external support conditions. This study posits that these three factor types should be examined together to understand sustainable GAI integration in future teaching.

We aim to investigate the factors influencing pre-service teachers' continuance intention toward GAI in their future teaching practice. Considering that understanding post-acceptance behavior requires examining multiple factor types simultaneously, we included perceptual factors (perceived usefulness and perceived ease of use), psychological factors (GAI self-efficacy and GAI anxiety), and contextual factors (social influence and facilitating conditions) in our research model. To test this model, we conducted a quantitative study using survey data from Chinese pre-service teachers. The findings are expected to provide insights into sustainable GAI integration in teacher education and offer practical guidance for supporting pre-service teachers' continued technology use.

2. Literature and Research Hypotheses

2.1. Theoretical Framework

This study draws on the following two established theoretical frameworks to examine pre-service teachers' intentions to continue using GAI in their future teaching: the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology

(UTAUT). TAM posits two fundamental beliefs that influence technology adoption: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). Davis [10] defines perceived usefulness as "the degree to which a person believes that using a particular system would enhance his or her job performance." UTAUT builds upon TAM by incorporating Social Influence (SI) and Facilitating Conditions (FC). Social influence is defined as "the degree to which an individual perceives that important others believe he or she should use the new system" [11]. Facilitating conditions include the organizational resources and available support for technology use. Both frameworks have demonstrated considerable predictive capability within educational settings [12]. This investigation categorizes the factors into three separate groups: Perceptual Factors (PU and PEOU), Contextual Factors (SI and FC), and Psychological Factors (GAI anxiety and GAI self-efficacy).

While TAM and UTAUT explain why people start using technology, this study seeks to understand why pre-service teachers continue using AI after they try it. Bhattacherjee's [6] Expectation Confirmation Model (ECM) extends TAM's construct of time by asking whether people will keep using a technology after they start. This difference matters because adoption fails not only when people first try technologies, but when people stop using them later. We have thus drawn on ECM's conceptualisation of continuance intention (whether people plan to keep using technology) to extend TAM-UTAUTs construct of usage behavior and intentions. This addition better explains how pre-service teachers decide to keep using generative AI in teaching. Like others [13,14] who have used ECM, we have not taken a longitudinal approach to continuance intention; rather we use this construct to foreground teachers' anticipated future use.

2.2. Literature Review

2.2.1. Psychological and Perceptual Factors: GAI Anxiety and GAI Self-Efficacy

GAI anxiety refers to the fear and discomfort that people feel when they use artificial intelligence tools [15]. Venkatesh [11] found that computer anxiety works as a barrier. This barrier makes technology harder to use. His study showed that anxiety explained 60% of the differences in how easy people found new technology. This result held true even after controlling for confidence levels, suggesting that anxiety is not just a temporary feeling but a distinct psychological factor that needs its own solutions beyond technical training. Recent studies show that GAI anxiety has different types of concerns. These include fear of learning AI, concerns about losing jobs to generative AI, uncertainty about GAI's implications for society, and worries about operating AI tools correctly. The question then is how these different concerns affect pre-service teachers in their work.

There are two components to AGI anxiety. On the one side, anxiety makes teachers see AI tools more negatively. Teachers who feel anxious about GAI think the tools are harder to use. They also think GAI is less helpful for teaching [12]. Furthermore, anxiety weakens teachers' psychological resources over time. Generative AI technology changes rapidly. This rapid change makes teachers feel more anxious because they struggle to keep up. This anxiety then reduces their confidence, hope, and ability to cope with challenges. Teachers then become less willing to use GAI in the long term. However, self-efficacy may serve as a protective factor against these negative associations.

GAI self-efficacy refers to teachers' belief in their ability to use generative AI successfully. Bandura [16] argued that people who believe they can complete a task see it as easier and more valuable. For pre-service teachers, higher self-efficacy leads to stronger confidence in using AI tools. This confidence reduces perceptions of difficultly [8]. Research with 606 pre-service teachers showed that self-efficacy directly improved how easy and how useful teachers found AI to be. Self-efficacy also increased their intention to use generative AI through these better perceptions [5]. Moreover, self-efficacy helps teachers continue using AI over time. Teachers with higher self-efficacy develop trust in AI tools. This trust makes them more willing to keep using the technology even when they face problems [17,18]. Recent studies show that hands-on practice with AI can increase pre-service teachers' self-efficacy [19]. Anxiety and self-efficacy do not work alone. They affect each other and together shape how teachers accept technology.

The relationship between anxiety and self-efficacy works in both directions. Self-efficacy can reduce anxiety. This happens when teachers build successful experiences and feel less threatened. At the same time, anxiety can weaken self-efficacy. This happens when anxiety increases mental barriers and reduces confidence [20]. This two-way relationship means that teacher education programs should address both factors simultaneously. Programs cannot just focus on building skills. They must also work to reduce anxiety. Importantly, self-efficacy does not directly affect continuance intention. Instead, it works through teachers' perceptions of how easy and useful AI tools are. Based on these ideas from theory and research findings, the following hypotheses are proposed:

H1-a: *GAI anxiety negatively influences perceived usefulness.*

H1-b: *GAI anxiety negatively influences perceived ease of use.*

H2-a: *GAI self-efficacy positively influences perceived usefulness.*

H2-b: *GAI self-efficacy positively influences perceived ease of use.*

2.2.2. Contextual and Perceptual Factors: Facilitating Conditions and Social Influence

Facilitating conditions refer to the support and resources that organizations provide to help people use new technology. This support includes hardware equipment, software tools, training programs, and technical help. Venkatesh [11] argued that when people believe their organization supports technology use, they are more likely to adopt it. This concept comes from the UTAUT model. The model suggests that environmental support reduces barriers to technology use. For pre-service teachers, facilitating conditions include university training programs, technical support from IT staff, access to AI tools, and help from supervisors. Studies show that these resources play an important role in technology adoption. Research with mathematics teachers in China found that facilitating conditions were the most important factor affecting how teachers used technology. This factor was even more important than how easy or useful teachers thought the technology was [21]. However, the way facilitating conditions work for pre-service teachers needs closer examination because research shows mixed results.

