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A Study of Chinese Undergraduate Intentions to Purchase AIGT Educational Products: An Empirical Analysis Based on a Multi-Theoretical Model

Donghe Li	School of Mathematics and Computer Science, Jilin Normal University, Siping, China	donghelii@163.com
GuiJie Zhang*	School of Mathematics and Computer Science, Jilin Normal University, Siping, China	zhangguijie@hrbeu.edu.cn
Xiaowen Liu	School of Physics, Northeast Normal University, Changchun, China	liuxw122@nenu.edu.cn

* Corresponding author

Abstract

Aim/Purpose	This study aims to investigate the decision-making mechanisms underlying Chinese undergraduate students' purchase intentions toward artificial intelligence generation tools (AIGT) educational products by integrating three theoretical frameworks: the Theory of Planned Behavior (TPB), the Technology Acceptance Model (TAM), and the Value-based Adoption Model (VAM).
Background	With the popularization of AIGT in the education field, its acceptance and demand are becoming increasingly prominent. While AIGT demonstrates substantial potential in enhancing pedagogical outcomes and personalizing learning experiences, its market penetration, particularly in adoption rates among university student populations, remains contingent upon multifactorial determinants, which are of interest to our community of practice.
Methodology	This study integrates the TPB, the TAM, and the VAM to construct a theoretical framework for the purchase intention of AIGT education products. Thereafter, an online survey was conducted among 523 undergraduate students from different regions of China, and a structural equation model was used to analyze the obtained data.

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Contribution	This study bridges theoretical gaps by integrating TPB, TAM, and VAM into a novel framework, offering a holistic understanding of the adoption of AIGT educational products and providing empirical evidence for understanding the purchase intention of undergraduates towards AIGT educational products.
Findings	The results show that while brand perception has no direct significant impact on purchase intention, the rest of the investigated factors all have significant impacts on purchase intention to varying degrees, and there are also strong correlations among the investigated factors. Among them, the perceived fee was the most critical factor with a significant negative impact. However, perceived usefulness could increase consumers' threshold regarding perceived fee, exerting a significant positive impact on it. Brand perception did not directly affect perceived value; it influenced the latter indirectly via the mediating variable of enjoyment.
Recommendations for Practitioners	Educational technology firms should prioritize enhancing product functionality and adopt tiered pricing strategies, while universities should integrate AIGT into curricula and foster industry partnerships to align products with pedagogical needs.
Recommendations for Researchers	Future studies should expand sampling to diverse populations, incorporate cultural or policy variables, and employ mixed-method methodologies to deepen insights into AIGT adoption dynamics.
Impact on Society	AIGT adoption could democratize access to personalized education and bridge learning gaps, but equitable pricing and ethical AI deployment are critical to prevent socioeconomic disparities.
Future Research	Validate the framework in cross-cultural contexts, investigate AI ethics and cultural adaptability, and assess long-term educational outcomes of AIGT integration through longitudinal studies.

Keywords	AIGT education product, purchase intention, technology acceptance model, theory of planned behavior, value-based adoption model

INTRODUCTION

With the breakthrough advances of artificial intelligence algorithmic innovations, the application of Artificial Intelligence Generation Tools (AIGT) in the field of education has gradually increased, bringing a revolutionary change to the education industry (Bahroun et al., 2023). AIGT refers to artificial intelligence-powered tools or systems that automatically generate content such as text, images, or audio.

