

Article

Determinants of Higher Education Learners' Behavioral Intention Toward Generative AI Tools: A Hybrid SEM–Machine Learning Approach

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Abstract

As generative artificial intelligence (GenAI) increasingly permeates educational contexts, understanding the factors driving learners' Behavioral Intention (BI) toward GenAI-powered tools has become critical. This study integrates the Technology Acceptance Model (TAM), the Task-Technology Fit (TTF) framework, and privacy and ethical risk considerations to explore the determinants of Chinese higher education students' Behavioral Intention to adopt these tools. Data were collected from 716 students via a structured self-reported questionnaire. A multi-stage analytical approach was employed by integrating structural equation modeling (SEM) with artificial neural networks (ANN) and support vector regression (SVR). SEM was first utilized to validate the theoretical hypotheses and the measurement model. Subsequently, ANN and SVR models were constructed to explore non-linear relationships and rank the importance of core predictors for Behavioral Intention, including Perceived Ease of Use (PEU), Privacy and Ethical Concerns (PEC), Perceived Technical Features (PTF), and TTF. The modeling performance of the two algorithms was then rigorously compared. The SEM results indicate that PTF exerts an indirect impact on Behavioral Intention via the sequential mediation of Task-Technology Fit and Perceived Usefulness (PU), while PEU positively influences both Perceived Usefulness and Behavioral Intention. Notably, PEC did not exhibit a significant negative effect on users' Attitude (ATT) or Behavioral Intention. These findings were further elucidated by the machine learning analyses, where PTF and PEU emerged as the dominant predictors, whereas the non-linear contribution of PEC was marginal. Furthermore, SVR outperformed ANN in terms of predictive accuracy and model stability. This study demonstrates the efficacy of combining theoretical modeling with machine learning techniques to elucidate the adoption mechanisms of GenAI in higher education. In addition, preliminary teaching observations in undergraduate mathematics and logistics management courses link quantitative results with actual learning scenarios. We acknowledge that future research should validate these patterns using observed behavioral data.

Keywords: generative artificial intelligence; behavioral intention; Technology Acceptance Model; support vector regression; artificial neural network; higher education; logistics management



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1. Introduction

GenAI has seen remarkable progress over the past several years. In China, widely used GenAI tools include DeepSeek, Doubao, and Kimi, among others. GenAI carries

significant potential to reshape how undergraduate students acquire knowledge and engage with course materials [1]. GenAI can deliver tailored learning experiences, automated content creation, intelligent tutoring support, and streamlined task completion based on learners' abilities and requirements [2]. A GenAI chatbot can offer rapid responses to students' questions and deliver personalized feedback on their academic assignments [3]. In addition, employing GenAI to create dynamic materials tailored to each learner's individual requirements makes the educational process more engaging and effective [4].

Our definition of learners' behavior encompasses a wide range of activities both inside and outside the classroom [5]. Higher education learners in this study are defined as individuals who are currently pursuing or have recently completed higher education, including full-time undergraduate and junior college students, graduate students (master's and doctoral students), as well as in-service personnel engaged in part-time learning activities such as continuing education and vocational training. GenAI enables students to participate in personalized learning, access more information [6], and enhance their critical thinking, problem-solving abilities, and creativity [7].

Although the pedagogical potential of GenAI has drawn substantial scholarly attention, its application in higher education remains restricted [8]. Consequently, only a small body of studies has examined the effects of GenAI applications on college students' learning [7]. Understanding the driving forces behind learners' Behavioral Intention is key to assessing the potential educational benefits of GenAI learning tools, and exploring the factors that influence this intention is of considerable theoretical and practical importance.

The Technology Acceptance Model has been widely adopted in technology acceptance research. This framework suggests that Perceived Ease of Use and Perceived Usefulness collectively shape user attitudes [9] and Behavioral Intentions toward new technologies [10,11]. In subsequent studies, variables such as Perceived Technical Features [12], Task-Technology Fit [13], and Privacy and Ethical Concerns [14] have been incorporated to enhance the explanatory capacity of the model.

In studies of continuous usage intention for GenAI tools, Task-Technology Fit theory plays an important role, emphasizing that technology should support individual tasks [15]. The extent to which the capabilities of a GenAI-powered learning tool align with the learning task directly affects users' evaluation of its technical usefulness. Dishaw [10] argued that the integration of the Technology Acceptance Model with the Task-Technology Fit framework contributes to clarifying users' willingness to embrace new technology. Accordingly, this paper incorporates Task-Technology Fit constructs into the Technology Acceptance Model to enhance the explanatory capacity regarding higher education learners' acceptance of GenAI tools.

In addition, Privacy and Ethical Concerns [16] also represent challenges that GenAI tools must confront in practical applications. Existing research has verified the existence of the so-called "Privacy Paradox." Some scholarly works have revealed that such privacy and ethical considerations exert a substantial negative effect on users' Behavioral Intentions [17]. Meanwhile, other studies have indicated that users may continue to use related technologies even when they are concerned [18,19]. Privacy calculus theory is often utilized and combined with other frameworks to examine users' decision-making processes from a cost-benefit standpoint [20]. On this basis, the present study introduces Privacy and Ethical Concerns into the Technology Acceptance Model to comprehensively investigate how privacy-related factors shape the Behavioral Intentions of higher education learners regarding the use of GenAI tools.

This study proposes a two-stage hybrid analytical framework: the first stage employs a structural equation model to test the theoretical hypotheses concerning the linear paths; the second stage utilizes artificial neural networks and support vector regression to explore non-

linear associations and rank the relative importance of the key determinants of Behavioral Intention. Through variable importance ranking and importance-performance analysis (IPA), we offer practitioners practical insights and enhance our theoretical understanding of GenAI tools in higher education. This study contributes to research in related fields by investigating the factors that influence the willingness of higher education learners to continue using GenAI learning tools. This investigation's findings are expected to enhance higher education learners' willingness to use GenAI tools and offer a theoretical foundation for educational decision-makers. Given that our data are cross-sectional and self-reported, the machine learning models are employed for explanatory and exploratory purposes rather than for predicting actual future behaviors. The present work is driven by the following research inquiries: (1) How do Perceived Ease of Use, Perceived Usefulness, Task-Technology Fit, privacy and ethical considerations, and Attitude affect the readiness of higher education learners to continue using GenAI learning tools? (2) Between the artificial neural network and support vector regression models, which one provides greater robustness and stability in capturing non-linear structures? How should the relative importance of each variable be ranked?

The innovations of this study are as follows:

(1) In examining ongoing usage of GenAI-powered learning tools, Task-Technology Fit and privacy and ethical considerations were integrated, and structural equation modeling was applied to assess the direct and indirect influences of Perceived Ease of Use, Perceived Usefulness, Task-Technology Fit, Privacy and Ethical Concerns, and Attitude on Behavioral Intention.

(2) The performance of artificial neural network and support vector regression in educational technology non-linear modeling for educational technology was systematically compared, and SVR was found to offer superior stability and fit accuracy in capturing complex data patterns.

(3) By integrating variable importance analysis and performance ranking, an importance-performance analysis map was developed to provide targeted optimization strategies for educational institutions and AI development teams.

The rest of the manuscript is structured as follows: Section 2 reviews the relevant literature and presents the theoretical framework and hypotheses. Section 3 details the methodological approach employed, including data collection and the two-stage analysis that combines SEM and machine learning. Section 4 outlines the outcomes of the SEM and machine learning (ANN and SVR) analyses. Section 5 provides a comprehensive discussion of the results, interpreting the findings in relation to existing literature and highlighting their theoretical and practical implications. Section 6 synthesizes the primary findings and addresses the study's limitations, and discusses potential avenues for future inquiry.

2. Literature Review

2.1. Generative AI Recommendations for Education

Through training on large datasets and by responding to user prompts, GenAI can produce human-like outputs [21]. In recent years, GenAI has played an important role in sectors such as education, healthcare, business, and entertainment by providing innovative solutions [22].

In recent years, GenAI has become increasingly popular across various fields related to teaching and learning [23]. Researchers and practitioners have consistently shown great interest in the use of GenAI tools by education stakeholders [24]. How the broader student population adopts GenAI in educational settings is often influenced by their acceptance or rejection of other related technologies [25]. GenAI-powered systems continue to advance in learning capacity, reasoning skills, self-correction capabilities, and the ability to replicate

human judgment in certain domains. GenAI is poised to exert a significant influence on higher education [26]. As GenAI demonstrates increasing proficiency in performing tasks typically carried out by humans, researchers are continuously reflecting on the impact of higher education learners' trust in GenAI technology on their learning [27].

Within this context, machine learning techniques offer a flexible analytical framework for exploring higher education learners' perceptions of GenAI technology. Compared with traditional statistical methods, these models have an advantage in capturing complex non-linear structures and are able to identify nuanced associations among the various factors influencing learners' Behavioral Intention. The artificial neural network (ANN) model is a computational architecture inspired by the information processing logic of biological neurons. It is widely applied in behavioral research due to its strong pattern recognition ability [28]. Previous scholarly work has demonstrated that ANN can identify key determinants of users' adoption intentions toward AI tools, using predictors identified through structural equation modeling (SEM) [29]. On the other side of the spectrum, support vector regression (SVR) [30], as a supervised learning regression technique derived from the support vector machine paradigm, also exhibits strong non-linear fitting capability [31]. In comparison with ANN, SVR often demonstrates better stability and generalization ability in small-sample and high-dimensional data scenarios through the introduction of an $\mathcal{E}$ -insensitive loss function and high-dimensional kernel transformation [32]. In recent years, GenAI has made numerous breakthroughs, including in areas such as image and speech recognition, as well as robotics applications [33]. Based on the AI readiness index published by the Chinese government, China is currently ranked sixteenth [34]. Although China's readiness score is low, the country has accelerated the deployment of AI technology in public service sectors [34].

In this study, we employ a combination of structural equation modeling and machine learning models (ANN and SVR) to further explore the specific mechanisms underlying higher education learners' attitudes toward GenAI learning tools and their Behavioral Intention. This hybrid analysis framework can not only test theoretical hypotheses and uncover linear relationships between variables through the structural equation model, but also capture complex non-linear interaction effects using machine learning models, thereby more comprehensively identifying and ranking the key antecedents that influence Behavioral Intention. It should be noted that, given the cross-sectional nature of our survey data, the machine learning part is mainly used to evaluate the importance of variables and nonlinear patterns, rather than to predict actual future usage behavior.

2.2. Theoretical Foundation

This study adopts the Technology Acceptance Model as its core theoretical basis, incorporates two extended dimensions (Task-Technology Fit and Privacy and Ethical Concerns), and develops a Behavioral Intention research framework suitable for the context of GenAI learning tools.

The Technology Acceptance Model explores how characteristics of a new system or technology affect users' intrinsic attitudes, beliefs, and intentions [35]. Perceived Ease of Use and Perceived Usefulness can explain users' acceptance mechanisms regarding new technologies: PEU refers to the belief that technology is user-friendly, and PU refers to the belief that it can enhance performance [9]. The PEU and PU constructs influence users' attitudes and behaviors [36] and connect potential technology usage needs with external factors. However, the components of TAM and their interrelationships may not fully account for the specific performance differences across learner groups [37]. Moreover, individual differences in technical ability and attitudes also influence the process of technology acceptance. For example, some learners may be more receptive to new technologies

due to higher technical self-efficacy, while anxiety about technology may hinder its use. Within the educational domain, scholars have conducted extensive research confirming the role of Perceived Ease of Use and Perceived Usefulness within the Technology Acceptance Model framework to explain students' technology acceptance processes [38]. Lin et al. [39] further validated that Perceived Usefulness and Perceived Ease of Use directly impact individuals' Behavioral Intention.

Given the growing adoption of GenAI in educational contexts, the relevance of the classic Technology Acceptance Model framework has been empirically validated across numerous investigations. However, scholars note that it is challenging to fully capture the ethical dimensions and technology-specific factors involved in using GenAI tools when relying exclusively on the Technology Acceptance Model [40].

This study makes two expansions while retaining the core path of the TAM framework. First, Task-Technology Fit is introduced as a foundational lens to link functional attributes to the Behavioral Intention toward technology. Prior scholarship has established that the Perceived Technical Features of GenAI tools, including personalized responsiveness and interactivity, can significantly affect learners' perception of Task-Technology Fit, which subsequently affects their Behavioral Intention [14]. Second, this study includes Privacy and Ethical Concerns as an important negative element that limits technology acceptance. Within the setting of higher education in China, privacy and ethical considerations have been shown to affect learners' Behavioral Intentions [41].

The inhibitory effect of Privacy and Ethical Concerns on users' attitudes and adoption tendencies in GenAI-supported educational settings has been empirically supported [42,43]. In addition, in the TAM, Attitude is regarded as a core mediating variable between Perceived Usefulness and Perceived Ease of Use and Behavioral Intention [44]. Behavioral Intention can be broadly understood as a motivational state that drives potential subsequent behavior, and its strength is highly correlated with the likelihood of engaging in that behavior [45]. In view of the cross-sectional nature of our data, this study uses Behavioral Intention as the outcome variable and does not seek to predict intended usage behavior.

To understand learners' intention formation in GenAI-supported learning settings, this study proposes a composite path framework. On the one hand, Perceived Technical Features indirectly affect Attitude and Behavioral Intention by shaping learners' functional evaluations of GenAI tools (i.e., Perceived Usefulness and Perceived Ease of Use). On the other hand, Privacy and Ethical Concerns, as restrictive variables, directly and negatively affect Attitude and Perceived Usefulness [43]. The proposed conceptual model is illustrated in Figure 1. Subsequent machine learning analysis will complement the SEM results by exploring non-linear patterns and ranking variable importance, not merely serving as a predictive tool.

2.3. Research Hypothesis

2.3.1. Core TAM Pathways

Perceived Usefulness and Attitude are two core dimensions that explain Behavioral Intention. Perceived Usefulness refers to the degree to which individuals believe that using GenAI tools brings them benefits. This concept can also be defined from the perspective of whether technology can provide tangible value to users [46,47]. Attitude is an individual's positive or negative overall assessment of the technology. A large body of empirical studies has demonstrated that users' perception of the usefulness of a technology is a key precursor to forming a positive Attitude [48]. In contexts where learners perceive that GenAI tools can effectively help them enhance their learning efficiency and gain a better understanding of course content, they are more inclined to develop favorable attitudes toward GenAI tools.

H1. *Perceived Usefulness positively influences Attitude.*

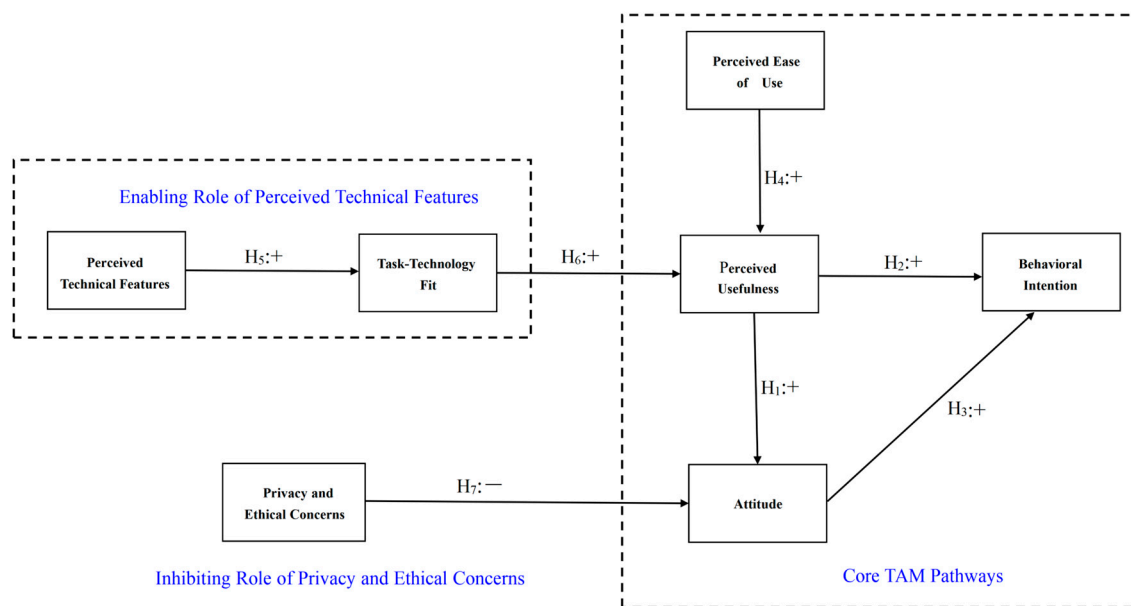


Figure 1. Research framework diagram.