Research indicates that facilitating conditions affect how teachers perceive AI tools. Studies involving graduate students support this claim. When universities provide good support, students find AI tools easier to use. Organizational support reduces technical difficulties. Consequently, the technology feels less complex [9]. However, a study of 606 pre-service teachers showed different results. Facilitating conditions improved the perceived ease of use. But these conditions did not affect perceived usefulness [5]. This finding suggests that good equipment and support help teachers feel confident. Yet, infrastructure alone cannot convince teachers that GAI will improve their teaching.

A key problem may lie in the focus of support programs. Many programs concentrate on technical skills. They do not show teachers how to use generative AI effectively in real classrooms. Facilitating conditions provide the foundation for technology use. However, social factors also play a critical role in shaping teachers' perceptions.

Social influence means the pressure people feel from others to use new technology. Venkatesh [11] defined social influence as how much a person believes that important people think they should use a new system. For pre-service teachers, important people include professors, classmates, and experienced teachers. When these people support GAI use, pre-service teachers feel more pressure to adopt it. This pressure can be positive or negative. Positive pressure happens when colleagues share successful teaching cases with GAI. Negative pressure happens when teachers worry about falling behind their peers [5]. Research shows that social influence works through several ways. First, people trust recommendations from colleagues and friends. Second, people want to fit in with their professional community. Third, people learn by watching others use technology successfully [22].

Studies show that social influence strongly leads to how pre-service teachers see GAI. Research with university teachers found that social influence was the most powerful factor predicting both perceived usefulness and perceived ease of use. This finding shows that peer support shapes teacher attitudes more than any other factor [22]. When professors and classmates believe GAI is helpful, pre-service teachers start to see GAI as more valuable and easier to use. Moreover, qualitative research shows that pre-service teachers learn best from concrete examples. They want to see how experienced teachers actually use GAI in real classrooms. Professional development programs should create communities where teachers can share experiences and learn from each other [5]. These communities help make GAI use feel normal rather than threatening. Based on these findings about how environmental and social factors shape technology perceptions, the following hypotheses are proposed:

H3-a: *Facilitating conditions positively influence perceived usefulness.*

H3-b: *Facilitating conditions positively influence perceived ease of use.*

H4-a: *Social influence positively influences perceived usefulness.*

H4-b: *Social influence positively influences perceived ease of use.*

2.2.3. Perceptual and Psychological Factors, and Continuance Intention

Teachers' beliefs about technology strongly shape whether they will keep using it in the long term. Some researchers found that when teachers thought AI tools were easy to use and useful, they were more likely to use generative AI in real teaching tasks [8].

This pattern held true not just for intentions but for pre-service teachers' actual behavior. The study showed that teachers who found GAI easy to use also started to see it as more useful. This happens because easy technology reduces effort. Teachers can focus on teaching benefits rather than technical problems [11]. Studies with pre-service teachers confirmed this relationship repeatedly. One study found that perceived ease of use improved perceived usefulness among pre-service teachers learning about GAI. Both factors then worked together to predict whether teachers would continue using GAI in their future teaching work. However, between these two beliefs, usefulness plays a much stronger role than ease of use.

Research also shows that usefulness matters more than ease of use for long-term adoption. A study with pre-service special education teachers found that perceived usefulness had the strongest direct association with behavioral intention. This association was much larger than perceived ease of use. Another study confirmed that usefulness explained more variance in continuance intention than any other factor including satisfaction and self-efficacy [7]. The reason is that teachers decide to keep using GAI based on whether it helps them achieve teaching goals. Ease of use is important, but usefulness matters more. If

GAI improves teaching performance, teachers will use it even if learning takes effort. This finding suggests that training programs should focus on demonstrating practical teaching benefits rather than just showing how to operate tools. Programs that prove GAI's value for real classroom tasks will see higher long-term adoption rates. Based on these findings, the following hypotheses are proposed:

H5: *Perceived ease of use positively influences perceived usefulness.*

H6: *Perceived usefulness positively influences generative AI continuance intention.*

H7: *Perceived ease of use positively influences teaching continuance intention.*

The framework of hypothesis is illustrated in Figure 1.

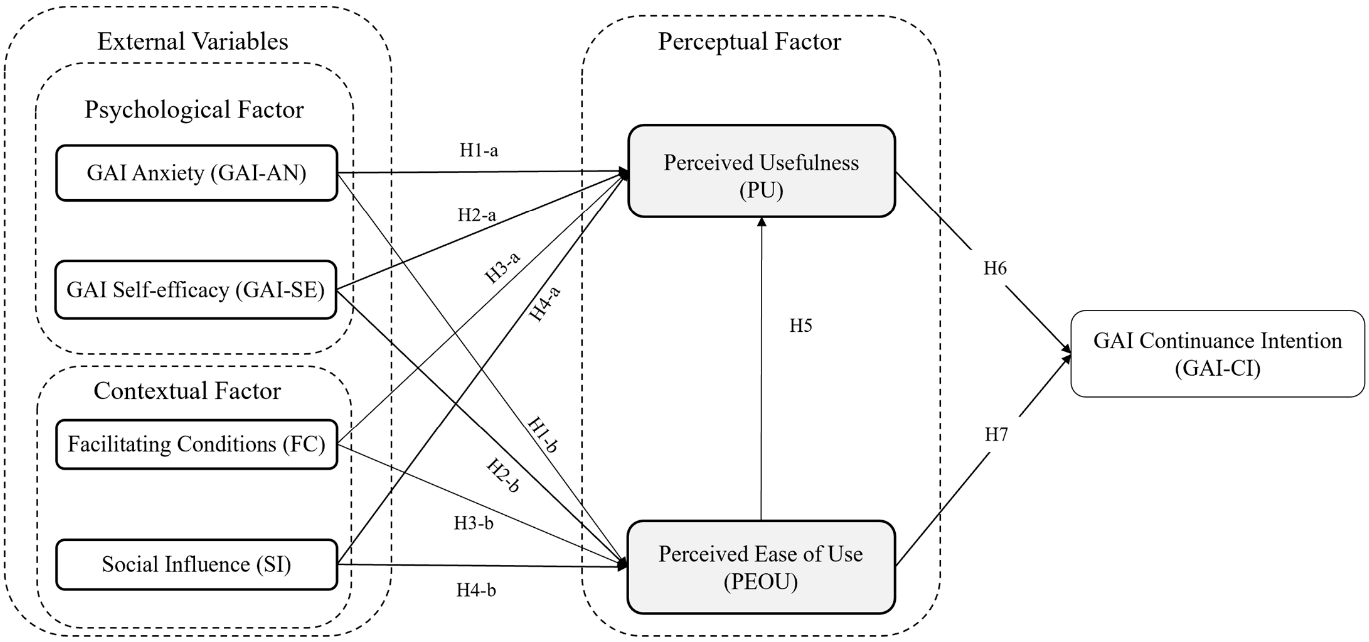

Figure 1. The proposed framework.