These tools are used directly by learners to support tasks like writing, studying, or problem-solving. In educational products and services, AIGT technology is widely applied to aspects such as the generation of personalized learning resources, the management of student learning (Crompton & Burke, 2023), student performance prediction (Lokare & Jadhav, 2024), and intelligent tutoring systems (Baillifard et al., 2025). The most intuitive change lies in the "AGI-orientation" of products, from learning machines to apps and smart teaching, GPT-like products have been integrated to some extent. Ivanov and Soliman (2023) pointed out that generative artificial intelligence is gradually becoming a core force in reshaping the educational field. These technologies can act as online teachers, curriculum developers, and contributors to academic publications, and promote the transformation of the teaching model from "teacher-student" interaction to "teacher-artificial intelligence-student" co-creation. This technological evolution has spurred a surge in scholarly attention, with recent empirical investigations systematically documenting the efficacy of AI-driven solutions across diverse educational domains, ranging from language acquisition through human-AI collaborative teaching models (Ji et al., 2022) to ethical AI integration in STEM education (Usher & Barak, 2024), and from mathematics learning analytics (Hwang & Tu, 2021) to medical training applications (Zhang et al., 2023).

While AIGT educational products demonstrate substantial potential in enhancing pedagogical outcomes and personalizing learning experiences, their market penetration, particularly in terms of adoption rates among university student populations, remains contingent upon multifactorial determinants. Previous studies have used a variety of theoretical perspectives to provide profound insights into the application of AIGT tools in different contexts (e.g., Chai et al., 2023; Saif et al., 2024; Sanusi et al., 2024; Tian et al., 2024), but they have rarely delved deeply into the multidimensional influencing factors of market acceptance. On the one hand, as an important consumer group in the education market, college students' acceptance of emerging technologies directly determines the market prospects of AIGT educational products. However, previous studies have usually simplified this aspect to a single intention of technology adoption. For example, Ma et al. (2024) explored the adoption of ChatGPT by Chinese users through the Davis (1989) Technology Acceptance Model, revealing the relationships among perceived usefulness, perceived ease of use, behavioral intention, and usage behavior, and analyzing the moderating effects of gender, geographical region, and educational background on these relationships, but ignoring the complex psychological factors behind them. On the other hand, when making purchase decisions, college students consider the technological value. They are also deeply influenced by factors such as social influence, performance expectancy, effort expectancy, and facilitating conditions (Feng et al., 2025). These factors have often not been fully incorporated into the analysis framework in previous studies, resulting in an incomplete understanding of the market acceptance of AIGT educational products and services. Therefore, conducting in-depth research on the intention of college students to purchase these products and services is of great significance for promoting the innovation and application of educational technology.

To address these deficiencies, the present study aims to comprehensively analyze university students' behavioral intentions towards AIGT education products and services by integrating three theoretical frameworks: the Theory of Planned Behavior (TPB), the Technology Acceptance Model (TAM), and the Value-based Adoption Model (VAM). This tripartite integration is strategically designed to overcome the limitations of single-model approaches observed in prior research. While TAM effectively captures core technological determinants (Davis, 1989), it insufficiently addresses socio-psychological influences. This critical limitation is effectively bridged by TPB's inclusion of subjective norms and perceived behavioral control (Ajzen, 1991). Furthermore, VAM's emphasis on cost-benefit calculus and enjoyment value (Y. Kim et al., 2017) complements TAM's utilitarian focus, thereby encapsulating the multifaceted decision-making process inherent in adopting paid educational technologies.

Such theoretical triangulation enables a holistic examination encompassing: (1) explore how the perceived usefulness, perceived ease of use, perceived fee, enjoyment, and brand perception of AIGT educational products influence college students' perceived value, attitude, subjective norms, and perceived behavioral control; and (2) explore how college students' perceived value, attitude, subjective norms, and perceived behavioral control further affect their intention to purchase and use AIGT educational products. This study provides valuable references for educational technology enterprises and universities, guiding the research, development, and promotion of AIGT educational products, and facilitating the intelligent development in the field of education.

Literature Review and Hypotheses Development

Theoretical Foundations

TPB, as proposed by Ajzen (1991), represents a foundational theory in psychology for explaining and predicting individual behavior. It comprises three core elements: attitude, subjective norm, and perceived behavioral control, which reflect an individual's evaluation of the behavior, perceived social pressure, and cognition of the ease or difficulty of performing the behavior, respectively. This theory has been widely applied in the field of education. For example, Wang et al. (2020) used this model to explore the mechanisms for improving learning performance in Chinese MOOCs and proposed suggestions for enhancing MOOC learning outcomes. Also using TPB, Knauder and Koschmieder (2018) examined the factors affecting elementary school teachers' willingness and actual behavior in implementing personalized student support.