Behavioral Intention is broadly defined as a behavioral tendency shaped by motivational factors, meaning that the actual performance of behavior is strongly linked to an individual's intention [45]. Users' belief about technology's usefulness serves as the key psychological mechanism driving their behavioral responses. Perceived Usefulness is one of the strongest determinants of users' technology acceptance behavior [49]. Numerous studies have confirmed that Perceived Usefulness positively influences Behavioral Intention [50,51]. When students perceive GenAI as capable of assisting their learning, providing personalized support, and improving academic performance, their intention to adopt the tools becomes stronger. Even when confronted with negative factors such as Privacy and Ethical Concerns, Perceived Usefulness remains a core driving factor for technology acceptance [52].

H2. *Perceived Usefulness positively influences Behavioral Intention.*

As a central mediating factor connecting cognitive evaluation and Behavioral Intention, Attitude plays a significant role in technology adoption theory. Ajzen's Theory of Planned Behavior [45] states that an individual's attitude toward a particular behavior serves as a core antecedent of Behavioral Intention. When learners hold a favorable attitude toward GenAI tools, they become more likely to form Behavioral Intention. Extensive empirical research has offered robust support for the positive relationship between Attitude and Behavioral Intention. Attitude ranks among the strongest determinants of Behavioral Intention [53] and exerts a positive influence on students' Behavioral Intention toward GenAI tools [54]. Polyportis et al. [55] found that Attitude and Behavioral Intention are significant positive predictors of students' self-reported ChatGPT usage behavior.

H3. *Attitude positively influences Behavioral Intention.*

Perceived Ease of Use indicates the extent to which learners perceive GenAI learning tools as easy to use [9]. Research has shown that a causal link exists between PEU and PU, with PEU serving as a potential antecedent of PU. This association has been confirmed in research on technology adoption, including research on multimedia technology [56] and non-contact technology [47].

In the proposed model, Perceived Ease of Use is regarded as a fundamental external cognitive variable. According to classic technology acceptance theory, if users believe a technology is easy to use, they tend to regard it as useful. When students find the GenAI learning tools intuitive and user-friendly, they are more likely to recognize their value for enhancing learning efficiency.

H4. *Perceived Ease of Use positively influences Perceived Usefulness.*

2.3.2. Enabling Role of Perceived Technical Features

According to Task-Technology Fit theory [15], abundant technical functions directly shape users' assessment of how well technology matches tasks. When incorporating Task-Technology Fit into the TAM framework, Dishaw and Strong [10] further noted that Task-Technology Fit emphasizes the fit between user task requirements and the functionalities offered by information technology. In the context of GenAI learning tools, if learners perceive that GenAI tools provide diverse technical features such as promoting autonomous learning, assisting understanding, and completing course tasks, they will be more likely to perceive that these functions can achieve a good fit with their learning tasks, thereby develop a higher level of Task-Technology Fit. This theoretical expectation has also received empirical support. Previous studies have demonstrated that Perceived Technical Features exert a significant positive effect on Task-Technology Fit [14,57].

H5. *Perceived Technical Features positively influence Task-Technology Fit.*

The positive impact of Task-Technology Fit on Perceived Usefulness has been explicitly articulated in the classic integration model. When incorporating Task-Technology Fit into the technology acceptance model, Dishaw and Strong [10] pointed out that users' evaluation of the fit between task requirements and tool functions serves as the key antecedent driving Perceived Usefulness. In developing the Task-Technology Fit theory, Goodhue and Thompson [15] emphasize that only when technical functions are highly compatible with task demands do users believe that the technology is practically valuable for improving job performance. In recent years, empirical studies in educational technology have offered ample evidence supporting this theoretical relationship. Wang et al. [14] confirmed the statistical significance of the TTF → PU path. In their work, Kowalska and Szelegowska-Rudzka [58] find that when ChatGPT's functions align with students' learning task needs, students' Perceived Usefulness of the tool reaches a high level of Perceived Usefulness. Hu and Gong [59] integrate TAM and TTF models, showing that Task-Technology Fit exerts a significant positive impact on Perceived Usefulness and subsequently affects use attitude and Behavioral Intention. Ünal and Uzun [60] demonstrate that TTF has a significant positive effect on PU, and that TTF ranks as a strong antecedent for explaining Behavioral Intention.

When learners perceive that the functions of GenAI tools are highly aligned with their learning tasks, they become convinced that using these tools can effectively improve the efficiency and quality of task completion. This sense of alignment then strengthens their perception of the practical value of the technology, namely Perceived Usefulness.

H6. *Task-Technology Fit positively influences Perceived Usefulness.*

2.3.3. Inhibiting Role of Privacy and Ethical Concerns

Privacy and Ethical Concerns are another extended construct of this study. Given the widespread application of GenAI tools in education, data privacy protection and ethical risks have drawn growing attention from researchers. Even though students generally

recognize the educational value of GenAI, Privacy and Ethical Concerns remain significantly associated with adoption willingness in some regions [61]. Within Chinese higher education, Privacy and Ethical Concerns represent a critical ethical issues in the educational application of GenAI, and their impact extends to students' perceptions and Behavioral Intentions [41].

Only when learners regard GenAI tools as tools that offer practical benefits will they form a positive attitude toward them. Conversely, if learners believe that the use of GenAI tools carries a high risk of violating their privacy, negative cognition may emerge. The correlation between Privacy and Ethical Concerns and users' attitudes has likewise been supported by previous studies on technology acceptance. Mathew [62] confirmed that privacy risk is negatively correlated with attitude toward use. Similarly, Zhang et al. [42] found that Privacy and Ethical Concerns not only directly influence users' attitudes, but also indirectly exert a negatively influence on attitudes by weakening trust.

Privacy and Ethical Concerns represent a negative emotional and cognitive appraisal [63] that can undermine users' overall attitude towards GenAI learning tools. According to privacy calculus theory, when users decide whether to adopt GenAI learning tools, they engage in a trade-off between potential costs (such as the risk of privacy disclosure) and expected benefits. Even when learners recognize some of the advantages of GenAI tools, their concerns about potential risks can trigger a sense of resistance and distrust, leading to a negative evaluation of using GenAI tools to assist learning.

H7. *Privacy and Ethical Concerns negatively influence Attitude.*

3. Methodology

3.1. Data Collection

This study focuses on higher education learners as the research population. The data were gathered via an online survey conducted in December 2025. The primary research participants are: (1) individuals who are currently pursuing or have completed higher education within the last three years, including undergraduate, associate degree, graduate, and continuing education learners; and (2) those who have had experience with GenAI learning tools (such as Doubao, DeepSeek, and similar applications) in the past six months. Consistent with the exploratory and explanatory nature of our machine learning section, the current data are cross-sectional and self-reported, measuring learners' perceptions and Behavioral Intention, rather than tracking their intended usage behavior over time.

The questionnaire comprises two parts: (1) respondents' demographic information; and (2) survey items aligned with the constructs in the proposed conceptual framework. To ensure the reliability and validity of the instrument, all measurement items were adapted from prior research. In total, 26 items were used to measure higher education learners' perceptions and Behavioral Intention regarding GenAI-based learning systems. All measurement items were rated on a standard 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). A complete list of constructs, items, and their respective sources is presented in Table 1.

Table 1. Measurement items and corresponding literature sources.

Variable	Item	Measurement Items	References
Perceived Ease of Use (PEU)	PEU1	I find it easier to learn using generative AI tools.	[9,64,65]
	PEU2	I am confident that I can quickly master the relevant operations of GenAI tools to assist learning.	[9,64,65]
	PEU3	I believe that I can quickly become proficient in using GenAI tools for learning support.	[9,64,65]

Table 1. Cont.

Variable	Item	Measurement Items	References
Perceived Usefulness (PU)	PU1	In my view, GenAI tools offer practical help for my daily learning.	[9,66]
	PU2	Employing GenAI tools can effectively enhance my learning efficiency or help me complete tasks.	[9,66]
	PU3	GenAI learning tools can spark my inspiration for learning and assist me in developing innovative ideas.	[9,66,67]
	PU4	GenAI learning tools can satisfy my desire for new knowledge and curiosity.	[9,66]
	PU5	The output quality of the GenAI learning tools (e.g., text, code, diagrams) meets my expectations.	[66,68]
Privacy and Ethical Concerns (PEC)	PEC1	I am concerned that the use of GenAI-enabled learning tools may result in unauthorized access to my personal learning data or privacy violations.	[69–71]
	PEC2	I have little trust in the privacy protection measures implemented by GenAI learning tools.	[69,72]
	PEC3	I fear that the output generated by these tools could be misused.	[69,71]
Attitude (ATT)	ATT1	I am pleased with my choice to use GenAI learning tools for learning support.	[66,73]
	ATT2	I have a positive attitude toward using GenAI learning tools to support my learning process.	[66,73]
	ATT3	In my view, it is a wise and reasonable decision to use GenAI learning tools to assist learning.	[66,73]
Behavioral Intention (BI)	BI1	I intend to use GenAI learning tools in my future educational activities.	[64,65,68,74]
	BI2	I will prioritize leveraging GenAI learning tools to address my academic challenges.	[64,65,68,74]
	BI3	I will encourage my peers to use GenAI learning tools to assist in learning.	[64,65,68,74]
	BI4	If permitted by the instructional context, I will frequently use GenAI learning tools to aid my studies.	[64,65,68,74]
Perceived Technical Features (PTF)	PTF1	These GenAI learning tools can support me in reducing my direct reliance on others (e.g., teachers or classmates).	[75,76]
	PTF2	GenAI learning tools help me better grasp the course content and completing the learning tasks.	[9,75,76]
	PTF3	GenAI learning tools can make it easier for me to learn independently without relying on traditional classroom questions.	[67,75,76]
	PTF4	GenAI learning tools can provide real-time interpretation, translation, or summarization of learning materials.	[9,75]
	PTF5	GenAI learning tools allow me to flexibly arrange my learning schedule and location without undue restrictions.	[75,76]
Task-Technology Fit (TTF)	TTF1	GenAI learning tools can fully meet my daily learning needs.	[14,15]
	TTF2	The usage patterns of GenAI learning tools are highly consistent with my personal learning habits.	[15,77]
	TTF3	GenAI learning tools can help me handle complex learning tasks that are difficult to complete using traditional methods.	[10,78]

In total, 761 questionnaires were collected. The demographic data indicated that the gender distribution was 51.64% male and 48.36% female. Furthermore, all participants were aged above 18 during data collection, and the majority of participants were full-time college students (71.79% of the sample), including undergraduate and junior college students. Regarding the frequency of using GenAI learning tools, 43.43% of respondents used the tools up to 5 times per day, 29.61% used them 5–10 times per day, and 6.98% used them more than 10 times per day.

In the data cleaning stage of the questionnaire, we removed the following types of invalid responses: those with completion duration too short (less than 30 s), those whose standard deviation was 0.15 times below the average standard deviation of the entire dataset (i.e., there was an obvious straight-line pattern or uniform responses), those with over 95% identical responses, those with four or more logically contradictory answers, and those that did not pass the attention-check questions. The distribution of questionnaire completion times is shown in Figure 2.

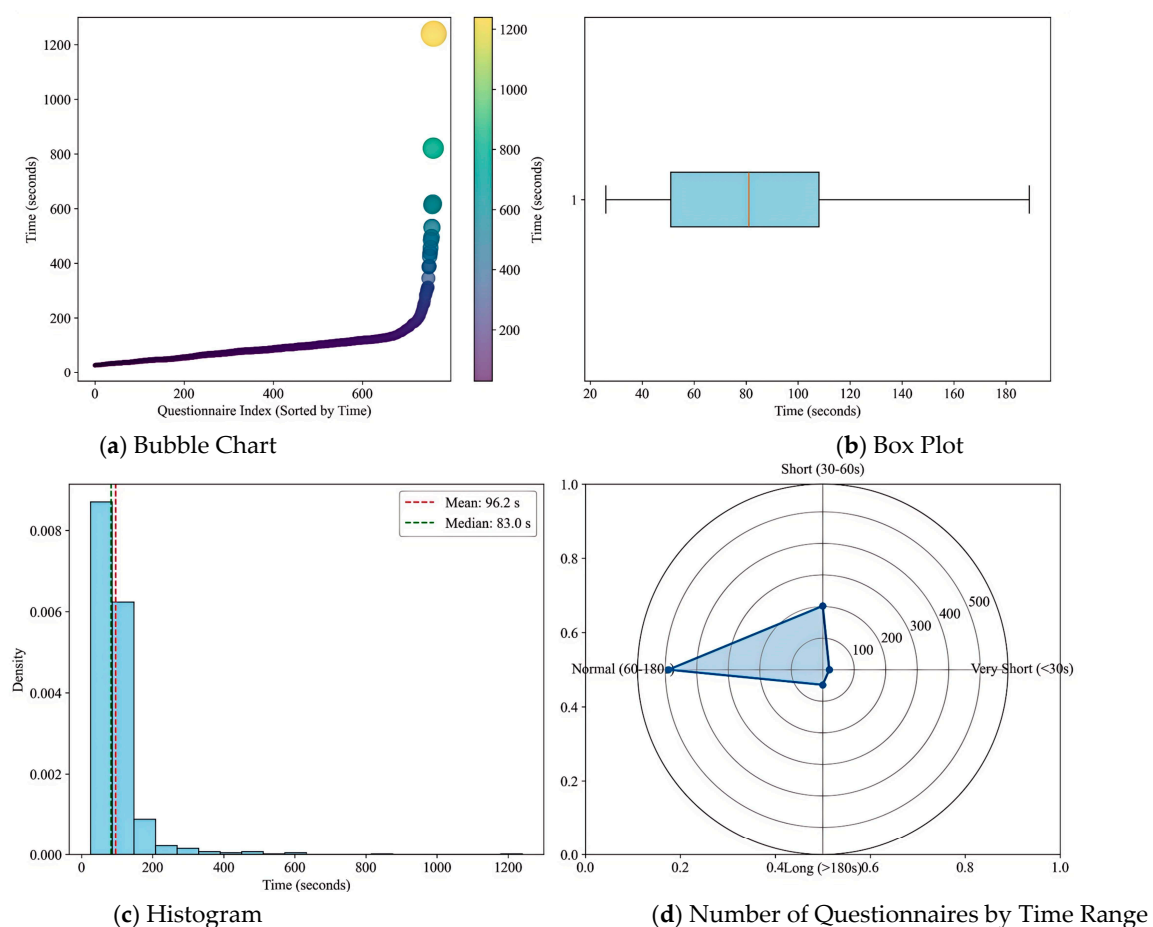


Figure 2. Questionnaire completion time analysis.

Following rigorous screening, a total of 45 invalid questionnaires were eliminated: 21 cases with identical answers, 21 cases with excessively short completion times, and 3 cases with a single-option response pattern. Figure 3 presents the distribution of invalid questionnaires. After data cleaning, the final valid sample consisted of 716 questionnaires, corresponding to a valid response rate of 94.9%. All subsequent analyses in this study were performed using these 716 valid questionnaires after data cleaning.