3. Methods

3.1. Research Instruments

The questionnaire used in the current study comprised two sections. Section 1 focused on demographic data collection, aiming to gather fundamental participant information such as gender and age. The Section 2 including subscales that measured seven factors, namely the following: GAI anxiety (GAI-AN), GAI self-efficacy (GAI-SE), facilitating condition (FC), social influence (SI), perceived ease of use (PEoU), perceived usefulness (PU), and GAI continuous intention (GAI-CI). A 5-point Likert scale was utilized, with 1 indicating "strongly disagree" and 5 indicating "strongly agree".

The GAI anxiety and GAI self-efficacy subscales represent the psychological factors. The GAI anxiety subscale (eight items) was adapted from scales developed by Wang [23] and Liu and Liu [24]. It assesses multidimensional concerns including learning anxiety and job replacement fears; for instance, one item states: *"I worry that GAI technology will replace some teaching tasks"* (GAI-AN4). Conversely, the GAI self-efficacy subscale (8 items), adapted from Wang and Chuang [25] and Chiu, Ahmad, and Çoban [26], evaluates students' confidence in their technological skills and pedagogical integration capabilities (e.g., *"I can design learning activities that appropriately integrate generative AI tools"*, GAI-SE7).

Regarding contextual factors, the Facilitating Conditions and Social Influence subscales (8 items each) were adapted from instruments by Wang and Chu [27] and Naseri, Syahrivar, Saari, Yahya, and Muthusamy [28]. The former measures perceived organizational support (e.g., *"My university provides adequate training opportunities for generative AI technology"*, FC1), while the latter assesses normative influences from professors and peers (e.g., *"My professors believe that using generative AI in teaching is beneficial"*, SI1).

The perceptual factors, Perceived Ease of Use and Perceived Usefulness (8 items each), were grounded in the Technology Acceptance Model [10] to fit the AI educational context. These scales measure the efficiency and usability of AI tools; for example, an item for usefulness states: *"Using AI tools will help me accomplish teaching tasks more efficiently"* (PU1). Finally, the outcome variable, generative GAI continuous intention (8 items), was adapted from Chai, Liang, and Wang [29] and Bhattacherjee [6]. This subscale assesses the commitment to continuously integrate GAI into future practice, illustrated by the following item: *"I intend to use AI tools in my teaching when I become a teacher"* (GAI-CI1).

Table 1 summarizes the measurement constructs, their original sources, the number of items per scale, and representative sample items.

Table 1. Survey Items (Sample).

#	Construct	Number of Items	Sample Item	References
1	GAI Anxiety	8	Learning to use AI tools for teaching makes me anxious. (GAI-NX1)	Wang & Wang [23]; Liu and Liu [24]
2	GAI Self-Efficacy	8	I am confident in my ability to learn how to use AI tools for teaching. (GAI-SE1)	Wang & Chuang [25]; Chiu et al. [26]
3	Facilitating Conditions	8	My university provides adequate training opportunities for AI technology in education. (FC1)	Wang & Chu [27]; Naseri et al. [28]
4	Social Influence	8	My professors believe that using AI in teaching is beneficial. (SI1)	Naseri et al. [28]
5	Perceived Ease of Use	8	Learning to use AI tools for teaching is easy for me. (PEOU1)	Davis [10]
6	Perceived Usefulness	8	Using AI tools will help me accomplish teaching tasks more efficiently. (PU1)	Davis [10]
7	GAI Continuous Intention	8	I intend to use AI tools in my teaching when I become a teacher. (GAI-CI1)	Chai et al. [29]; Bhattacherjee [6]

3.2. Participants and Ethical Considerations

The target population of this study was Chinese pre-service teachers. This study employed convenience sampling. Pre-service teachers from multiple Chinese universities were recruited via Wenjuanxing, an online survey platform. Eligibility criteria required participants to have (a) prior AI tool-use experience and (b) practical teaching experience (e.g., teaching practicum/placement).

The questionnaire primarily employed a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). Three embedded validation (attention-check) items were included to enhance response quality. Data were collected via an online survey administered through Wenjuanxing. The survey was distributed electronically and remained open for one month. A total of 610 questionnaires were returned. After excluding ineligible cases (i.e., respondents reporting no AI tool-use experience and/or no teaching practicum experience) and responses that failed the embedded validation checks, the final analytic sample comprised 549 valid questionnaires. This represents a usable-response rate of 90.0% (549/610) among submitted questionnaires. Age categories were based on the following typical progression of teacher preparation programs in China: early undergraduates (18–20), senior undergraduates and early postgraduates (21–25), advanced graduate students (26–30), and mature learners (31 and above) (see Table 2). In the Chinese teacher education system, teaching practice typically begin in the second year of study, so participants aged 18–20 had already gained practical classroom experience. Similar classifications have been adopted in previous studies [8].

Table 2. Demographic information of the participants.

Demographic Variable		**Sample (N = 549)**	
		Number	**Proportion**
Gender	Male	151	27.50%
	Female	365	66.48%
	Prefer not to specify	33	6.01%
Age	18–20	100	18.21%
	21–25	310	56.47%
	26–30	103	18.76%
	Above 31	36	6.56%
Practical teaching experience	None	2	0.36%
	Less than 3 months	52	9.47%
	3–6 months	201	36.61%
	6–12 months	155	28.23%
	Above 1 year	139	25.32%
GAI tool-use experience	Occasional use (a few times)	17	3.10%
	Sometimes (about once a month)	170	30.97%
	Often (about once a week)	225	40.98%
	Very often (about every day)	137	24.95%

The study strictly followed established research ethics principles, with particular emphasis on protecting participant privacy and voluntary participation. The questionnaire was completed anonymously. Basic demographic information, including gender and age, was collected for research purposes; however, no personally identifiable information, such as names, student ID numbers, or contact details, was obtained. All responses were used solely for research purposes and were not used for any other purpose.