With the development of the theory, TPB has gradually been introduced into the field of product design and market acceptance research, becoming a powerful tool for understanding consumer behavior and predicting the success of products. For instance, TPB has been used to explain aspects such as smart home products (H. Yang et al., 2017), mobile data services (K. Yang & Jolly, 2009), wearable devices (Lunney et al., 2016), and intelligent transportation systems (Larue et al., 2015). Hence, TPB provides a robust framework for understanding how social and psychological factors, such as subjective norms and perceived behavioral control, shape individual decision-making. It is particularly valuable for analyzing the complex interplay between external influences and personal attitudes in the context of purchasing AIGT educational products.

TAM is an important theoretical framework for analyzing users' behavioral intentions to accept information technology (Davis, 1989). The TAM model comprises two key dimensions – perceived usefulness and perceived ease of use – which elucidate users' willingness to accept technology. Perceived usefulness refers to the extent to which users believe that technology can enhance their work performance, while perceived ease of use pertains to users' assessment of the ease or difficulty of learning and using the technology. These two factors jointly influence users' behavioral intention. TAM not only provides a solid foundation for understanding general information technology acceptance behavior but also demonstrates strong explanatory power in its application to the field of education. Arpaci (2017) examined the causal relationship between expectations of knowledge management practices and the perceived usefulness of cloud computing. E. Kim et al. (2021) integrated TAM to reveal the key factors influencing students' willingness to use online learning systems. G. Liu and Ma (2023) used TAM to assess the acceptance and usage of ChatGPT among foreign language learners in informal digital English learning environments. TAM offers a clear and practical lens for examining how the functional attributes of technology directly influence users' acceptance and willingness to adopt AIGT educational products, highlighting the importance of technological utility in driving consumer intentions.

VAM, proposed by Y. Kim et al. (2017), is a theoretical framework constructed from the perspective of value maximization to address users' acceptance attitudes towards mobile internet. VAM retains the technological characteristics of TAM, incorporates enjoyment and perceived fee, and proposes that users' perceived value of mobile internet is a critical factor determining their willingness to adopt it. As the theory continues to evolve, VAM primarily participates in the formulation of product innovation and marketing strategies, becoming a crucial tool for assessing product market potential and optimizing user experience. For example, VAM is used to analyze consumers' value perceptions and acceptance behaviors towards AI technology (Dhiman et al., 2023), IoT services (Y. Kim et al., 2017), augmented reality technology (Yoon & Oh, 2022), online financial services (Sun et al., 2021), and travel services (Vishwakarma, 2024), among others. VAM complements these perspectives by emphasizing the role of perceived value, cost-benefit considerations, and emotional satisfaction, providing a comprehensive framework to understand how economic and experiential factors jointly influence the adoption of paid educational technologies.

Therefore, by integrating these three theories, a multidimensional and multifaceted analytical framework can be constructed, thereby enabling a more accurate analysis of college students' purchase intentions for AIGT education products and services in the market.

APPLICATION OF AIGT IN EDUCATIONAL PRODUCTS

The continuous advancement of AIGT technology has brought revolutionary changes to the traditional education sector, particularly in teaching and learning applications, which are gradually demonstrating tremendous potential and value (Chen et al., 2024). In teaching, traditional instructional models often adopt a "one-size-fits-all" approach, making it difficult to satisfy the diverse learning needs of students. However, AIGT educational products can intelligently generate learning resources and tutorial materials tailored to students' individual characteristics by analyzing their learning behaviors. Based on this analysis, they can also predict students' learning outcomes in subject studies. For example, Lokare and Jadhav (2024) proposed a learning style prediction model that effectively predicts students' learning styles to achieve personalized and effective learning. Li et al. (2022) used AI to predict students' mathematics learning outcomes on online platforms. Karataş et al. (2024) integrated ChatGPT into foreign language teaching, enhancing students' learning experiences in writing, grammar, and vocabulary acquisition.