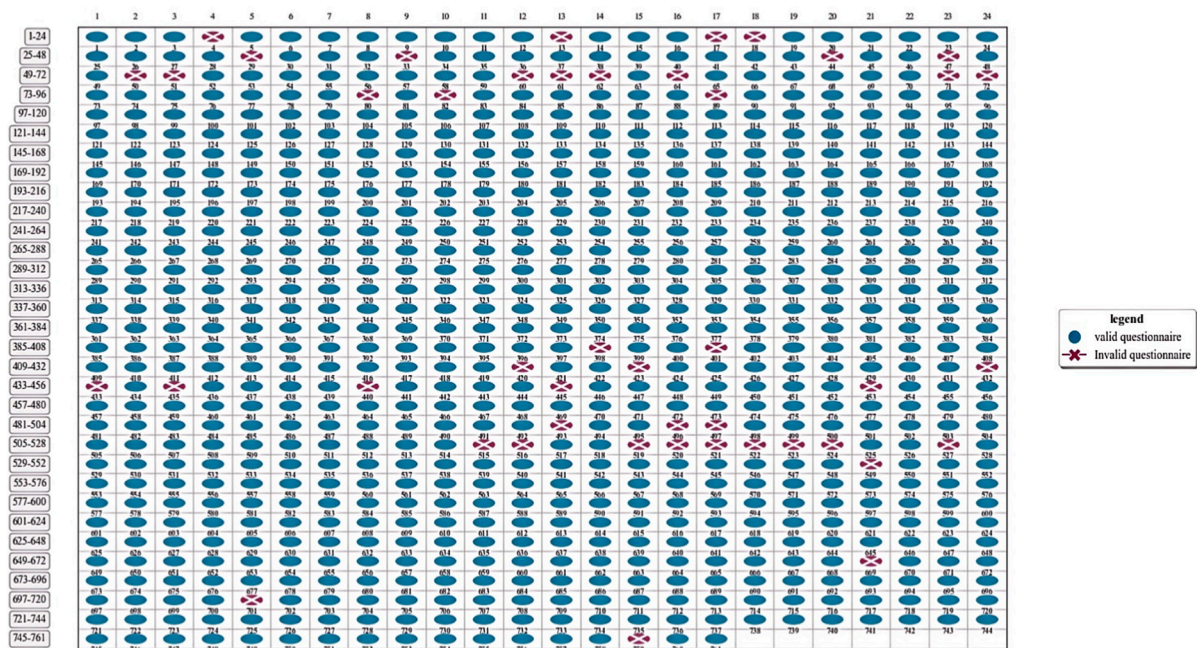


Figure 3. Distribution of invalid questionnaires.

Based on the 716 valid questionnaires obtained after data cleaning, statistical analysis was performed on 26 measurement items. Figure 4 displays the distribution of response counts for the 26 measurement items across Likert scale categories (ranging from ‘strongly disagree’ to ‘strongly agree’). As illustrated in Figure 4, the most frequent responses of the majority of items cluster in the ‘agree’ and ‘strongly agree’ segments, suggesting that participants hold generally favorable attitudes toward the constructs measured by the scale.

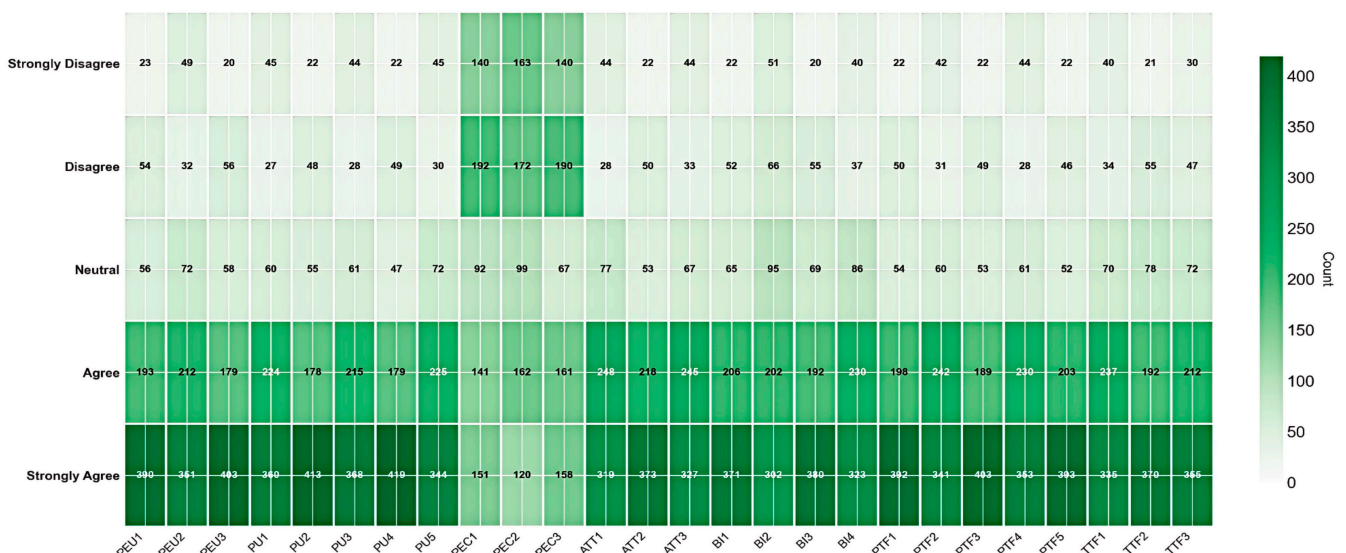


Figure 4. Heatmap of scale items (response counts).

Figure 5 shows the mean scores of the 26 scale items. The red dotted line in this figure represents the overall mean of all items. The mean values of most items exceed the median value, and the mean scores of most items range between 4.0 and 4.5. It is worth noting that the scores of some items (such as PU4, PTF3, and PTF5) are notably above the overall mean, indicating strong endorsement of these positive statements. In contrast, the mean values of PEC1, PEC2, and PEC3 are relatively low (2.96, 2.87, and 3.01, respectively), with an overall construct mean of 2.945. Given that these items are negatively worded (assessing privacy

concerns and distrust), their lower means suggest that respondents tended to disagree with these statements, implying relatively low levels of Privacy and Ethical Concerns in our sample.

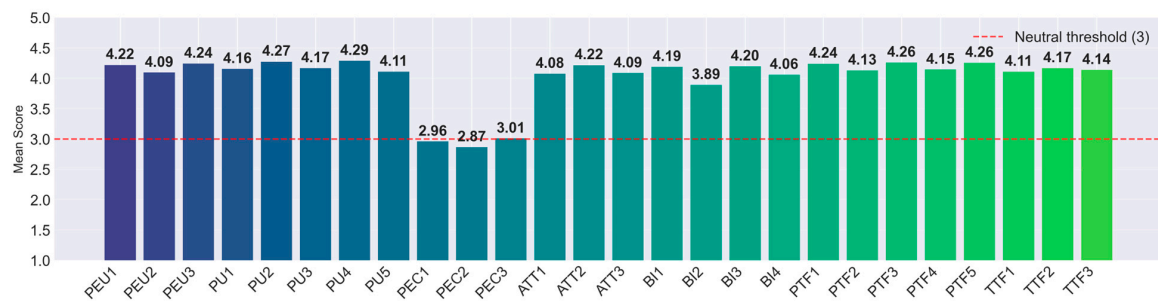


Figure 5. Mean score trend across scale items.

Figure 6 displays the standard deviation of each scale item. The standard deviation of most items falls within a low range of 1.0 to 1.3, suggesting that respondents largely agree on most measurement items and that the data distribution is relatively concentrated.

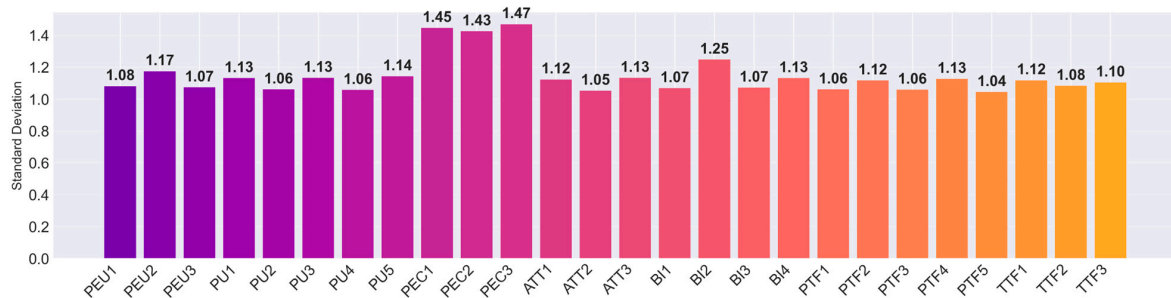


Figure 6. Standard deviation of scale items (lower = more consensus).

The box plot in Figure 7 further shows the detailed data distribution of the 26 scale items. The median line for most boxes is shifted toward the higher end of the scale (4 or 5 points), reflecting the positively skewed distribution of the data. In Figure 7, scattered dots appear below some items, indicating that a few respondents gave scores deviating from the majority, yet they constitute a small proportion of the total sample and do not substantially distort the overall distribution.

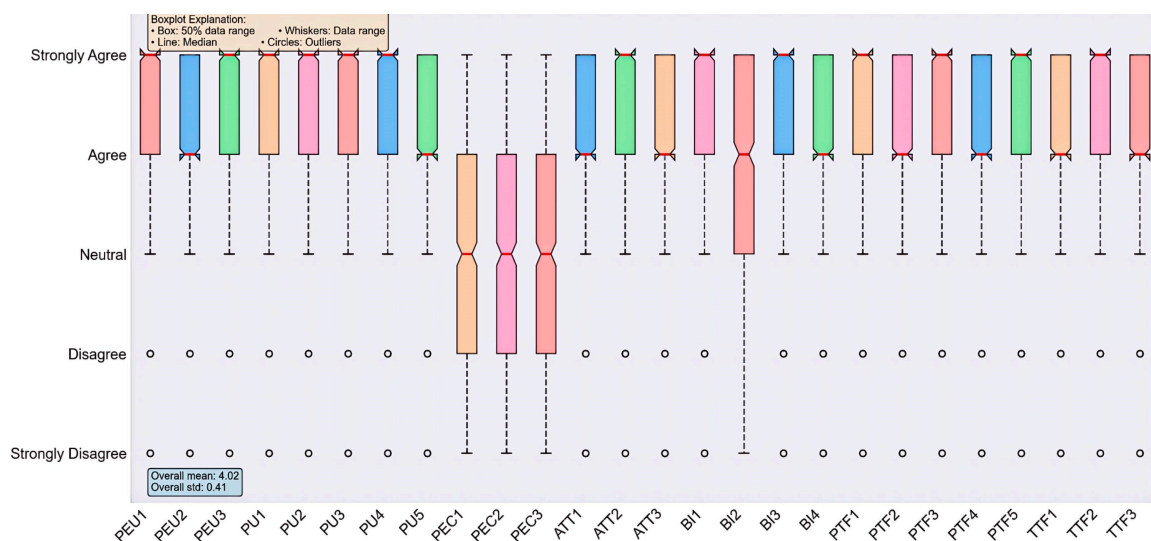


Figure 7. Boxplot of scale items.

3.2. Construct Measurement and Variable Computation

All constructs in this study were measured using validated multi-item scales from previous literature, and the details are shown in Table 1. In the structural equation model analysis, the measurement model was estimated using the covariance matrix of 26 indicator items, and each construct was considered a latent factor.

For the machine learning analysis (ANN and SVR), the input features were computed as the mean scores of the multi-item scales corresponding to each construct, rather than using SEM-derived latent factor scores. Specifically, each respondent's score for a given construct (e.g., Perceived Usefulness, Perceived Ease of Use, Privacy and Ethical Concerns) was obtained by averaging the responses to the items measuring that construct. Similarly, the target variable (Behavioral Intention) was computed as the mean score of its respective items for each respondent. This approach ensures consistency and interpretability across the SEM and machine learning stages, aligning with the approach adopted in prior studies employing hybrid SEM-ANN/SVR frameworks [29,64]. It should be noted that while Table 2 presents summary statistics of these construct scores across the entire sample, the ANN and SVR models were trained on the 716×7 matrix of individual-level construct means (i.e., each row corresponds to one respondent's computed scores for the seven constructs in our framework). A summary of the construct means, standard deviations, and item composition is provided in Table 2.

Table 2. Construct summary statistics and variable computation.

Construct	No. of Items	Mean	SD	Computation Method
PEU	3	4.185	0.973	Mean score of PEU1–PEU3
PU	5	4.199	0.932	Mean score of PU1–PU5
PEC	3	2.945	1.338	Mean score of PEC1–PEC3
ATT	3	4.126	0.964	Mean score of ATT1–ATT3
BI	4	4.084	0.953	Mean score of BI1–BI4
PTF	5	4.206	0.917	Mean score of PTF1–PTF5
TTF	3	4.137	0.985	Mean score of TTF1–TTF3

Before training the ANN and SVR models, all input features and target variables were normalized using min-max scaling to the [0, 1] range to avoid scale-induced biases. Standardized parameters (mean and standard deviation) were calculated only from the training set to avoid data leakage, and then the same parameters were applied to the test set. The dataset was split using stratified sampling: a training set for network weight training (60%, $n = 430$), a validation set for early stopping to prevent overfitting (20%, $n = 143$), and a test set for independent evaluation of model generalization ability (20%, $n = 143$). To ensure a fair comparison between ANN and SVR, both models used the same partitioned data and random seeds for training and evaluation.

3.3. SEM

Structural equation modeling, as a widely adopted second-generation multivariate statistical method, enables simultaneous testing of complex interrelationships among multiple latent variables [79]. Given that the model includes 7 latent variables and 7 hypothesized paths, the covariance-based SEM (CB-SEM) approach was adopted. This approach is guided by theory testing and provides global fit indices to evaluate the degree of congruence between the proposed model and empirical data. Since the degrees of freedom for the specified model in this study are 0, it represents a just-identified model, which can exactly reproduce the sample covariance matrix. The traditional overall fit indices (such as chi-square, RMSEA, CFI, etc.) show perfect fit values and thus lack discriminative power, so they are no longer used as the basis for model evaluation.

The model used in this study is a just-identified model ($df = 0$). Therefore, the global fit indices (such as chi-square, RMSEA, CFI) yield perfect values algebraically ($\chi^2 = 0$, RMSEA = 0, CFI = 1), which cannot provide meaningful empirical evidence for assessing model fit. Therefore, model evaluation in this study focuses mainly on local fit indices, rather than global fit indices. This approach is consistent with previous SEM applications that used a saturated model when the theoretical framework does not support additional constraints [80]. Specifically, we evaluate the quality of the measurement model through factor loadings, composite reliability, and discriminant validity; the quality of the structural model is evaluated by path coefficients, their significance, and the coefficient of determination (R^2).

We employed a two-step method [81] for model evaluation. First, the measurement model was assessed to verify the reliability and validity of each construct. Next, the structural model was examined to evaluate the significance of the hypothesized relationships, as well as the explanatory power of the model.

Based on the features of the research framework, the structural model assessment relies mainly on the following local indicators:

- (1) Path coefficient (β) and its significance: robust standard errors and p -values are derived using the bootstrap method to test whether each hypothesized path is supported.
- (2) Coefficient of determination (R^2): evaluates the proportion of variance in endogenous latent variables (PU, ATT, TTF, BI) is accounted for.
- (3) Effect size (f^2): quantifies the contribution of exogenous latent variables on endogenous latent constructs.

3.4. Machine Learning Model

Given that the structural equation model can only test linear relationships between variables, some hypothesized paths might not reach statistical significance, and non-linearity or interaction effects could remain undetected. For this reason, we employed two machine learning methods, an artificial neural network and support vector regression, as complementary analytical tools. The roles of these machine learning methods in this study are as follows:

- (1) To explore potential non-linear associations between the antecedent variables (Perceived Ease of Use, Perceived Usefulness, Task-Technology Fit, and Perceived Technical Features) with Behavioral Intention, as well as between Privacy and Ethical Concerns and Attitude;
- (2) To rank the relative importance of each antecedent variable in explaining Behavioral Intention;
- (3) To provide complementary evidence regarding the relationships identified in the SEM analysis, with particular attention to whether non-linear patterns may supplement the linear findings.