3.3. Data Analysis and Reliability

After deciding on the questions for the survey, we hired a professional translator to translate it into Chinese. To make sure the translation was correct, we used a back-translation method. Once the translation was ready, we distributed the questionnaire in digital formats.

The data analysis employed IBM SPSS 27.0 and IBM SPSS AMOS 26.0, along with fuzzy-set Qualitative Comparative Analysis (fsQCA) to clarify intricate causal relationships. Initially, a descriptive analysis was performed to calculate the means and standard deviations of each construct. Following this, reliability was assessed via Cronbach's alpha to confirm internal consistency; the coefficients for each subscale surpassed 0.80, yielding an overall reliability of 0.905. Subsequently, Confirmatory Factor Analysis (CFA) was employed to examine the measurement models in line with the empirical data. Subsequently, Structural Equation Modeling (SEM) was utilized to evaluate model fit and to test the proposed hypotheses. In the fsQCA analysis, multi-item latent variables were synthesized through the calculation of mean values, which were then subjected to fuzzy-set calibration. This calibration utilized the three-anchor method, incorporating thresholds at the 5th, 50th, and 95th percentiles, as outlined by Ragin [30]. To comply with the requirements of fsQCA 3.0 software, membership scores of 0.5 were adjusted to 0.501 to reduce complete ambiguity, as recommended by Schneider and Wagemann [31]. Ultimately, fsQCA facilitated the identification of configurational pathways, thereby capturing the asymmetric characteristics of human behavior, which are not adequately represented by linear methodologies.

4. Findings

4.1. Descriptive Statistics

We calculated the mean, standard deviation, skewness, and kurtosis to check the data distribution. Table 3 shows the results. The mean values ranged from 3.15 to 3.66. GAI anxiety had the lowest mean (3.15). This suggests that teachers felt only moderate anxiety about using generative AI. GAI continuous intention had the highest mean (3.66). This indicates that teachers were willing to keep using GAI in their teaching.

Table 3. Descriptive statistics.

Construct	*N*	Mean	Std. Deviation
GAI Anxiety (GAI-AN)	549	3.15	0.913
GAI Self-efficacy (GAI-SE)	549	3.61	0.754
Facilitating Condition (FC)	549	3.44	0.802
Social Influence (SI)	549	3.45	0.771
Perceived Ease of Use (PEoU)	549	3.55	0.754
Perceived Usefulness (PU)	549	3.63	0.750
GAI Continuous Intention (GAI-CI)	549	3.66	0.864

The standard deviations ranged from 0.750 to 0.913. These values show that responses were fairly consistent across all constructs. For skewness, six constructs had negative values. This means most responses were above the average. GAI anxiety was the exception. It had a value close to zero (0.022), showing a balanced distribution. For kurtosis, all values were between −2 and +2. This confirms that the data followed a normal distribution. Therefore, the data were suitable for structural equation modeling.

4.2. Reliability and Validity Analysis

The reliability of the measurement scales was assessed using Cronbach's alpha coefficient; all seven constructs demonstrated satisfactory internal consistency, with Cronbach's alpha values ranging from 0.889 (Social Influence) to 0.918 (GAI Anxiety). These values exceeded the recommended threshold of 0.7 [32], indicating acceptable reliability for all constructs. Prior to conducting factor analysis, sampling adequacy was examined using the Kaiser–Meyer–Olkin (KMO) test and Bartlett's Test of Sphericity. The KMO value was 0.948, which surpassed the recommended minimum of 0.6 [33]. Additionally, Bartlett's Test yielded a chi-square value of 16,671.704 (df = 1431, $p < 0.001$), confirming that the correlation matrix was appropriate for factor analysis (see Table 4).

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Table 4. Factor Loadings and Convergent Validity.

Construct	Code	Factor Loading	AVE	CR
GAI Anxiety (GAI-AN)	GAI-AN 1	0.782	0.585	0.919
	GAI-AN 2	0.763		
	GAI-AN 3	0.786		
	GAI-AN 4	0.731		
	GAI-AN 5	0.786		
	GAI-AN 6	0.746		
	GAI-AN 7	0.764		
	GAI-AN 8	0.761		
GAI Self-efficacy (GAI-SE)	GAI-SE 1	0.711	0.522	0.897
	GAI-SE 2	0.718		
	GAI-SE 3	0.71		
	GAI-SE 4	0.743		
	GAI-SE 5	0.745		
	GAI-SE 6	0.685		
	GAI-SE 7	0.764		
	GAI-SE 8	0.7		
Facilitating Condition (FC)	FC 1	0.733	0.554	0.908
	FC 2	0.785		
	FC 3	0.743		
	FC 4	0.758		
	FC 5	0.722		
	FC 6	0.746		
	FC 7	0.736		
	FC 8	0.727		
Social Influence (SI)	SI 1	0.695	0.503	0.890
	SI 2	0.721		
	SI 3	0.688		
	SI 4	0.738		
	SI 5	0.757		
	SI 6	0.732		
	SI 7	0.659		
	SI 8	0.679		
Perceived Ease of Use (PEoU)	PEoU 1	0.692	0.532	0.901
	PEoU 2	0.781		
	PEoU 3	0.743		
	PEoU 4	0.684		
	PEoU 5	0.734		
	PeoU 6	0.758		
	PEoU 7	0.744		
	PEoU 8	0.692		
Perceived Usefulness (PU)	PU 1	0.708	0.546	0.906
	PU 2	0.761		
	PU 3	0.720		
	PU 4	0.722		
	PU 5	0.734		
	PU 6	0.714		
	PU 7	0.76		
	PU 8	0.791		
GAI Continuous Intention (GAI-CI)	AI-CI 1	0.754	0.594	0.898
	AI-CI 2	0.75		
	AI-CI 3	0.800		
	AI-CI 4	0.783		
	AI-CI 5	0.749		
	AI-CI 6	0.787		

Confirmatory factor analysis (CFA) was subsequently performed to evaluate construct validity. The model fit indices indicated a good fit between the hypothesized model and the observed data. The chi-square to degrees of freedom ratio (CMIN/DF = 1.296) was below the threshold of 3.0 [34]. The root mean square error of approximation (RMSEA = 0.023) was well below the cut-off value of 0.08, suggesting excellent model fit [35]. Furthermore, the incremental fit indices, including IFI (0.975), TLI (0.973), and CFI (0.975), all exceeded the acceptable threshold of 0.9 [36]. The root mean square residual (RMR = 0.035) was also below the recommended limit of 0.05. Taken together, these results provide evidence that the measurement model demonstrated adequate reliability and validity for subsequent structural analysis.