Meanwhile, AIGT educational products play a significant role in the field of learning. They not only provide students with abundant learning resources (Rawas, 2023) but also utilize intelligent algorithms to track and analyze current learning situations in real-time, thereby adjusting learning strategies and methods, and ultimately enhancing students' learning outcomes. Furthermore, AIGT educational products offer students an interactive learning experience, enabling them to deepen their understanding and mastery of knowledge through interaction. For example, W. Yang et al. (2024) explored the multidimensional impact of AIGT tools on learning outcomes in human-computer collaboration from the perspective of college students. Lin et al. (2024) developed a chatbot to provide guidance on academic writing and offer peer feedback, enhancing students' learning experience.

AIGT has not only driven the innovation of teaching modes and learning methods but also directly given rise to numerous unprecedented educational products, especially intelligent teaching assistants and online tutoring platforms, which not only enhance the convenience of education but also make the allocation of educational resources more reasonable and efficient, significantly promoting the process of achieving educational equity. For example, Baillifard et al. (2025) demonstrated that a personal AI tutor can improve students' learning outcomes. G. Liu et al. (2024) studied the experience of Chinese English learners using AI tutoring platforms in informal learning and found that it significantly improved English learning efficiency.

However, despite the tremendous potential demonstrated by AIGT educational products in teaching and learning, their market acceptance is still influenced by various factors. Therefore, this study constructs a comprehensive theoretical model, aiming to analyze the behavioral intentions of college students towards AIGT educational products and services in the market from multiple dimensions.

HYPOTHESIS DEVELOPMENT

The conceptual model for all hypotheses in this study is shown in Figure 1. According to TAM (Davis, 1989), perceived usefulness refers to the degree to which users believe that technology can enhance their work efficiency or meet their needs, and it directly influences their attitude towards and intention to use the technology. However, TAM alone does not explain how users consider cost when making decisions. To address this, we draw on the VAM (Y. Kim et al., 2017), which emphasizes that users weigh the benefits and costs of a product. When consumers highly recognize the perceived usefulness of a product or service, they are more likely to accept a higher price because they see the product as worth the investment. Perceived fee, as used in this study, refers to users' subjective perception of the economic cost of the product, including its affordability and value for money. For example, Xu et al.'s (2021) study on young Chinese intentions to purchase "Online Paid Knowledge," where an online course that significantly enhances learning outcomes may be considered cost-justifiable by consumers despite its relatively high price, due to the substantial value it provides. This is because they view the expenditure as an investment in obtaining efficient learning outcomes, suggesting that perceived usefulness can reduce users' sensitivity to the perceived fee, making them more likely to make a purchase. These findings have also been supported by other empirical research, such as Pillai and Sivathanu (2020) and Pillai et al. (2023), which found that perceived usefulness significantly increased users' attitudes toward and willingness to adopt AI chatbots, even in paid contexts. Therefore, perceived usefulness not only directly affects users' attitude and intention but also influences how they judge the perceived fee, which in turn affects their decision-making. Based on the above research findings, the following hypotheses are proposed:

- **H1a** Perceived usefulness has a positive effect on attitudes towards using AIGT educational products.
- **H1b** Perceived usefulness has a positive effect on purchase intention towards using AIGT educational products.
- **H1c** Perceived usefulness has a positive effect on the perceived fee towards using AIGT educational products.