3.4.1. ANN

(1) Variables and data preprocessing

Four constructs—Perceived Ease of Use (PEU), Perceived Usefulness (PU), Perceived Technical Features (PTF), and Task-Technology Fit (TTF)—were used as input features to explore their relationships with Behavioral Intention (BI). In addition, following the method of previous hybrid SEM-ANN studies [29], an auxiliary ANN model was constructed with PEC as the sole input feature and Attitude (ATT) as the output variable to test whether PEC exhibits a nonlinear effect on Attitude, thus complementing the non-significant linear path (H7) observed in SEM. All input features and output variables were calculated as each respondent's mean score across the items of each scale (see Section 3.2 for details), derived from the 716 valid responses. The structure of the ANN is presented in Figure 8.

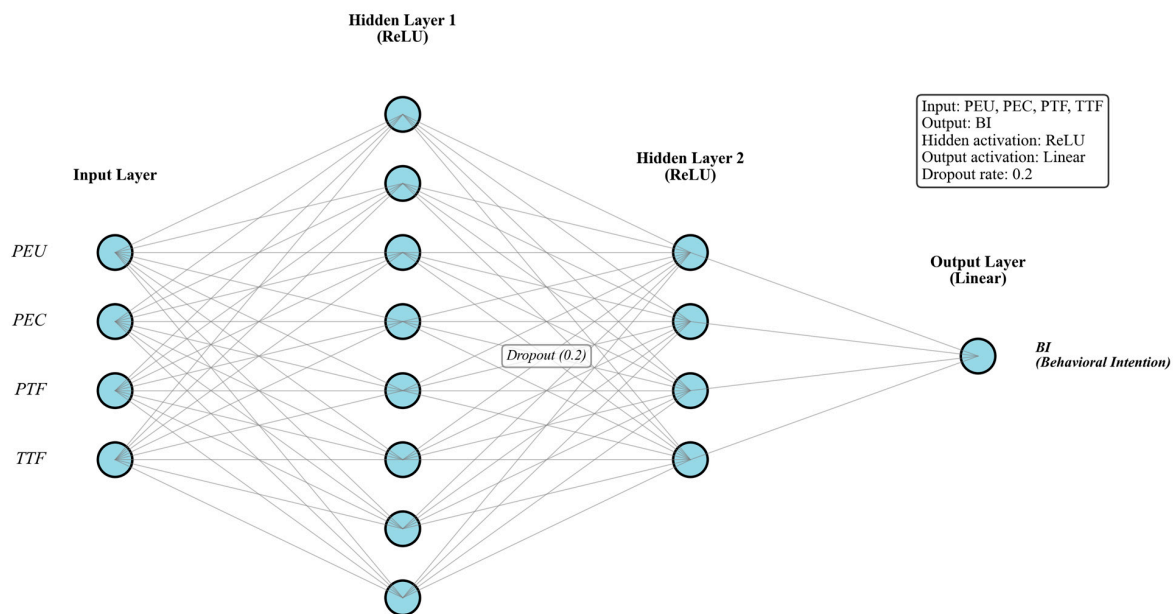


Figure 8. ANN architecture (60/20/20 split).

To mitigate the influence of scale differences and to better accommodate the neural network activation function (e.g., ReLU and Linear), the input features and output variables were each normalized using min-max scaling, which mapped the data into the $[0, 1]$ interval. The normalization formula is: $x_{\text{norm}} = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$, where $x_{\max}$ and $x_{\min}$ are the maximum and minimum values of the corresponding variable, respectively.

(2) Data partitioning

The normalized dataset was divided into three subsets by stratified random sampling:

- (1) Training set: 60% (approximately 429 samples), used for network weight learning.
- (2) Validation set: 20% (approximately 143 samples), used for early stopping to prevent overfitting.
- (3) Test set: 20% (approximately 144 samples), used for the independent evaluation of the model's generalization ability.

(3) Network architecture

We developed a feedforward fully connected neural network (a Multilayer Perceptron, MLP) that consists of:

- (1) Input layer: 4 neurons (corresponding to the features PEU, PEC, PTF, and TTF) for the main model and 1 neuron (PEC) for the auxiliary model.
- (2) Hidden layer: This network consists of two hidden layers. The first hidden layer has 8 neurons, and the second has 4 neurons. The activation function is ReLU (Rectified Linear Unit) to introduce nonlinear transformation.
- (3) Output layer: 1 neuron (BI), with a linear activation function (as the output variable is continuous).

To mitigate overfitting, a dropout layer was added after the first hidden layer, with a dropout rate of 0.2. The total number of trainable parameters is $(4 \times 8 + 8) + (8 \times 4 + 4) + (4 \times 1 + 1) = 81$. The effective sample size for parameter estimation is the training set ($n = 430$), yielding a sample-to-parameter ratio of $430/81 \approx 5.3$, which exceeds the recommended empirical threshold of 5:1 [82] and suggests acceptable model robustness. To ensure reproducibility, all random seeds used for data splitting and model initialization were fixed and recorded in the supplementary repository.

(4) Training strategy

- (1) Loss function: Mean Squared Error (MSE).
- (2) Optimizer: the Adam algorithm, with an initial learning rate of 0.001.
- (3) Batch size: 32.
- (4) Maximum number of iterations (epochs): 200.
- (5) Early Stopping: Validation loss is tracked. If no improvement occurs for 20 consecutive epochs, training is terminated and the optimal weights are restored.

To reduce the effect of random initialization, the aforementioned training process was conducted 10 times, with the mean and standard deviation of the performance metric calculated on the test set.

(5) Model evaluation indicators

The following metrics are calculated on independent test sets:

(1) Root mean square error (RMSE): $\sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$, reflecting the magnitude of the fitting error;

(2) Coefficient of determination (R^2): $R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$, which indicates the fraction of variance accounted for by the model;

(3) Mean absolute error (MAE): $\frac{1}{n} \sum |y_i - \hat{y}_i|$, which measures the average absolute deviation.

In addition, the residuals on the test set (differences between estimated and observed values) are computed to detect any systematic bias.

(6) Variable importance analysis

The Olden connection weight method [83] was employed to assess the relative contribution of each input variable to the output variable. This method computed the aggregate of the absolute values of all connection weights from the input layer to the first hidden layer, from the first hidden layer to the second hidden layer, and from the second hidden layer to the output layer, ultimately yielding the importance score for each input feature. To mitigate the effect of any single random initialization, the relative importance of each variable was presented (with the sum normalized to 1) based on the mean importance across the 10 repeated training runs.

3.4.2. SVR

Support vector regression is a regression approach rooted in structural risk minimization. It projects data into a high-dimensional feature space for linear regression via a kernel function. The SVR schematic diagram is presented in Figure 9.

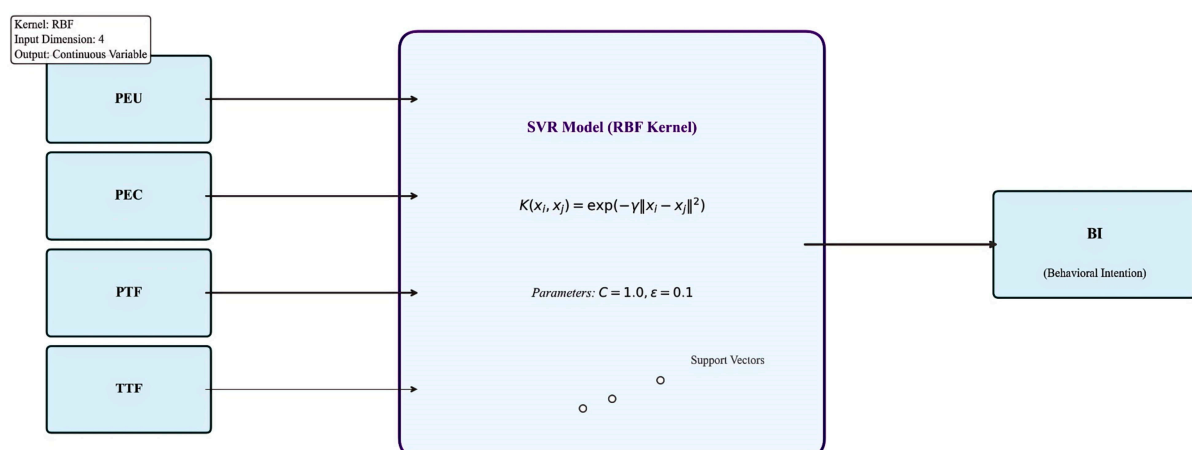


Figure 9. Concept Diagram: SVR Framework.

Compared with an artificial neural network (ANN), support vector regression (SVR) has a global optimal solution and is less sensitive to parameter initialization. To ensure a fair and methodologically sound comparison, the SVR model was evaluated using the exactly same data partitions (identical training and testing sets) as the ANN model.

(1) Basic principle

Support vector regression is an adaptation of support vector machines to regression problems. Its central concept is to seek an optimal hyperplane such that the deviation (error) from all sample points to the hyperplane is kept within an ε -insensitive tube. Unlike traditional regression, which minimizes the squared error loss, SVR imposes a penalty on the sample points lying outside the tube, which leads to a sparse solution and improved generalization ability. The objective function can be expressed as: $\min_{w,b} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^N \xi_i + \xi_i^*$.

The constraints are: $|y_i - (w^\top \phi) + b| \leq \varepsilon + \xi_i$, $\xi_i, \xi_i^* \geq 0$. Where C is the regularization parameter, ξ_i and ξ_i^* are slack variables, and $\phi(\cdot)$ is the kernel function mapping.

(2) Kernel function selection

SVR handles nonlinear relationships via the kernel trick. In this study, the radial basis function (RBF) kernel was adopted, and its expression is: $K = \exp(-\gamma \|x_i - x_j\|^2)$.

The RBF kernel only needs to adjust the hyperparameter γ and can map to an infinite-dimensional space, which makes it suitable for complex pattern modeling of small- to medium-sized samples.

(3) Hyperparameter optimization

The main hyperparameters of the SVR model include the penalty coefficient C , the kernel coefficient γ , and the insensitive loss parameter ε :

(1) C governs the penalty assigned to samples that fall outside the ε -insensitive tube, and a larger C tends to increase the risk of overfitting.

(2) γ determines the influence range of a single sample. The smaller γ is, the wider the influence range becomes.

(3) The width ε of the insensitive tube directly affects the number of support vectors that are retained.

To achieve an optimal configuration, we applied 5-fold cross-validation and grid search on the training set. The search ranges were $C \in [0.1, 1, 10, 100]$; $\gamma \in [0.001, 0.01, 0.1, 1]$; $\varepsilon \in [0.01, 0.1, 0.2, 0.5]$. The R^2 value computed on the validation folds served as the scoring metric for model selection. The grid search results indicated that the parameters combination $C = 1.0$, $\varepsilon = 0.1$, and $\gamma = \text{'scale'}$ (i.e., the default settings) yielded the highest cross-validated R^2 . Since extending the grid search did not yield any significant performance improvement, the final SVR model was configured with the default setting provided by the Python (version 3.11 in Pycharm 25.2.2) scikit-learn library.

(4) Variable importance calculation

Unlike the Olden weight method used for ANN, the variable importance of SVR was calculated using permutation importance. The core logic of this method is to keep the target variable unchanged, randomly permute the order of values of a feature to break its association with the target variable, and then calculate the decline in model fitting performance (e.g., the coefficient of determination, R^2). The greater the performance decline, the greater the contribution of this feature to explaining the output variable, i.e., higher importance. To ensure result stability, we randomly permuted each feature 10 times and took the average R^2 decline, and then normalized the average decline of each feature (so that the sum equals 1). Finally, the relative importance of each input feature was obtained.

(5) Data partition and evaluation

SVR uses the same 60/20/20 data partitioning and min-max normalization as those used for ANN, and the test set performance indicators (RMSE, MAE, R^2) were consistent with those of ANN. Since SVR is a deterministic algorithm with a closed-form solution, repeated training does not introduce random fluctuations due to different initializations; thus, the variability observed in the experimental results stems solely from the data partitioning, not the model initialization. SVR and ANN are evaluated with the same data partition to ensure that the performance comparison between the two models is not affected by differences in data partitions.

3.4.3. Purpose and Positioning of the Machine Learning Analysis

Figure 10 provides a visual overview of the positing of the machine learning component within the overall hybrid analytical framework.

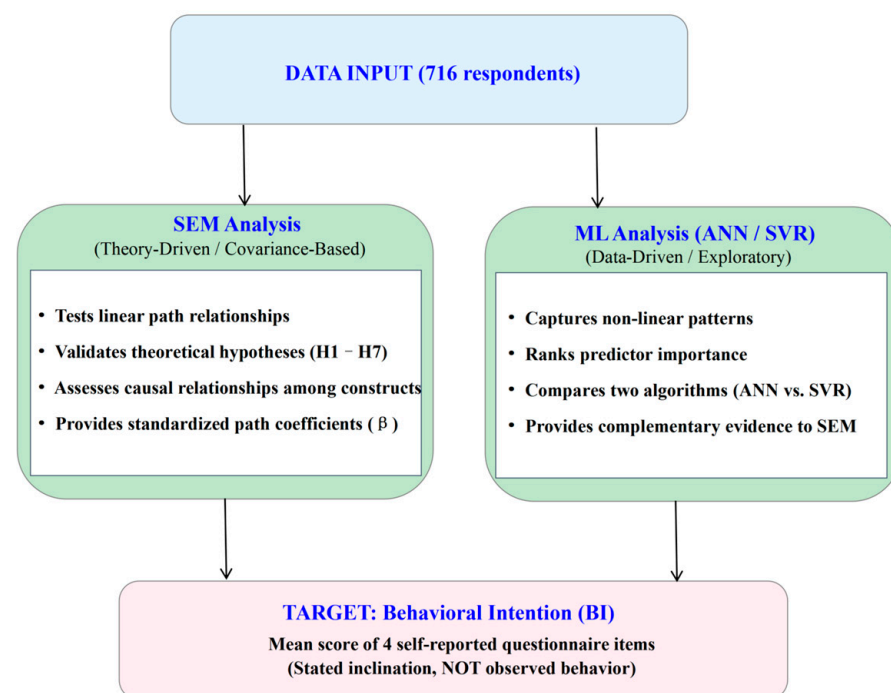


Figure 10. Positioning of the machine learning.

(1) Define the analysis target. In the ANN and SVR models, the target variable was Behavioral Intention (BI), operationalized as the average score of the four self-reported questionnaire items measuring higher education learners' willingness to continue using the generative AI tools (see Section 3.2). This variable reflects respondents' subjective tendency to continue using the tools in future learning activities, rather than their actual observed usage behavior. According to established technology acceptance theories [9,45], Behavioral Intention is the most proximal psychological antecedent of actual behavior, but it does not directly measure the behavior itself.

(2) The significance and added value of machine learning analysis. Since the outcome variables and explanatory constructs were measured simultaneously in the same cross-sectional survey, the ANN and SVR models were not used to predict future behavior. Their added value lay in three aspects. First, unlike SEM, which assumes linear relationships between hypothetical constructs, ANN and SVR can capture potential nonlinear patterns and complex interactions that may not be identified in traditional linear path analysis [29,32]. Second, the variable importance analysis enabled us to rank the relative contribution of

each predictor to the outcome variable, thus providing a supplementary perspective on the standardized path coefficients obtained from SEM. Third, comparing the performances of ANN and SVR helps determine which modeling method is more suitable for capturing the data structure in this specific educational technology context.

(3) Positioning and scope. In this study, the machine learning models were positioned as exploratory and explanatory tools to complement the theory-based structural equation model (SEM) analysis. They were not intended to replace SEM, nor were they used to infer causality or make practical projections about future behavior. The results of ANN and SVR should therefore be understood as evidence of nonlinear associations and variable importance rankings in the current sample, rather than as a generalizable explanatory model of future behavior.