Furthermore, convergent validity was assessed by examining factor loadings, Average Variance Extracted (AVE), and Composite Reliability (CR) for each construct. As presented in Table 4, all standardized factor loadings ranged from 0.659 to 0.791, exceeding the recommended minimum of 0.5 [37]. The AVE values for the seven constructs ranged from 0.503 (Social Influence) to 0.594 (GAI Continuous Intention), all surpassing the threshold of 0.5. This indicates that each construct captured more than half of the variance explained by its indicators [38]. Additionally, the CR values ranged from 0.890 (Social Influence) to 0.919 (GAI Anxiety), well above the acceptable benchmark of 0.7 [32]. These results collectively demonstrate that the measurement model exhibited satisfactory convergent validity, confirming that the indicators effectively reflected their underlying latent constructs.

Discriminant validity was tested using the Fornell-Larcker criterion [38]. This method compares the square root of AVE with the correlations between constructs. Table 5 presents the results. The bold diagonal values show the square root of AVE for each construct. These values ranged from 0.709 to 0.771. The off-diagonal values show the correlations between different constructs. The results showed good discriminant validity. All diagonal values were higher than the correlations in the same row and column. For example, GAI anxiety had a square root of AVE of 0.765. Its highest correlation with other constructs was only −0.438. GAI self-efficacy showed a similar pattern. Its square root of AVE (0.722) was higher than its strongest correlation (0.477). These findings confirm that each construct was distinct from the others.

Table 5. Correlation and the square root of AVE.

Construct	AVE	Correlation						
		GAI-AN	GAI-SE	FC	SI	PEoU	PU	GAI-CI
GAI Anxiety (GAI-AN)	0.585	**0.765**						
GAI Self-efficacy (GAI-SE)	0.522	−0.326 ***	**0.722**					
Facilitating Condition (FC)	0.554	−0.125 ***	0.194 ***	**0.739**				
Social Influence (SI)	0.503	−0.168 ***	0.229 ***	0.241 ***	**0.709**			
Perceived Ease of Use (PEoU)	0.532	−0.331 ***	0.443 ***	0.293 ***	0.355 ***	**0.744**		
Perceived Usefulness (PU)	0.546	−0.283 ***	0.372 ***	0.238 ***	0.353 ***	0.502 ***	**0.729**	
GAI Continuous Intention (GAI-CI)	0.594	−0.438 ***	0.477 ***	0.311 ***	0.430 ***	0.538 ***	0.537 ***	**0.771**

The table shows the square root of AVE on the diagonal and correlations between the latent constructs on the off-diagonal. *** $p < 0.001$.

4.3. Model Fit and Hypotheses Test

Several model fit indices were used to assess the fit of the structural model, including CMIN/df (chi-square degrees of freedom ratio), GFI (goodness-of-fit index), AGFI (adjusted goodness-of-fit index), RMSEA (root-mean-square error of approximation), NFI (normalised fit index), TLI (Tucker–Lewis index), and CFI (comparative fit index). All fit indices (χ^2/df = 1.456, GFI = 0.880, AGFI = 0.869, NFI = 0.914, TLI = 0.958, CFI = 0.960, RMSEA = 0.029) met the recommended thresholds set by Hu and Bentler (1999) [36], indicating an acceptable model fit (see Table 6).

Table 6. Model fit indices for the measurement model.

Goodness-of-Fit Measure	Recommend Value	Result	Interpretation
CMIN/df	between 1 and 3	1.456	Excellent
Goodness-of-fit Index (GFI)	≥0.80	0.880	Excellent
Adjusted Goodness-of-fit Index (AGFI)	≥0.80	0.869	Excellent
Normalized Fit Index (NFI)	≥0.90	0.914	Excellent
Tucker–Lewis Index (TLI)	≥0.90	0.958	Excellent
Comparative Fit Index (CFI)	≥0.90	0.960	Excellent
Root Mean Square Error of Approximation (RMSEA)	≤0.06	0.029	Excellent

The path analysis explored the relationships among seven constructs. These included GAI Anxiety (GAI-AN), GAI Self-efficacy (GAI-SE), Facilitating Condition (FC), Social Influence (SI), Perceived Ease of Use (PEoU), Perceived Usefulness (PU), and AI Continuous Intention (GAI-CI). Figure 2 shows the structural model. Table 7 presents the path coefficients. The results revealed that 10 out of 11 hypotheses were supported.