(4) Limitation statement. Given the cross-sectional design of this study, all results, whether from the structural equation models or the machine learning models, are limited to explaining the variability of self-reported intention to continue using GenAI tools at the time of survey. In the future, a longitudinal design or actual usage log data is needed to verify whether the patterns found here can be translated into observed usage behavior.

3.5. Two-Stage Analytical Procedure

In this study, a two-stage hybrid analysis strategy was used to combine structural equation modeling (SEM) with machine learning (ML) models in an orderly manner to address both theoretical hypothesis testing and non-linear pattern exploration. This two-stage analysis process is illustrated in Figure 11.

The process represents the progression from verifying a theoretical linear hypothesis to capturing complex nonlinear patterns, which preserves theoretical explanatory power while offering complementary insights from non-linear pattern exploration.

Phase 1: Confirmatory analysis (SEM)

(1) Model construction and identification. Based on relevant theory, the latent variable path model (hypotheses H1–H7) is constructed, and the model is identified by the fixed latent variable variance method.

(2) Parameter estimation and hypothesis testing. The maximum likelihood estimation method is used to calculate the standardized path coefficient, their significance, and the coefficient of determination (R^2), and to test whether each hypothesis was supported.

(3) Variable identification for the subsequent ML stage. The key antecedent variables that exert a statistically significant direct or indirect influence on Behavioral Intention are identified as the input features of the subsequent-stage machine learning model.

Phase 2: Exploratory analysis (Machine Learning).

(1) Model construction. Using the core antecedent variables (PEU, PEC, PTF, and TTF) identified in SEM as input and BI as the output, we constructed ANN and SVR explanatory models.

(2) Model training and evaluation. The 60/20/20 data partitioning, normalization, and early stopping strategy were used to train and evaluate the fitting performance of the models.

(3) Performance comparison. The fitting performance of different ML models was compared, and the relative strengths of each algorithm were assessed.

(4) Variable importance analysis. The variable importance index (Olden weight method for ANN and permutation importance for SVR) was used to quantify the relative contribution of each antecedent variable to BI, and the results were compared with the total effect of SEM.

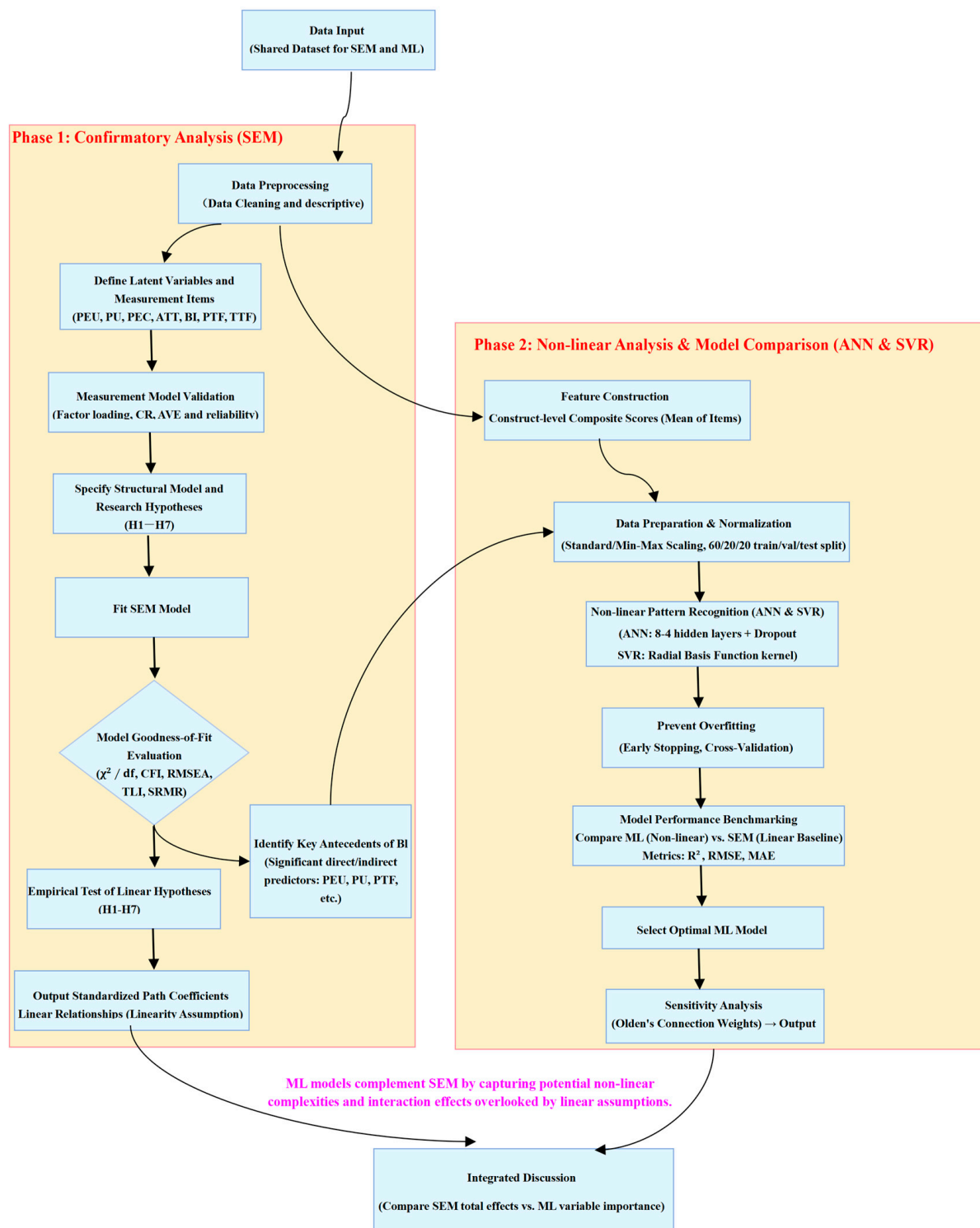


Figure 11. Two-stage hybrid analytical framework (SEM + ML).

3.6. Analysis of Effect

(1) Fitting performance assessment

For ANN and SVR models, the RMSE, MAE and R^2 computed on the independent test set (20% of the sample) were used as the main evaluation indicators. In addition, the loss curves for the training set and the validation set were recorded to ensure that the models did not show serious overfitting. That is, the validation loss converged and the difference from the training loss was less than 0.05. It should be noted that these indicators reflect

the model's fitting performance on the held-out test data, rather than its ability to predict future behavior, which is consistent with the exploratory nature of the machine learning analysis described in Section 3.4.3.

(2) Machine learning and SEM cross validation

(1) Simplified machine learning model: only the significant antecedent variables identified from SEM (PEU, PTF, and TTF) are included, and the non-insignificant variable PEC is eliminated.

(2) Complete machine learning model: it contains all four variables (PEU, PEC, PTF, and TTF). If the R^2 of the complete model was significantly higher than that of the simplified model ($\Delta R^2 > 0.03$), it indicates that PEC has a non-linear contribution beyond the linear effects captured by SEM. Otherwise, the ML result was consistent with the SEM finding that PEC does not exert a substantial effect on Behavioral Intention.

4. Results

4.1. Results of SEM

As noted in Section 3.3, the structural equation model specified in this study is a just-identified (saturated) model with zero degrees of freedom ($df = 0$). This specification was intentionally chosen to retain all theoretically hypothesized paths within the comprehensive framework, thereby avoiding the imposition of arbitrary constraints that might omit significant relationships often observed in technology adoption research [80].

Methodologically, it should be acknowledged that, under these conditions, the perfect global fit indices ($\chi^2 = 0$, RMSEA = 0, CFI = 1) are mathematical artifacts rather than empirical evidence of good model fit [84,85]. Therefore, traditional absolute fit indices do not provide additional diagnostic information. Instead, following established methodological practices for saturated models, the evaluation in this study focused on three critical criteria to ensure model validity: (1) the statistical significance and direction of the path coefficients (local fit); (2) the reliability and validity (convergent and discriminant) of the measurement model; and (3) the coefficient of determination (R^2) of the endogenous variables, which serves as a robust indicator of the model's explanatory power [86]. The results of these evaluations are presented below.

Our decision to adopt the saturated model was based on the study's reliance upon a mature theoretical framework. Different from exploratory research, this study aimed to test the specific hypothesized paths derived from a large body of previous literature. In this confirmatory context involving mature theories, fixing the variance of latent variables for scale setting is a standard procedure, aimed at focus estimation on the significance and magnitude of specific path coefficients, rather than testing the overall network structure.

In order to solve the problem of just-identified specifications, we consider constructing an alternative over-identified model by pruning unimportant paths. However, given the strong empirical support for these relationships in educational technology research, removing any hypothesized path may lead to misspecification of the model and undermine the theoretical integrity of the framework. Therefore, retaining the complete structural model ensures that all theoretically relevant mechanisms are considered. Consequently, confidence in the model rests on the robust psychometric properties demonstrated in Tables 3 and 4, as well as the substantial explanatory power (R^2) of the endogenous variables reported in the following section.

Table 3. Measurement model.

Construct	Item	Std_Loading	t-Value	p-Value	Result
PEU	PEU1	0.834	-	-	-
	PEU2	0.858	35.434	<0.001	Supported
	PEU3	0.833	33.036	<0.001	Supported
PU	PU1	0.851	-	-	-
	PU2	0.708	35.164	<0.001	Supported
	PU3	0.775	40.553	<0.001	Supported
	PU4	0.680	33.149	<0.001	Supported
	PU5	0.788	41.702	<0.001	Supported
PEC	PEC1	0.807	-	-	-
	PEC2	0.842	29.544	<0.001	Supported
	PEC3	0.887	31.723	<0.001	Supported
ATT	ATT1	0.858	-	-	-
	ATT2	0.767	39.616	<0.001	Supported
	ATT3	0.734	37.228	<0.001	Supported
BI	BI1	0.837	-	-	-
	BI2	0.705	35.278	<0.001	Supported
	BI3	0.764	39.677	<0.001	Supported
	BI4	0.768	39.994	<0.001	Supported
PTF	PTF1	0.849	-	-	-
	PTF2	0.820	32.204	<0.001	Supported
	PTF3	0.844	34.415	<0.001	Supported
	PTF4	0.859	35.998	<0.001	Supported
	PTF5	0.815	31.748	<0.001	Supported
TTF	TTF1	0.849	-	-	-
	TTF2	0.762	36.385	<0.001	Supported
	TTF3	0.970	54.948	<0.001	Supported

Table 4. Measurement model.

Construct	CR	AVE
PEU	0.880	0.709
PU	0.874	0.582
PEC	0.883	0.716
ATT	0.830	0.621
BI	0.853	0.593
PTF	0.922	0.702
TTF	0.898	0.747

4.1.1. Measurement Model Analysis

As shown in Table 3, the factor loadings for all measurement items exceed 0.60, with most surpassing 0.70, and all are statistically significant ($p < 0.001$), indicating that the scale exhibits adequate convergent validity. Table 3 shows that for scale identification, the loading of the first item of each construct is fixed at 1.0; thus, these reference indicators do not report t-values.

As shown in Table 4, the composite reliability (CR) values for all latent variables range between 0.830 and 0.922, and the average variance extracted (AVE) values falls between 0.582 and 0.747, both meeting the recommended thresholds ($CR > 0.7$, $AVE > 0.5$). These results indicate that the measurement model exhibited sufficient internal consistency and convergent validity.

As shown in Table 5, the vast majority of the Heterotrait–Monotrait Ratio (HTMT) values were below the conservative threshold of 0.85. The only exception was the HTMT between PU and ATT (0.852), which marginally exceeds 0.85 but remained well below the more lenient threshold of 0.90 [87]. Given that PU and ATT are theoretically sequential antecedents in the TAM framework, this slight elevation is theoretically expected and should not be considered to compromise discriminant validity.

Table 5. HTMT matrix for discriminant validity.

	PEU	PU	PEC	ATT	BI	PTF	TTF
PEU							
PU	0.845						
PEC	−0.084	−0.077					
ATT	0.839	0.852	−0.086				
BI	0.812	0.829	−0.093	0.840			
PTF	0.803	0.828	−0.083	0.832	0.823		
TTF	0.737	0.770	−0.110	0.736	0.758	0.764	

As shown in Table 6, the Variance Inflation Factor (VIF) values of all predictor constructs ranged from 1.013 to 4.247, far below the common threshold of 5.0 [86]. Notably, the VIF of TTF was only 1.942, which confirms that the strong path coefficient from PTF to TTF is not inflated by multicollinearity.

Table 6. VIF for discriminant validity.

Construct	PEU	PU	PEC	ATT	PTF	TTF
VIF	2.710	4.247	1.013	3.317	3.757	1.942

4.1.2. Measurement Model and Hypothesis Testing

As shown in Table 7, Perceived Ease of Use had positive effect on Perceived Usefulness ($\beta = 0.934$, $p < 0.001$), supporting Hypothesis H4. Task-Technology Fit positively influenced Perceived Usefulness ($\beta = 0.240$, $p < 0.001$), supporting Hypothesis H6. Perceived Usefulness exerted significant positive effects on both Attitude ($\beta = 0.809$, $p < 0.001$) and Behavioral Intention ($\beta = 0.520$, $p < 0.001$), supporting H1 and H2, respectively. Attitude also had a significant positive effect on Behavioral Intention ($\beta = 0.325$, $p < 0.001$), supporting Hypothesis H3. Perceived Technical Features had a significant positive effect on Task-Technology Fit ($\beta = 0.960$, $p < 0.001$), supporting H5.

Table 7. Hypothesis testing.

Hypothesis	Path	Standardized Estimate (β)	p -Value	Conclusion
H1	PU $\rightarrow$ ATT	0.809	<0.001	Supported
H2	PU $\rightarrow$ BI	0.520	<0.001	Supported
H3	ATT $\rightarrow$ BI	0.325	<0.001	Supported
H4	PEU $\rightarrow$ PU	0.934	<0.001	Supported
H5	PTF $\rightarrow$ TTF	0.960	<0.001	Supported
H6	TTF $\rightarrow$ PU	0.240	<0.001	Supported
H7	PEC $\rightarrow$ ATT	−0.019	0.676	Not significant

However, the effect of Privacy and Ethical Concerns on Attitude did not reach a significant level ($\beta = -0.019$, $p > 0.05$), leading to the rejection of H7. This nonsignificant result may be explained by multiple factors. First, consistent with the ‘privacy paradox’ [18,19]

reported in the literature, users may weigh the costs and benefits: although there is a moderate degree of concern about privacy (the mean PEC is 2.945), the perceived practicality of the generative AI tools and the degree of Task-Technology Fit may outweigh these concerns when shaping their attitudes. Second, the mean PEC in our sample is relatively low, indicating that privacy and ethical considerations are not the most prominent concerns of this group of higher education learners. Third, China's regulatory environment, especially the 'Personal Information Protection Law' (PIPL) and the 'Network Security Law', may increase users' overall awareness of data protection, thereby reducing the negative impact of personal privacy concerns on technology acceptance.

It should be noted that in this particular educational context, privacy and ethical issues may not constitute a major barrier, although this finding should be interpreted cautiously given the cross-sectional nature of the data.

Figure 12 is the path diagram of the structural equation model. The arrows in Figure 12 represent the influence paths between variables, and the value adjacent to each arrow is the standardized coefficient. *** means significance at the level of $p < 0.001$, ** means significance at the level of $p < 0.01$.

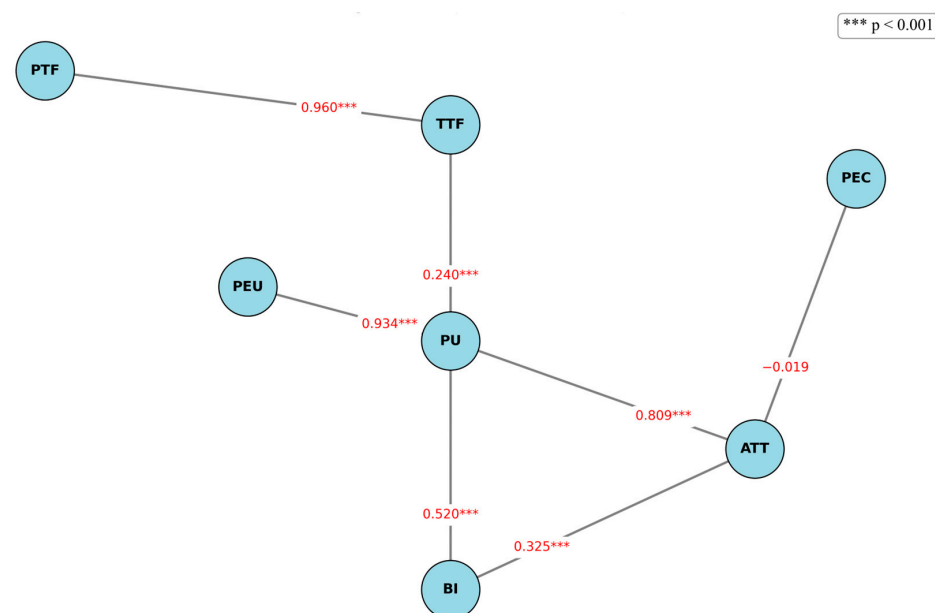


Figure 12. Structural equation model (standardized coefficients).

Table 8 presents the coefficient of determination (R^2) for the endogenous latent variables. Specifically, Perceived Ease of Use and Task-Technology Fit jointly accounted for 80.9% of the variance in Perceived Usefulness. Perceived Usefulness and Privacy and Ethical Concerns together explained 76.5% of the variance in Attitude. Perceived Usefulness and Attitude jointly explained 77.4% of the variance in Behavioral Intention. Perceived Technical Features accounted for 65.3% of the variance in Task-Technology Fit. Collectively, these results indicate that the model exhibits considerable explanatory power.

Table 8. Explanatory power of endogenous latent variables (R^2).

Endogenous Variable	PU	ATT	BI	TTF
R^2	0.809	0.765	0.774	0.653

As noted above, for a just-identified model, the global fit indices are algebraically determined, and therefore the validity of the structural model is primarily supported by its strong explanatory power. As shown in Table 8, the model explains the proportion of

variance in the endogenous structure: Perceived Usefulness is 80.9%, Attitude is 76.5%, and Behavioral Intention is 77.4%. These high R^2 values indicate that the specified path effectively captures the relationships in the data. Although the model lacks the traditional fit indices, it provides empirical support for its validity.

Table 9 presents the standardized direct, indirect, and total effects. The standardized total effect of Perceived Ease of Use on Behavioral Intention was 0.731, and this effect was fully mediated by PU and Attitude. The total effect of Perceived Technical Features on Behavioral Intention was 0.180, which was mediated by the Task-Technology Fit and Perceived Usefulness chain (i.e., PTF $\rightarrow$ TTF $\rightarrow$ PU $\rightarrow$ BI). The total effect of Privacy and Ethical Concerns on Behavioral Intention was close to zero and not significant, which is consistent with the rejection of H7. Taken together, these findings collectively illustrate the multiple pathways through which the antecedent variables relate to Behavioral Intention in this educational context.

Table 9. Standardization direct effect, indirect effect, and total effect.

Independent	Dependent	Direct	Indirect	Total
PEU	PU	0.934	0	0.934
PEU	ATT	0	0.755	0.755
PEU	BI	0	0.731	0.731
PEC	ATT	−0.0187	0	−0.019
PEC	BI	0	−0.006	−0.006
PTF	PU	0	0.230	0.230
PTF	ATT	0	0.186	0.186
PTF	BI	0	0.180	0.180
PTF	TTF	0.960	0	0.960

4.2. Results of Machine Learning Analysis

Although the structural equation model validates the research hypotheses, its reliance on linear regression may not fully capture the complex nonlinear relationships between variables. To further complement the analysis and assess the relative importance of each antecedent variable, this study adopted machine learning (ANN and SVR) for a two-stage analysis. Through sensitivity analysis using machine learning, one can identify the factors exerting the greatest influence on endogenous variables (such as Perceived Usefulness, Attitude, and Behavioral Intention) and their nonlinear weights, so as to provide more targeted suggestions for practice.

According to the SEM results, the main machine learning model used four exogenous variables as input features to explore their relationships with Behavioral Intention, and the auxiliary model used Attitude as the output to examine whether PEC has a nonlinear effect on Attitude that might capture the non-significant linear path observed in SEM (H7). Since Perceived Usefulness acts as a mediator in the theoretical model, it was not used as an input feature in the machine learning analysis, which focuses on the direct associations between the antecedent variables and Behavioral Intention. Variable definitions are presented in Table 10.

Table 10. Variable definitions for machine learning.

Variable Type	Latent Variable	Items
Input feature	PEU	PEU1~PEU3
	PEC	PEC1~PEC3
	PTF	PTF1~PTF5
	TTF	TTF1~TTF3
Output target (main model)	BI	BI1~BI4
Output target (auxiliary model)	ATT	ATT1~ATT3

4.2.1. Results of ANN

In order to test the nonlinear relationships and quantify the relative importance of each antecedent variable for Behavioral Intention, we constructed a feedforward neural network with four exogenous latent variables (PEU, PEC, PTF, and TTF) as the input layer and BI as the output layer. The network structure is 4-8-4-1. The numbers of neurons in the two hidden layers are 8 and 4, respectively; the activation function was ReLU, and a dropout layer with a rate of 0.2 was added after the first hidden layer.

Table 11 reports the RMSE of the main model across the 10 repeated runs, along with the corresponding training and testing errors for each run. Although the SSE and RMSE of each run fluctuate slightly, the overall error level remained within a stable range. The error levels of the model on the training set (RMSE = 0.544) and the test set (RMSE = 0.564) were similar, and there was no clear sign of overfitting. Although the error of the 9th run was slightly higher, the overall average performance suggested that the model has satisfactory generalization ability. The mean RMSE of the model on the test set was stable at about 0.564, and the standard deviation (SD) was 0.044, indicating that the ANN model was less affected by random initialization and is robust.

Table 11. ANN fitting performance across 10 runs.

Neural Network	Training Samples	Training SSE	Training RMSE	Testing Samples	Testing SSE	Testing RMSE
1	429	95.798	0.473	144	34.799	0.492
2	429	113.563	0.515	144	44.691	0.557
3	429	139.474	0.570	144	45.235	0.560
4	429	113.740	0.515	144	47.195	0.572
5	429	120.895	0.531	144	52.619	0.604
6	429	126.487	0.543	144	43.225	0.548
7	429	86.787	0.450	144	45.220	0.560
8	429	149.763	0.591	144	45.101	0.560
9	429	219.524	0.715	144	62.524	0.659
10	429	124.850	0.539	144	39.907	0.526
Average	-	129.088	0.544	-	46.052	0.564
SD	-	36.788	0.073	-	7.396	0.044

Olden's connection weight method was used to calculate the relative contribution of each input variable of the main model (as shown in Table 12). PTF (0.265) and PEU (0.256) were the two most important variables for explaining Behavioral Intention, with a total contribution of more than 52%. The importance values of TTF and PEC were 0.246 and 0.233, respectively. This ranking was generally consistent with the trend of the standardized total effect estimated from SEM.

Table 12. Importance of ANN main model details.

Neural Network	PEU	PEC	PTF	TTF
1	0.191	0.227	0.332	0.249
2	0.217	0.326	0.257	0.199
3	0.261	0.188	0.245	0.306
4	0.258	0.263	0.255	0.224
5	0.221	0.217	0.291	0.272
6	0.264	0.219	0.271	0.247
7	0.373	0.132	0.254	0.242
8	0.220	0.254	0.257	0.269
9	0.291	0.297	0.217	0.196
10	0.265	0.204	0.272	0.258
Average	0.256	0.233	0.265	0.246

As shown in Table 13, the average R^2 on the test set of the main model was 0.643 (SD = 0.049), the average RMSE was 0.564 (SD = 0.044), and the average MAE was 0.450. The average test R^2 of the auxiliary model (with ATT as output) was 0.632 (SD = 0.128), and the ranking of variable importance was TTF (0.271) > PTF (0.264) > PEU (0.252) > PEC (0.213), which was similar to that of the main model.

Table 13. Summary of ANN model fitting performance.

Model	Mean R^2	SD of R^2	Mean RMSE	Mean MAE
Main model (PEU, PEC, PTF, TTF → BI)	0.643	0.049	0.564	0.450
Auxiliary model (→ATT)	0.632	0.128	0.594	0.469
Reduced model (without PEC → BI)	0.674	0.038	0.537	0.427

In order to examine whether PEC has any potential nonlinear effects that might have been overlooked, we trained a simplified ANN without PEC (input: PEU, PTF, TTF). As shown in Table 13, the R^2 of the simplified model is 0.674 (SD = 0.038), which was higher than that of the complete model ($\Delta R^2 = +0.031$). Although this difference marginally exceeds the 0.03 threshold we had set for determining a nonlinear effect, it fell within the range of the standard deviation (SD = 0.038), suggesting that the improvement may not be statistically robust. This finding indicates that PEC may have a marginal nonlinear correlation with Behavioral Intention, but that its actual contribution is limited. This interpretation is broadly consistent with the SEM findings, namely, that PEC exhibited no significant linear effect on Attitude (H7).

Table 14 also presents the detailed importance values averaged over 10 runs of the main model (explaining BI) and the auxiliary model (explaining ATT). As shown in Table 14, the ANN results indicated that TTF (27.6%) ranked first in importance for explaining BI, followed by PTF (27.5%), PEU (22.5%), and PEC (22.4%).

Table 14. Variable importance comparison across ANN models.

Variable	Importance for Predicting BI	SD for BI	Importance for Predicting ATT	SD for ATT
PEU	0.225	0.026	0.253	0.052
PEC	0.224	0.048	0.213	0.048
PTF	0.275	0.066	0.264	0.049
TTF	0.276	0.070	0.270	0.028

In summary, the ANN results provide additional evidence that is generally consistent with the SEM conclusions regarding the non-significance of PEC. While the ranking of predictors (TTF vs. PTF) varied slightly due to the model's sensitivity to nonlinear patterns, no strong nonlinear pattern that would fundamentally change the interpretation of linear results was detected.

4.2.2. Results of SVR

SVR is a regression method based on structural risk minimization, using the radial basis function (RBF) kernel. We used the same data partitioning and standardization as for ANN, and the parameters ($C = 1.0$, $\mathcal{E} = 0.1$, $\gamma = \text{'scale'}$) were verified as optimal via a grid search with 5-fold cross-validation on the training set. The performance on the test set is shown in Table 15: $R^2 = 0.765 \pm 0.026$, RMSE = 0.455 ± 0.026 , MAE = 0.319 ± 0.015 , indicating superior fitting performance compared to ANN on this specific dataset.

Table 15. Detailed performance of SVR main model.

Run	Training RMSE	Testing RMSE	Testing R^2	Testing MAE
1	0.397	0.465	0.757	0.324
2	0.406	0.466	0.788	0.333
3	0.389	0.479	0.742	0.331
4	0.396	0.447	0.786	0.316
5	0.403	0.424	0.810	0.293
6	0.402	0.428	0.779	0.320
7	0.388	0.514	0.725	0.347
8	0.403	0.433	0.737	0.301
9	0.397	0.438	0.767	0.307
10	0.396	0.451	0.759	0.321
Average	0.398	0.455	0.765	0.319
SD	0.006	0.027	0.026	0.016

The importance of the variables was calculated using permutation importance (with 10 repetitions). As shown in Table 16, PTF (normalized importance: 0.470) and PEU (0.316) emerged as the most important variables in explaining BI. The dominant role of PTF in SVR is consistent with its high ranking in the ANN model. Although the relative order of TTF and PTF differs between the two algorithms, which may be due to their different approaches to capturing nonlinearity. Nevertheless, the two models consistently identified PTF and TTF as the top contributing factors, thus distinguishing them from PEC, which had a lower impact. The importance values for TTF and PEC were 13.9% and 7.5%, respectively.

Table 16. Importance of SVR main model details.

Run	PEU	PEC	PTF	TTF
1	0.309	0.070	0.467	0.154
2	0.380	0.079	0.435	0.106
3	0.277	0.083	0.547	0.093
4	0.197	0.071	0.550	0.183
5	0.353	0.098	0.451	0.098
6	0.367	0.055	0.404	0.174
7	0.436	0.078	0.403	0.083
8	0.291	0.078	0.434	0.197
9	0.326	0.097	0.426	0.151
10	0.226	0.036	0.588	0.149
Average	0.316	0.075	0.470	0.139

In order to test whether there is a nonlinear contribution of PEC, we trained a simplified SVR that excluded PEC (input: PEU, PTF, TTF). As reported in Table 17, the R^2 of the simplified model was 0.752 ± 0.025 , which was 0.0132 lower than that of the complete model. This indicates that PEC has a minor association with BI in the SVR framework, but the magnitude of its contribution is small. This finding is broadly consistent with the SEM finding that PEC was not a significant determinant of Attitude in the linear model.

Table 17. Summary of SVR model fitting performance.

Model	Mean R^2	SD of R^2	Mean RMSE	Mean MAE
Main model (PEU, PEC, PTF, TTF $\rightarrow$ BI)	0.765	0.026	0.454	0.319
Auxiliary model ($\rightarrow$ ATT)	0.763	0.045	0.450	0.313
Reduced model (without PEC $\rightarrow$ BI)	0.752	0.025	0.467	0.334

Table 18 presents the aggregated variable importance from the SVR analyses. As shown in Table 18, PTF (47.0%) was the most important variable for predicting BI, followed by PEU (31.6%), TTF (13.9%), and PEC (7.5%). This ranking is slightly different from the ANN results (in which TTF ranked first), but both models agree that PTF and PEU are the two explanatory variables. The difference in TTF ranking may reflect the different algorithmic properties of the two methods: ANN is more sensitive to the nonlinear interaction structure, while SVR prioritizes variables with strong linear relationships with the target.

Table 18. Variable importance in SVR.

Variable	Importance for Predicting BI	SD for BI	Importance for Predicting ATT	SD for ATT
PEU	0.316	0.069	0.330	0.051
PEC	0.075	0.017	0.066	0.020
PTF	0.470	0.063	0.443	0.039
TTF	0.139	0.039	0.161	0.030

4.2.3. Machine Learning Model Comparison

Although ANN showed some variation under repeated training (standard deviation of $R^2 = 0.049$), SVR was more stable across the different data partitions (standard deviation of R^2 across 10 partitions was 0.026). This result indicates that, in this research scenario, SVR with the RBF kernel can better capture the nonlinear relationships between antecedent variables and Behavioral Intention than a classical feedforward neural network. The possible reasons are as follows: (1) SVR obtains the global optimal solution through convex optimization, which avoids the risk of neural networks falling into local minima; (2) the RBF kernel function can adaptively adjust the complexity of feature mapping, making it more suitable for a dataset of moderate sample size ($N = 716$). Because SVR demonstrates superior fitting performance and stability, it was selected as the main model for subsequent Importance-Performance Analysis (IPA) and demographic difference tests.

Table 19 compares the test set performance of ANN and SVR. Since both models were evaluated on exactly the same test sets derived from identical data partitions, the performance metrics reported in Table 19 are directly comparable. The “Improvement” row represents the performance improvement of the SVR model relative to the ANN model, and the calculation formula is: $\frac{|SVR - ANN|}{ANN} \times 100\%$. For these metrics, RMSE, MAE and Std. Dev. are reduced (the lower, the better), and R^2 is the percentage increase (the higher, the better). SVR outperforms ANN across all indicators. R^2 is 0.122 higher (from 0.643 to 0.765), and RMSE and MAE are reduced by 19% and 29%, respectively. SVR also showed better stability, and its standard deviation of R^2 is 0.026, which was 46.9% lower than that of ANN (0.049).

Table 19. Comparative analysis of ANN and SVR test performance.