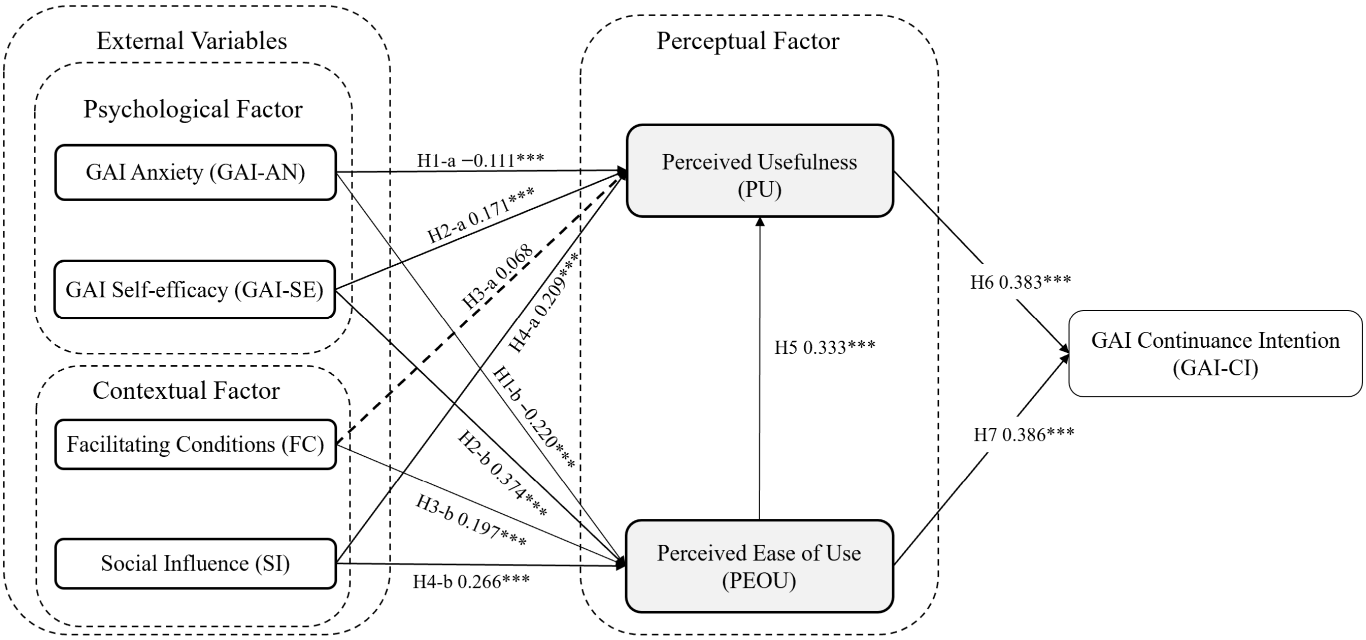

Figure 2. The hypothesis-testing result of model. Note: *** $p < 0.001$.

Table 7. Hypotheses-testing result.

Code	Path	Hypothesis	Result	Estimate(β)	S.E.	C.R.	*p*-Value	Hypotheses-Testing Result
H1-a	GAI-AN → PU	Negative	Negative	−0.111	0.038	−2.591	<0.010	Supported
H1-b	GAI-AN → PEoU	Negative	Negative	−0.220	0.036	−5.127	<0.001	Supported
H2-a	GAI-SE → PU	Positive	Positive	0.171	0.052	3.621	<0.001	Supported
H2-b	GAI-SE → PEoU	Positive	Positive	0.374	0.048	7.863	<0.001	Supported
H3-a	FC → PU	Positive	Positive	0.068	0.043	1.596	0.111	Unsupported
H3-b	FC → PEoU	Positive	Positive	0.197	0.040	4.591	<0.001	Supported
H4-a	SI → PU	Positive	Positive	0.209	0.049	4.585	<0.001	Supported
H4-b	SI → PEoU	Positive	Positive	0.266	0.045	5.906	<0.001	Supported
H5	PEoU → PU	Positive	Positive	0.333	0.059	6.105	<0.001	Supported
H6	PU → GAI-CI	Positive	Positive	0.383	0.053	7.815	<0.001	Supported
H7	PEoU → GAI-CI	Positive	Positive	0.386	0.058	7.714	<0.001	Supported

The analysis first examined how individual psychological factors influenced teachers' perceptions of generative AI. GAI anxiety was negatively associated with both PEoU and PU. Teachers with higher GAI anxiety viewed AI as less useful (H1-a, $\beta = -0.111$, $p = 0.010$).

They also found AI tools harder to use (H1-b, $\beta = -0.220$, $p < 0.001$). These findings suggest that anxiety toward GAI may reduce teachers' positive perceptions of AI tools. In contrast, GAI self-efficacy showed the opposite pattern. It positively affected PU (H2-a, $\beta = 0.171$, $p < 0.001$) and PEoU (H2-b, $\beta = 0.374$, $p < 0.001$). Teachers who felt confident in using AI were more likely to see it as easy and useful. Among all predictors, GAI self-efficacy had the strongest positive association with PEoU ($\beta = 0.374$, $p < 0.001$).

Beyond individual factors, the analysis also examined how external factors shaped teachers' perceptions. Facilitating condition positively influenced PEoU (H3-b, $\beta = 0.197$, $p < 0.001$). However, its association with PU was not statistically significant (H3-a, $\beta = 0.068$, $p = 0.111$). This finding indicates that a supportive environment helps teachers feel generative AI is easy to use. But it does not directly change their views on whether GAI is useful. Similarly, Social Influence positively affected both PU (H4-a, $\beta = 0.209$, $p < 0.001$) and PEoU (H4-b, $\beta = 0.266$, $p < 0.001$). This result highlights the role of peers and institutions. When colleagues and schools support AI use, teachers tend to hold more positive attitudes toward GAI.

The findings also revealed a strong positive relationship between Perceived Ease of Use and Perceived Usefulness (H5, $\beta = 0.333$, $p < 0.001$). This finding is consistent with the Technology Acceptance Model [10]. Teachers who found GAI easy to use also considered it more useful.

Furthermore, both Perceived Usefulness (H6, $\beta = 0.383$, $p < 0.001$) and Perceived Ease of Use (H7, $\beta = 0.386$, $p < 0.001$) significantly predicted GAI Continuous Intention. These results indicate that teachers who perceive AI as easy to use and useful are more likely to continue using generative AI in their teaching practice.

Overall, the path analysis highlighted the complex interactions among individual psychological factors (GAI Anxiety and Self-efficacy), external factors (Facilitating Conditions and Social Influence), technology perceptions (Ease of use and Usefulness), and behavioral intention. The results suggest that reducing GAI anxiety and enhancing GAI self-efficacy, while providing supportive environments and peer encouragement, may contribute to teachers' continuance intention to use GAI in education.

4.4. fsQCA Analysis

CB-SEM is useful for examining linear relationships between variables. However, this method has limitations. It cannot capture the complex and asymmetric relationships in human behavior, as symmetric methods fail to account for the complex interplay of multiple causal conditions [39]. This study therefore employed fuzzy-set qualitative comparative analysis (fsQCA) to complement the CB-SEM with AMOS findings.

Data calibration is essential for determining the membership degree of causal variable sets. This research employed calibration techniques based on the standard thresholds of 95%, 50%, and 5% [40]. In the fsQCA analysis, multi-item latent variables were constructed by calculating mean values. Fuzzy-set calibration then proceeded using the three-anchor method, with thresholds established at the 5th, 50th, and 95th percentiles of the data distribution [30]. In accordance with the technical specifications of fsQCA 3.0 software, membership scores of 0.5 were adjusted to 0.501 to avoid conditions of complete ambiguity [31]. The calibration anchors for all conditional variables and the outcome variable are detailed in Table 8.

Table 8. Calibration Thresholds.