Model	RMSE	MAE	R^2	Reduction in Variance (%)
SVR	0.454	0.319	0.765	0.026
ANN	0.564	0.450	0.643	0.049
Improvement	19.5%	29.1%	19.0%	−46.9%

To further investigate the role of PEC, we compared the simplified models (without PEC) against the complete models. As shown in previous sections, the R^2 (0.674) of the simplified ANN model was higher than that of the complete model (0.643) (see Table 13), while the R^2 (0.752) of the simplified SVR model was slightly lower than that of the complete model (0.765) (see Table 17). This difference may arise from how the two models capture

nonlinear patterns: PEC in ANN may introduce variability that does not improve fitting, while PEC in SVR provides a weak positive contribution. However, both models show that the relative contribution of PEC is small, which is generally consistent with the conclusion that PEC in SEM is not significant.

Although SVR outperformed ANN in terms of fitting performance on the test set, this finding does not mean that ANN is without value. The variable importance ranking from ANN was highly consistent with the total effects estimated from SEM, and its nonlinear mapping ability provides supplementary evidence supporting the limited role of PEC. Therefore, these two models play a complementary role in this study.

Figure 13 compares the importance of normalized variables for explaining Behavioral Intention (BI) between the ANN and SVR models, and the error bars are expressed as standard deviations of the SVR model based on 10 replicates.

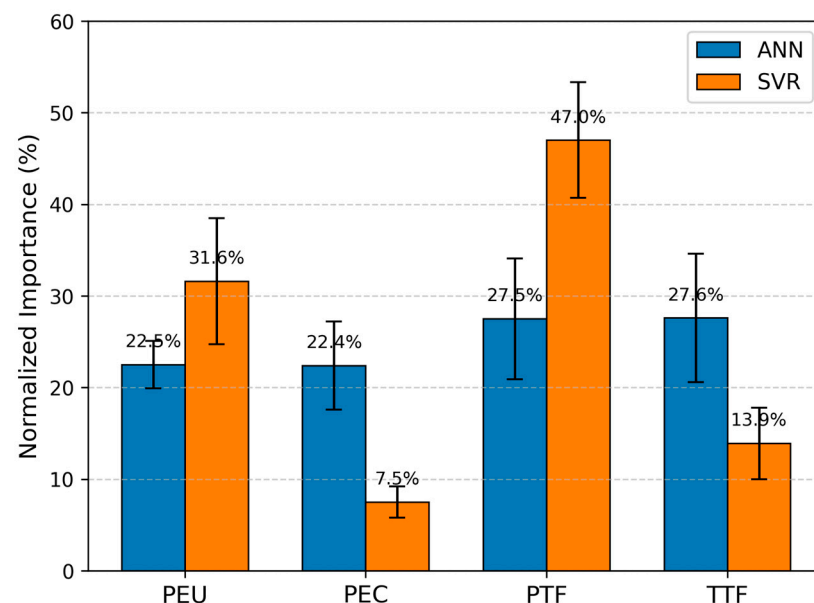


Figure 13. Comparison of Variable Importance between ANN and SVR Models.

It is worth noting that although both models identify PTF and TTF as key contributing factors, their relative importance rankings are slightly different. In the ANN model, TTF is the most important contributing factors (27.6%), followed by PTF (27.5%). In contrast, in the SVR model, the influence of PTF is dominant (47.0%), and the influence of TTF ranks third (13.9%). This difference may be due to the different mechanisms of these algorithms in dealing with multicollinearity and nonlinearity. In view of the high correlation between PTF and TTF ($r = 0.808$), the permutation importance measure of SVR may assign more variance to PTF due to its strong linear component or specific kernel mapping, while the connection weight of ANN may more evenly distribute explanatory power or prioritize the complex nonlinear interaction of TTF. Despite this ranking difference, the consensus that PTF and TTF are the main drivers and that PEC plays a secondary role in the two analysis methods is still reliable.

To explore the upper bound of performance, we also implemented stacking ensemble learning (base learners: LR, RF, GBRT, SVR, ANN; meta-learner: ridge regression) and a weighted average ensemble. Due to the high correlation among the fitted values of the base learners (correlation coefficients > 0.85), ensemble learning did not achieve substantially better performance than the best single model (SVR). Therefore, SVR was selected as the primary model for the subsequent IPA analysis and the demographic difference tests.

4.3. Two-Stage Mixed Model Analysis

4.3.1. Descriptive Statistics and Correlation Matrix

To preliminarily understand the distribution characteristics and linear correlations of each latent variable, we calculated the mean, standard deviation, and Pearson correlation matrix for each variable. Table 20 presents the descriptive statistical results of the core latent variables. In terms of means, the respondents had a positive evaluation for Perceived Ease of Use (PEU, $M = 4.185$), Perceived Usefulness (PU, $M = 4.198$), Perceived Technical Features (PTF, $M = 4.206$), Task-Technology Fit (TTF, $M = 4.137$), Attitude (ATT, $M = 4.126$), and Behavioral Intention (BI, $M = 4.084$) (on a 1–5 point scale), while Privacy and Ethical Concerns (PEC, $M = 2.945$) were at a relatively low level, suggesting that the sample as a whole reported relatively low concern about privacy and ethical issues regarding GenAI learning tools. The standard deviation of each variable ranged between 0.917 and 1.338, indicating that there were notable individual differences within the sample.

Table 20. Descriptive statistics of core latent variables.

Variable	PEU	PU	PEC	PTF	TTF	ATT
Mean	4.185	4.198	2.945	4.206	4.137	4.126
SD	0.973	0.932	1.338	0.917	0.999	0.964

Table 21 lists the Pearson correlation coefficients among the variables. The results show that there are moderate to strong positive correlations between PEU and PTF ($r = 0.828$, $p < 0.001$), between PEU and TTF ($r = 0.756$, $p < 0.001$), between PTF and TTF ($r = 0.808$, $p < 0.001$), between PEU and ATT ($r = 0.838$, $p < 0.001$), and between PTF and BI ($r = 0.854$, $p < 0.001$). Notably, PU also exhibited strong positive correlations with PTF ($r = 0.877$), ATT ($r = 0.874$), and BI ($r = 0.858$). All of these correlations are statistically significant (see Table 22 for specific p -values). The absolute values of the correlation coefficients between PEC and all other variables ranged from 0.088 to 0.117, and although some of these coefficients were statistically significant but weak (e.g., PEC and PEU: $r = -0.088$, $p = 0.018$; PEC and PU: $r = -0.082$, $p = 0.027$), suggesting that the linear correlations between Privacy and Ethical Concerns and the other technology acceptance constructs are very weak. The directions of all correlation coefficients were consistent with theoretical expectations, and no unexpected negative correlations were observed. These correlation results further support the finding of the structural equation modeling analysis and the variable importance rankings from machine learning analyses. Although some bivariate correlations appear to be high, subsequent analyses using the heterotrait–monotrait ratio (HTMT) and variance inflation factor (VIF) confirmed that discriminant validity has been established and that multicollinearity was not a concern (see Tables 5 and 6).

Table 21. Correlation matrix.

Variable	PEU	PU	PEC	PTF	TTF	ATT	BI
PEU	–						
PU	0.867	–					
PEC	−0.088	−0.082	–				
PTF	0.828	0.877	−0.090	–			
TTF	0.756	0.811	−0.117	0.808	–		
ATT	0.838	0.874	−0.090	0.857	0.753	–	
BI	0.817	0.858	−0.100	0.854	0.782	0.845	–

Table 22. *p*-values.

	PEU	PU	PEC	PTF	TTF	ATT	BI
PEU	–						
PU	<0.001						
PEC	0.018	0.027	–				
PTF	<0.001	<0.001	0.016	–			
TTF	<0.001	<0.001	0.002	<0.001	–		
ATT	<0.001	<0.001	0.016	<0.001	<0.001	–	
BI	<0.001	<0.001	0.008	<0.001	<0.001	<0.001	–

Table 22 lists the two-tailed *p*-values of the correlation coefficients for all variable pairs. Overall, with the exception of PEC, the correlations among the other variables were highly statistically significant ($p < 0.001$). Specifically, the *p*-values for the correlation coefficients between PEU/PU and PTF, TTF, ATT, and BI were all less than 0.001, indicating that these linear correlations between these variables are unlikely to be attributable to random error; similarly, the *p*-values for PTF with TTF, ATT, and BI, and for TTF with ATT and BI, are also less than 0.001. The *p*-values for PEC with all other variables are between 0.002 and 0.018. Although these correlations are still statistically significant, their correlation strength is extremely weak (see the absolute values of the correlation coefficients in Table 21, all < 0.12). This pattern is consistent with the finding that the PEC path was not significant in SEM. It should be noted that no correction for multiple comparisons was applied, so the results are interpreted at the original significance level. The hypothesis tests in this study (Table 7) were directly based on the theory-driven path model and did not use the *p*-value matrix for variable screening. All variables were retained in the final model to ensure theoretical integrity.

4.3.2. Importance-Performance Analysis

Importance-performance analysis (IPA) is often used to assess the impact of intervening antecedents on a target outcome. In our SVR model, the input variables were four exogenous variables: PEU, PEC, PTF, and TTF, and the output was BI (Behavioral Intention). Therefore, the IPA diagram (Figure 14) only shows the importance of these four variables (derived from SVR permutation importance) and their perceived performance (operationalized as the mean user ratings of each construct).

Through IPA, we found that:

(1) Keep up (high importance, high performance): Perceived Ease of Use and Perceived Technical Features fell into this quadrant. This indicates that these two factors are perceived as important contributors to Behavioral Intention, and users also report high evaluation of the current system's performance in these two aspects. Therefore, managers should maintain the existing resource allocation strategy to ensure that these advantageous attributes are not weakened to guarantee user satisfaction.

(2) Possible overkill (low importance, high performance): Task-Technology Fit was located in this quadrant. Although the system achieved a high score for Task-Technology Fit, its relative importance (based on SVR analysis) was significantly lower than that of Perceived Ease of Use and Perceived Technical Features. This means that the current system has sufficient Task-Technology Fit, and investing further resources in the expansion of technical functions is likely to yield diminishing marginal returns. It is recommended to reallocate these resources to other more influential factors.

(3) Low priority (low importance, low performance): Privacy and Ethical Concerns were in this quadrant. In view of its low importance to the users' Behavioral Intention and its current performance at a moderately low level (mean of about 2.95), this should be

regarded as the lowest priority of management intervention. Unless key factors such as Perceived Ease of Use and Perceived Technical Features have been sufficiently optimized, limited resources should not be spent on addressing Privacy and Ethical Concerns.

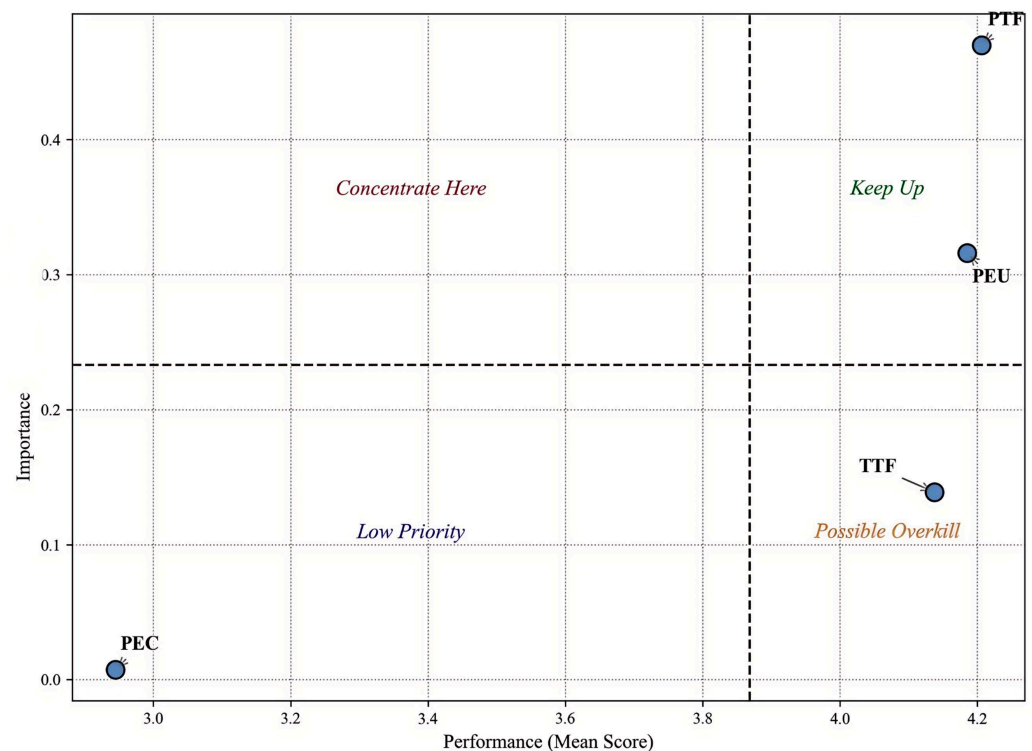


Figure 14. Importance-performance analysis (IPA).

4.3.3. Difference Tests of Demographic Variables for BI

As shown in Table 23, an independent-samples *t*-test showed that gender had no significant effect on Behavioral Intention ($t(714) = 0.243$, $p = 0.808$). One-way analysis of variance (ANOVA) revealed that willingness to use differed significantly across age group ($F(7, 708) = 12.794$, $p < 0.001$) and education level ($F(3, 712) = 27.762$, $p < 0.001$). Post hoc comparison (LSD) showed that Behavioral Intention was significantly higher in the young group (aged 19–21 years) and those with higher education (undergraduate degree or above) than among other groups.

Table 23. Difference tests of demographic variables on Behavioral Intention.

Variable	Test	Statistic	<i>p</i> -Value	Significant
Gender	<i>t</i> -test	0.243	0.808	No
AgeGroup	ANOVA	12.794	<0.001	Yes
Education	ANOVA	27.762	<0.001	Yes

5. Discussion

5.1. Interpretation of Key Findings

(1) The core mediating role of task-technology fit. The results of this study indicate that Perceived Technical Features (PTF) have a significant positive impact on Task-Technology Fit (TTF) ($\beta = 0.960$, $p < 0.001$), supporting the applicability of Goodhue and Thompson's [15] TTF theory to GenAI educational contexts. When GenAI learning tools provide diverse technical functions, higher education learners perceive a strong alignment between these functions and their learning tasks. More importantly, the influence of TTF on Perceived Usefulness (PU) ($\beta = 0.240$, $p < 0.001$), along with the influences of PU on Attitude

(ATT) ($\beta = 0.809$) and Behavioral Intention (BI) ($\beta = 0.520$), together constitute a complete mediating chain: $PTF \rightarrow TTF \rightarrow PU \rightarrow (ATT) \rightarrow BI$.

(2) The fundamental role of Perceived Ease of Use. The path coefficient from PEU to PU is $\beta = 0.934$ ($p < 0.001$), which is the strongest direct predictor of PU among the hypothesized paths. This finding is consistent with classic TAM studies [9,66], although the coefficient observed here is larger than those reported previously. One possible explanation is that current adoption of GenAI tools is still in a relatively early stage, where ease of use serves as the fundamental premise for learners to develop Perceived Usefulness.

(3) The nonsignificant effect of Privacy and Ethical Concerns and its explanation. One of the key findings of this study is that H7 ($PEC \rightarrow ATT$) was not supported ($\beta = -0.019$, $p = 0.676$). This result is inconsistent with the findings of some existing studies [17] but is consistent with the observation of the ‘privacy paradox’ in other studies [18,19]. Based on our quantitative data and descriptive statistics, this phenomenon can be interpreted from the following aspects:

(1) The cost–benefit trade-off mechanism of the privacy paradox. In the context of this study, learners’ perceived value of GenAI learning tools in terms of usefulness ($M = 4.199$) and task matching ($M = 4.137$) may have outweighed their concerns about privacy risks ($M = 2.945$). When tools are perceived to improve learning efficiency and task completion quality, the weight of Privacy and Ethical Concerns in Attitude formation becomes relatively reduced.