Conditional and Outcome Variables	Calibrations		
	Full Affiliation (95%)	**Intersection Point (50%)**	**Totally Unaffiliated (5%)**
GAI Anxiety	4.75	3.13	1.75
GAI Self-efficacy	4.75	3.63	2.25
Facilitating conditions	4.75	3.38	2
Social Influence	4.75	3.5	2.052
Perceived Ease of Use	4.75	3.63	2.13
Perceived Ease of Use	4.75	3.63	2.25
GAI Continuance Intention	4.83	3.83	2

The necessity condition test determines whether a constant condition intersection exists within the result set. This test calculates consistency and coverage using established algorithms. The threshold for consistency is 0.9 and for coverage is 0.5 [31]. The necessity analysis results are presented in Table 9. The results reveal that the consistency for high and non-high continuance intention ranges from 0.529 to 0.797. All values are below the 0.9 threshold. This indicates that no single condition is necessary for the outcome.

Table 9. Necessity Analysis Results.

Conditional Variable	High Continuance Intention		Non-High Continuance Intention	
	Consistency	**Coverage**	**Consistency**	**Coverage**
GAI Anxiety	0.559	0.580	0.729	0.734
~GAI Anxiety	0.743	0.739	0.582	0.561
GAI Self-efficacy	0.787	0.774	0.569	0.543
~GAI Self-efficacy	0.536	0.562	0.763	0.777
Facilitating conditions	0.740	0.716	0.618	0.580
~Facilitating condition	0.566	0.605	0.697	0.722
Social Influence	0.748	0.768	0.565	0.563
~Social Influence	0.574	0.577	0.767	0.747
Perceived Ease of Use	0.779	0.800	0.548	0.546
~Perceived Ease of Use	0.558	0.560	0.799	0.778
Perceived Usefulness	0.797	0.777	0.572	0.541
~Perceived Usefulness	0.529	0.560	0.764	0.785

Note. ~ denotes the absence (negation) of the condition.

This study set the consistency threshold at 0.8 and the frequency threshold at 1 for constructing the truth table [39]. The fsQCA software generates complex, intermediate, and parsimonious solutions through Boolean algebra minimization. This study reports the intermediate solution. As shown in Table 10, six configurations were identified for high continuance intention. The overall solution consistency is 0.906. The overall solution coverage is 0.679. All six configurations exhibit consistency values above 0.90.

After classifying the six configurations, three distinct driving patterns are identified.

Pattern 1: Intrinsic-value driven (C1, C2, and C3). These three configurations share the same core conditions, as follows: low GAI anxiety, high GAI self-efficacy, and high perceived usefulness. They differ in their contextual drivers. In C1, facilitating conditions serve as a core condition, reflecting institutional resource support. In C2, social influence acts as the core contextual condition, reflecting peer and supervisor endorsement. In C3, perceived ease of use serves as the core supplement, reflecting user-friendly technology perception. The low unique coverage values (0.010–0.025) indicate substantial case overlap among the three pathways, while their moderate raw coverage (0.481–0.521) confirms that each pathway still explains a considerable share of cases. This pattern reflects equifinality:

the same core mechanism produces high continuance intention through different contextual combinations. The "do not care" conditions in these configurations (e.g., social influence in C1, perceived ease of use in C2) indicate that within each specific configuration, these conditions are neither necessary nor negating, as the other present conditions are already sufficient to produce the outcome [30].

Table 10. Configurational Pathways to Continuance Intention.

Variable	Pre-Service Teachers' Continuance Intention Toward AI					
	C1	**C2**	**C3**	**C4**	**C5**	**C6**
GAI Anxiety	⊗	⊗	⊗		⊗	⊗
GAI Self-efficacy	●	●	●	●	●	
Facilitating conditions	●				●	●
Social Influence		●		●	●	●
Perceived Ease of Use			●	●	●	●
Perceived Usefulness	●	●	●	●		●
Raw coverage	0.481	0.493	0.521	0.524	0.433	0.442
Unique coverage	0.010	0.014	0.025	0.065	0.020	0.029
Consistency	0.936	0.934	0.934	0.933	0.945	0.946
Coverage	**0.679**					
Consistency	**0.906**					

Note: Large circles indicate core conditions and small circles peripheral conditions. Black circles ("●") indicate the "presence" of a condition, crossed-out circles ("⊗") indicate its "negation," and blank spaces in the solutions indicate "do not care."

Pattern 2: Efficacy-capability driven (C4). This pattern shows that high GAI self-efficacy, combined with complete technology perceptions and strong social influence, increase continuance intention regardless of anxiety levels. The configuration validates Bandura [16] self-efficacy theory: strong capability beliefs override psychological barriers when supported by comprehensive technology assessments and peer endorsement. For pre-service teachers experiencing elevated anxiety, building robust self-efficacy through hands-on training proves more effective than anxiety reduction interventions.

Pattern 3: External-support driven (C5 and C6). While Pattern 1 is founded on intrinsic motivation, C5 and C6 depend primarily on environmental conditions. Both configurations require low GAI anxiety and high perceived ease of use as core conditions, but they address different gaps in individual readiness. C5 features social influence as the core driver, sustaining continuance intention even without strong perceived usefulness. C6 relies on facilitating conditions and perceived usefulness as core drivers, maintaining continuance intention even when self-efficacy is low. The raw coverage values (0.433 and 0.442) and unique coverage values (0.020 and 0.029) indicate moderate explanatory power with partial case overlap. This pattern suggests that strong institutional and social support can temporarily sustain AI adoption among pre-service teachers who have not yet developed sufficient internal readiness.

5. Discussion

This study integrated psychological, contextual, and perceptual factors into an extended TAM-UTAUT framework. Utilizing SEM and fsQCA, the research validated 10 out of 11 hypotheses. Notably, the path from facilitating conditions to perceived usefulness was non-significant, being inconsistent with the theory. Complementing these findings, fsQCA identified six configurations clustered into three distinct driving patterns.

Regarding psychological factors, GAI self-efficacy demonstrated the strongest positive associations with both perceived ease of use (β = 0.374) and perceived usefulness (β = 0.171) among all antecedent variables. This finding is in line with Bandura [16] self-efficacy theory and recent research by Wang, Ruan, Zhang, Fu, and Duan [5], suggesting that pre-service teachers who believe in their ability to use AI tools are more likely to see them as easy to use and useful. In contrast, GAI anxiety negatively influenced both perceived ease of use ($\beta = -0.220$) and perceived usefulness ($\beta = -0.111$). This result is consistent with Venkatesh's [11] argument that technology-related anxiety acts as a barrier to positive perceptions. The stronger association between anxiety and perceived ease of use suggests that anxious pre-service teachers may primarily struggle with how to operate AI tools rather than whether GAI is useful.