(2) The sample’s overall level of privacy concern is low. The overall mean value of PEC in this study was 2.945, which is at a moderately low level. This indicates that Privacy and Ethical Concerns were not a salient psychological factor among the 716 higher education learners surveyed.

(3) China’s unique data protection regulatory environment. In recent years, China has successively implemented a series of data protection regulations, including the “Personal Information Protection Law” (PIPL) and the “Network Security Law”. The introduction and enforcement of these regulations may have enhanced users’ overall trust in data security at the macro level and further weakened the impact of individual-level privacy concerns on technology adoption decisions.

(4) The discriminant validity of this study warrants a transparent discussion. The discriminant validity test in this study revealed a high correlation among the positively correlated constructs (PEU, PU, ATT, BI, PTF, TTF). This phenomenon deserves further discussion. One possible explanation is that, in the early adoption stage of GenAI learning tools, learners may not have yet formed a refined distinction between constructs such as ‘ease of use’, ‘usefulness’, ‘attitude’, ‘technical function’, and ‘task matching’. Consequently, respondents may tend to give consistent answers to all positively worded evaluative questions, that is, ‘I think this tool is good, so I agree with all the positive descriptions.’

5.2. Theoretical Contributions

(1) The introduction of TTF and PEC into the TAM framework extends the applicability of this classical model to the GenAI educational context. This study found that TTF, serving as a mediating variable between PTF and PU, provides a key cognitive link for understanding users’ Behavioral Intention regarding GenAI tools. Furthermore, the introduction of PEC and its nonsignificant effect suggest that, within a specific educational technology setting and regulatory environment, the ‘ $PEC \rightarrow ATT$ ’ path may be offset by other, stronger positive perceptions, thereby enriching the theoretical understanding of the privacy paradox across different technological contexts.

(2) The two-stage hybrid analysis method combining SEM with machine learning (i.e., artificial neural network and support vector regression) offers a methodological contribu-

tion to behavioral research. In this study, ANN and SVR were introduced alongside SEM to leverage the exploratory capacity of machine learning for exploring nonlinear correlations and variable importance rankings. This approach demonstrates the complementarity between theory-driven verification and data-driven exploration.

(3) These findings further provide empirical evidence for the manifestation of the ‘privacy paradox’ within the GenAI educational context. Specifically, the nonsignificant effect of PEC on ATT ($\beta = -0.019$, $p = 0.676$) combined with its marginal explanatory contribution in the machine learning models (7.5% in SVR and 22.4% in ANN) provides new empirical evidence supporting the privacy paradox in this specific setting.

5.3. Implications for Higher Education Institutions

(1) Maintain ease of use and technical functional advantages. This study found that Perceived Ease of Use (PEU) and Perceived Technical Features (PTF) are the two most important variables influencing Behavioral Intention toward GenAI tools among the variables examined; in the machine learning importance rankings, PEU and PTF contributed 78.6% in SVR and 50% in ANN. The IPA also placed them in the ‘Keep Up’ quadrant representing ‘high importance, high performance’. Therefore, educational institutions should ensure that the ease of use and richness of technical functions of GenAI tools remain unaffected by resource reallocations, ensuring learners’ satisfaction with these key attributes.

(2) Prudently consider additional investment in Task-Technology Fit. Although Task-Technology Fit (TTF) significantly affected PU in the SEM analysis ($\beta = 0.240$) and ranked first in the importance ranking of ANN (27.6%), its relative importance in SVR was lower (13.9%) and it was placed in the ‘Possible Overkill’ quadrant of ‘low importance, high performance’ by the IPA. This finding suggests that current learners already perceive a relatively high level of TTF ($M = 4.137$). Further investment in expanding technical functions to further enhance TTF may face diminishing marginal returns. It is therefore recommended to reallocate some resources toward the optimization of PEU and PTF instead.

(3) Suspend interventions regarding Privacy and Ethical Concerns. In this study, Privacy and Ethical Concerns (PEC) did not significantly affect Attitude (ATT) ($\beta = -0.019$, $p = 0.676$), and its relative contribution in machine learning models was low (7.5% in SVR). This indicates that, at the current stage, learners’ concerns about privacy and ethics regarding GenAI tools may not represent a primary barrier to their Behavioral Intention.

5.4. Preliminary Observations from Teaching Practice

To supplement the empirical findings based on the questionnaire, this study conducted exploratory teaching observations in two types of undergraduate courses: one is the basic mathematics course for lower grades ($n = 45$), and the other is the logistics management course for higher grades ($n = 30$).

5.4.1. Teaching Practice in Lower-Level Mathematics Courses

In mathematics courses for lower-grade students who use GenAI tools such as DeepSeek and Doubao to solve mathematical problems involving calculus and linear algebra, we observed that students who reported that the GenAI tool was ‘easy to use’ were more likely to engage with the tool for after-school assignments and learning tasks. This finding is consistent with the significant path from Perceived Ease of Use (PEU) to Perceived Usefulness (PU) ($\beta = 0.934$) and the finding that PEU ranked highly in the SVR importance ranking (contributing 31.6% in the current study’s model). In contrast, those students who encountered difficulties in writing prompts or faced obstacles with the interface during their first use often abandoned the tool quickly. Notably, even students with a generally positive Attitude toward GenAI tools tended to do so when they encountered such difficul-

ties. This observation suggests that PEU serves as a key variable helping students cross the threshold from ‘first attempt’ to ‘regular adoption’. This may be especially important for lower-grade students, as they tend to lack both experience and patience when exploring new technologies.

5.4.2. Teaching Practice in Upper-Level Logistics Management Courses

In a senior logistics management course, we guided students in applying GenAI tools to three types of tasks: (i) AI-assisted programming for problem solving and debugging, where students used Python(version 3.11 in Pycharm 25.2.2)/Lingo(version 21.0) to solve operations research models and leveraged DeepSeek, Kimi, and other tools for code debugging, algorithm tuning, and anomaly detection throughout the process, thereby cultivating their engineering skills in human–machine collaboration; (ii) simulation model development, in which students built a high-fidelity model in FlexSim to verify the feasibility of the logistics system solution; and (iii) AI-assisted optimization, for which students were guided to use AI algorithms (e.g., genetic algorithms) to automatically optimize key parameters of the simulation model, achieving a transition from ‘solution validation’ to ‘intelligent optimization’.

We observed that when students realized that the GenAI tools could effectively help them complete tasks such as ‘simulation parameter tuning’ and ‘code exception detection’, tasks that had traditionally required substantial trial-and-error effort, their Behavioral Intention toward the tools was significantly enhanced. This finding was consistent with the key paths from Task-Technology Fit (TTF) to Perceived Usefulness (PU) ($\beta = 0.240$) and from Perceived Technical Features (PTF) to TTF ($\beta = 0.960$) identified in this study. Furthermore, some students began to spontaneously apply the tools to previously unassigned tasks (e.g., analyzing anomalous experimental data), which aligns with the mediating path of $PU \rightarrow Attitude (ATT) \rightarrow Behavioral Intention (BI)$ found in this study.

Although the above teaching observations are preliminary, they offer a useful reference for understanding how the quantitative findings of this study manifest in real-world teaching contexts.

6. Conclusions

6.1. Summary of Findings

Based on the Technology Acceptance Model, Task-Technology Fit, and Privacy and Ethical Concerns, this study constructs an integrated structural equation model and a hybrid machine learning analytical framework, aiming to identify the key determinants of higher education learners’ Behavioral Intention toward generative AI learning tools and to explore the non-linear patterns among these determinants. Through the analysis of 716 valid questionnaires, we draw the following main conclusions:

(1) The SEM results verify the core path of our theoretical hypotheses. Perceived Ease of Use positively influences Perceived Usefulness (PU). Task-Technology Fit(TTF) positively influences PU. PU positively influences Attitude and Behavioral Intention. ATT has a further significant positive impact on BI. Perceived Technical Features (PTF) positively influences TTF. The above hypotheses (H1–H6) are supported, with path coefficients between 0.240 and 0.960, and all reach $p < 0.001$. However, the direct positive impact of Privacy and Ethical Concerns (PEC) on BI was not supported ($p > 0.05$), so hypothesis H7 is rejected. Factors such as the privacy paradox, the sample’s relatively low average PEC level ($M = 2.945$), and China’s data protection regulatory environment may explain this non-significant finding.

(2) The measurement model exhibits good reliability and validity. The standardized factor loadings for all measurement items exceed 0.68. Composite reliability ranges from

0.830 to 0.922, and the average variance extracted falls between 0.582 and 0.747. The coefficients of determination (R^2) of endogenous latent variables reveal that the model has high explanatory power for PU ($R^2 = 0.809$), ATT (0.765), BI (0.774), and TTF (0.653), indicating that the constructed theoretical model effectively accounts for the variance in these key outcomes.

(3) The machine learning analysis explores non-linear associations and provides complementary evidence regarding the importance of key variables. The comparative analysis between artificial neural network and support vector regression shows that SVR is significantly better than ANN in all evaluation metrics: the test set R^2 of SVR reached 0.765 ± 0.026 , while that of ANN is only 0.643 ± 0.049 ; the RMSE (0.454) and MAE (0.319) of SVR were also substantially lower than those of ANN. Variable importance analysis shows that in SVR, Perceived Technical Features (47.0%) and Perceived Ease of Use (31.6%) are the most important variables for explaining Behavioral Intention. Task-Technology Fit also shows a notable relative contribution (13.9%), while Privacy and Ethical Concerns (7.5%) contributed very little. In the ANN model, Task-Technology Fit (27.6%) ranks first in importance for BI, which further highlights the role of Task-Technology Fit as a consistent contributor across both modeling approaches. In addition, the R^2 of the simplified SVR model (excluding PEC) only decreases by 0.013, further confirming that PEC's contribution to the model is limited in this specific context.

(4) Importance-performance analysis provides specific management implications. The IPA matrix, combining the SVR-derived importance scores and users' perceived performance, indicates that Perceived Ease of Use and Perceived Technical Features fall into the 'Keep up' quadrant, and they are the key focus for effectively improving users' Behavioral Intention. Task-Technology Fit (TTF) is positioned in the 'Possible overkill' quadrant, suggesting that while current task-technology fit is perceived as sufficient, its relative importance is comparatively lower than that of PEU and PTF, and further investment solely in this area may yield diminishing marginal returns. Privacy and Ethical Concerns fall into the 'Low priority' quadrant, indicating that managers should prioritize improvements in technical function-task matching rather than over-emphasizing privacy issues at this stage.

(5) Demographic difference analysis reveals differences in Behavioral Intention among groups. Gender has no significant effect on BI, but there are significant differences among age groups ($F = 12.794$, $p < 0.001$) and across education levels ($F = 27.762$, $p < 0.001$). Younger groups (19–21 years old) and those with a bachelor's degree or higher have a significantly higher willingness to use generative AI learning tools, suggesting that promoting these tools could be tailored to these groups by designing content and functions appropriate for their specific learning needs.

All findings in this study are based on self-reported Behavioral Intention and do not claim to forecast actual usage behaviors, with a clear recommendation for future longitudinal research.

6.2. Limitations and Future Research Directions

6.2.1. Practical Limitations

(1) Cross-sectional design limits causal inference. This study used a cross-sectional design of the questionnaire survey, and all variables were collected at the same time point through self-report. On the one hand, cross-sectional data do not allow causal inference between variables. The path relationship of this study is based on theoretical assumptions rather than time series verification. On the other hand, the core outcome variable 'Behavioral Intention' measures self-reported intention rather than intended usage behavior. Therefore, the results of this study should not be interpreted as indicators of actual usage behavior.

(2) The discriminant validity of the measurement model is limited. This study found that under the Fornell-Larcker standard, the discriminant validity between theoretically related constructs (PEU, PU, ATT, BI, PTF, TTF) is not fully established. This phenomenon may reflect the characteristics of the current GenAI learning tools at an early stage of application. Learners have not yet formed a refined distinction between constructs such as ‘ease of use’, ‘usefulness’, ‘attitude’, ‘technical function’, and ‘task matching’, and tend to respond consistently to all positive evaluative questions.

(3) The overfitting risk of the just-identified structural model. The structural model is specified as just-identified ($df = 0$) to maintain theoretical integrity. Therefore, the traditional global fit index cannot be used to evaluate the overall model fit. Although the model shows strong explanatory power (R^2), the just-identified specification means that the model fits the current sample exactly. This increases the possibility of overfitting. However, given that our model is grounded in well-established theories rather than data-driven exploration, we believe the risk of capitalizing on chance is minimized.

(4) The limited interpretability of machine learning models. The machine learning models (ANN and SVR) of this study are also based on the BI mean score modeling of self-reports, and their value should be used to explore nonlinear associations and variable importance rankings, rather than to predict actual behavior. SVR performs better than ANN on this dataset, but this finding is only applicable to the specific conditions of this study (sample size, variable structure, etc.) and may not be universal.

(5) The representativeness of the sample is limited. The data in this study are all from Chinese higher education learners, and the applicability of the research conclusions may be limited by cultural, institutional, and educational backgrounds. In particular, data protection regulations such as the Personal Information Protection Law (PIPL) and the Cybersecurity Law implemented in China in recent years may enhance learners’ institutional trust in data security to some extent and reduce the negative effects of privacy concerns. This regulatory buffer effect may not exist in other countries or regions with different legal environments, so the generalization of the conclusions of this study to other cultural or institutional backgrounds requires caution.

6.2.2. Possible Future Improvements

To address these limitations, future studies could focus on the following directions:

(1) Using longitudinal design and objective behavior data. In view of the limitations of cross-sectional and self-reported data, future research can use a longitudinal tracking design (such as repeated measurements at 3, 6, and 12 months), combined with actual platform usage logs (login frequency, duration of use, number of function calls, etc.) as objective behavioral indicators, to more reliably investigate the transformation mechanism from ‘intention’ to ‘behavior’ and what factors promote long-term adoption.

(2) Optimize measurement tools and test model identification. To solve the problem of insufficient discriminant validity, future research should develop more sophisticated measurement tools, such as designing contextualized measurement items, introducing a paired comparison method or a situational experiment method, to help respondents better distinguish conceptually related but theoretically different constructs. At the same time, after the theoretical framework becomes more mature, researchers may prune some paths and construct an overidentified model ($df > 0$) to obtain a meaningful global fit index, and use new sample data for cross-validation to test the stability and generalization of the model.

(3) Reduce the risk of overfitting in the just-identified structural model. Future research can use new sample data for cross-validation, use alternative estimation methods (such as

PLS-SEM), or construct overidentified models ($df > 0$) to obtain valid global fit indices and reduce the risk of overfitting.

(4) Expand the application boundaries of machine learning methods. In view of the exploratory nature of machine learning models, future research should examine the performance differences between SVR and ANN under broader conditions (different sample characteristics, technical situations, measurement tools) to test the generalizability of the selected algorithms. At the same time, researchers may introduce deep learning methods (such as LSTM for processing time series data) or interpretable AI methods (such as SHAP, LIME) to further reveal the complex relationship patterns between variables.

(5) Conduct cross-cultural comparison and institutional analysis. In view of the limitations of sample representativeness and institutional context, future research can conduct cross-cultural comparisons in different countries or regions to test the regulatory role of the institutional environment in the relationship between privacy concerns and technology acceptance, and to understand the role of institutional factors in the technology acceptance model more comprehensively.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki. According to Article 32 of China's Measures for Ethical Review of Life Science and Medical Research Involving Humans (National Health Commission et al., 2023) and the exemptions permitted under the Measures for Ethical Review of Science and Technology Evaluation (Trial Version) (2023), formal ethical review and approval were waived for this study. This exemption applies because the research involved an anonymous questionnaire survey with consenting adults, posed no more than minimal risk, and involved no physical or psychological interventions.

Informed Consent Statement: Informed consent was obtained from all participants involved in the study.

Data Availability Statement: The source code and data are available at: <https://github.com/psfxiao/Higher-Education-Learners-Continue-Intention-toward-Generative-AI-Tools-SEM-Machine-Learning-Approach> (accessed on 30 June 2026).

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