Among the 11 hypotheses, the unsupported one is H3-a: facilitating conditions positively influence perceived usefulness. The data indicate that facilitating conditions positively influenced perceived ease of use ($\beta = 0.197$, $p < 0.001$) but did not significantly affect perceived usefulness ($\beta = 0.068$, $p = 0.111$), thus not supporting this hypothesis. This finding is partially inconsistent with the UTAUT model but consistent with Wang, Ruan, Zhang, Fu, and Duan [5], who reported similar results among 606 Chinese pre-service teachers. The Chinese educational context helps explain this result. Providing hardware, software, and technical training may help pre-service teachers feel generative AI is easy to use, yet such support primarily emphasizes technical access without demonstrating how GAI enhances specific teaching tasks. Moreover, in China's collectivist culture, pre-service teachers tend to form beliefs about usefulness through recommendations from professors and peers rather than resource availability [41]. This is supported by the significant social influence to perceived usefulness path ($\beta = 0.209$) in our model, indicating that social endorsement outweighs infrastructure in shaping perceptions of AI's pedagogical value.

In contrast, social influence significantly affected both perceived ease of use ($\beta = 0.266$) and perceived usefulness ($\beta = 0.209$). This result supports the finding of Sallam, Al-Adwan, Mijwil, Abdelaziz, Al-Qaisi, Ibrahim, and Sallam [22] that peer support shapes teacher attitudes more than other factors. When professors and classmates support AI use, pre-service teachers not only find AI easier to use but also see its value for teaching. This suggests that what important others think matters for both how easy and how useful pre-service teachers believe generative AI to be. Additionally, consistent with the Technology Acceptance Model [10], perceived ease of use positively related to perceived usefulness ($\beta = 0.333$), and both factors had comparable direct associations with continuance intention ($\beta = 0.386$ and $\beta = 0.383$).

The fsQCA results improve the SEM findings by showing that different combinations of factors can lead to high continuance intention. The six configurations clustered into three patterns. Pattern 1 (Intrinsic-value driven), including C1, C2 and C3, shows that low anxiety combined with high self-efficacy and high perceived usefulness leads to continuance regardless of external conditions. Pattern 2 (Efficacy-capability driven), represented by C4, shows that strong self-efficacy can overcome anxiety when combined with positive technology perceptions and social support. This supports Bandura's [16] view that confidence in one's abilities can reduce emotional barriers. Pattern 3 (External-support driven), including C5 and C6, shows that strong external factors can make up for weak internal motivation, though this may be less stable over time.

Overall, this study highlights the importance of both psychological and contextual factors for pre-service teachers' continuance intention in future teaching. The findings suggest that teacher education programs should focus on building GAI self-efficacy through hands-on practice while also creating environments where teachers and peers openly support AI use. Universities should recognize that providing equipment alone is not enough; they also need to show pre-service teachers how generative AI can help with actual teaching tasks. The fsQCA findings further suggest that helping pre-service teachers move from relying on external support to developing internal motivation is important for long-term AI use.

6. Conclusions

This study investigated the factors influencing pre-service teachers' continuance intention to use generative AI in their future teaching practice. Utilizing SPSS 27.0, AMOS 26.0, and fsQCA 3.0, the research examined data from 549 participants to identify relationships among key constructs, including GAI anxiety (GAI-AN), GAI self-efficacy (GAI-SE), facilitating conditions (FC), social influence (SI), perceived ease of use (PEoU), perceived usefulness (PU), and GAI Continuous Intention (GAI-CI). The empirical results were largely consistent with the theoretical frameworks. Specifically, GAI self-efficacy exerted the most substantial positive relationship with both perceived ease of use and perceived usefulness. Furthermore, social influence was found to significantly impact both perceptual factors. However, facilitating conditions did not significantly influence perceived usefulness, a finding that is partially inconsistent with the UTAUT model.

One limitation is that, despite using validated scales with no technical issues, the data were collected at a single point in time. Bhattacherjee [6] suggests that continuance intention develops over time as users gain more experience with a technology. Zheng, Ma, Sun, Wu, and Hu [7] further indicate that the factors influencing continuance intention may change at different stages of technology use. That is, pre-service teachers' perceptions of AI tools may differ between the early trial stage and the later sustained use stage, including changes in how they view GAI's usefulness, how confident they feel about using GAI, and how much they rely on external support. Meanwhile, the sample was limited to pre-service teachers from Chinese universities, which may limit the generalizability of the findings. Venkatesh [11] points out that cultural factors can influence how individuals perceive and adopt technology. Additionally, all measures relied on self-reported data, which may be subject to social desirability bias. Social influence and social desirability bias are interrelated, but the relationship is more complex than just wanting to be seen to fit it. While the compliance mechanism has been noted to relate to adoption, it comprises a complex interplay of contributing factors like critical mass, social networks, and social capital [42]. The only way to capture technology adoption more objectively is measurement of people's actual beliefs and behaviors. Pre-service teachers may overestimate their willingness to use GAI or underestimate their anxiety levels when responding to survey items.

Future research can further understand why facilitating conditions did not significantly influence perceived usefulness, identify factors that contribute to this unexpected finding, and explore ways to enhance pre-service teachers' beliefs about GAI's teaching value. Since providing equipment and technical training is important for pre-service teachers to access and operate AI tools, future research could investigate how we can design institutional support that not only addresses operational barriers but also helps pre-service teachers see the practical benefits of GAI for their future teaching.

Given that this study only included pre-service teachers from a Chinese cultural context, future research can compare results across different countries to see whether the relationships found here apply more broadly [11]. Since the fsQCA results identified three configurational pathways, future research could use qualitative methods to explore why different combinations of factors lead to high continuance intention [20]. Overall, sustainable GAI integration in teacher education requires attention to both psychological readiness and contextual support.

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Abbreviations

The following abbreviations are used in this manuscript:

GAI-AN	Generative AI Anxiety
GAI-SE	Generative AI Self-efficacy
FC	Facilitating Conditions
SI	Social Influence
PEoU	Perceived Ease of Use
PU	Perceived Usefulness
GAI-CI	Generative AI Continuous Intention

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