Perceived ease of use refers to users' subjective perceptions of the ease or difficulty of learning to use a particular technology. It reflects the effort required by users when using technology, as well as whether the technology is easy to understand and operate. According to TAM (Davis, 1989), perceived ease of use influences both perceived usefulness and users' attitudes, as easier systems tend to be seen as more helpful and likable. In the context of AIGT educational products, which often involve novel interfaces or learning formats, perceived ease of use reduces cognitive effort and promotes favorable evaluations. Therefore, in our integrated model, perceived ease of use indirectly influences purchase intention via perceived usefulness and attitude. S. Liu et al. (2023) confirmed this by studying the adoption of ChatGPT among language learners, showing that ease of use led to stronger perceived usefulness and more positive attitudes. Similar effects have been reported in AI tools (Ma et al., 2024), online learning (E. Kim et al., 2021), paid media (Youn & Lee, 2019), and Smart Products (Zeng et al., 2024). These findings support the inclusion of perceived ease of use as a key antecedent of perceived usefulness and attitude in our model. Based on the above research findings, the following hypotheses are proposed:

- **H2a** Perceived ease of use has a positive effect on attitudes towards using AIGT educational products.
- **H2b** Perceived ease of use has a positive effect on perceived usefulness towards using AIGT educational products.

In VAM (Y. Kim et al., 2017), perceived fee and enjoyment are key factors determining perceived value. Perceived fee reflects users' subjective perception of the economic cost of the product, while enjoyment reflects the emotional satisfaction experienced during product use. Unlike TAM, which emphasizes functionality, VAM considers both rational and affective factors. Al-Debei and Al-Lozi (2014) explained that users' adoption decisions are influenced by both the enjoyment derived from using a product and their evaluation of its cost, which together shape their perceived value and attitudes. This supports the idea that perceived fee and enjoyment jointly shape users' perceived value and attitudes. S. Liu et al. (2023) further confirmed that when users perceive a product as reasonably priced, their perceived value improves, and when they find it enjoyable, their attitudes become more positive.

Thus, in our integrated model, perceived fee and enjoyment are treated as antecedents of both perceived value and attitude. When the cost is low, consumers feel they have greater economic control over their purchase behavior, that is, a higher level of perceived behavioral control. For example, Jing et al. (2022) showed in their study on "the effectiveness of price promotions in purchasing affordable luxury products" that when promotional prices are very affordable, consumers feel that they can easily decide whether to purchase, without being overly constrained by economic pressure. Their sense of behavioral control during the purchase process is enhanced. Moreover, when consumers perceive the cost of a product to be too high and not worth its value, they will express dissatisfaction within the group, thereby influencing the group's perception of the product's price and changing existing subjective norms. For instance, Basri et al. (2016) showed in their study on the impact of word-of-mouth communication on consumers that perceived fee is an important attribute for consumers when making purchase decisions during group communication. These findings suggest that perceived fee also affects perceived behavioral control and subjective norm, linking VAM with TPB. Based on the above research findings, the following hypotheses are proposed:

- **H3a** Perceived fee has a negative effect on perceived value towards using AIGT educational products.
- **H3b** Perceived fee has a negative effect on subjective norms towards using AIGT educational products.
- **H3c** Perceived fee has a negative effect on perceived behavioral towards using AIGT educational products.
- **H3d** Perceived fee has a negative effect on attitude towards using AIGT educational products.
- **H4a** Enjoyment has a positive effect on perceived value towards using AIGT educational products.
- **H4b** Enjoyment has a positive effect on attitudes towards using AIGT educational products.

Brand perception also has a significant impact on user-perceived value. Brand serves as a symbol of product quality and credibility, and consumers' cognition and trust in a brand often influence their evaluations and choices of products. In Coelho et al.'s (2019) study on brand quality, it was demonstrated that products with good brand image and reputation tend to have higher user-perceived value. This suggests that brand perception enhances perceived value by increasing users' expectations of product quality and reliability. Furthermore, brand perception has a significant positive effect on enjoyment. When consumers form positive impressions of a brand, including its brand image, reputation, and quality perception, it triggers positive psychological expectations, making it easier for them to experience satisfaction and enjoyment when using the product or service. For example, Bloemer and Kasper's (1995) study indicated a positive relationship between brand and consumer satisfaction. From the perspective of VAM, enjoyment is an affective component of perceived value and brand perception. Enhancing anticipated satisfaction indirectly contributes to the emotional dimension of users' value judgments. Therefore, in our integrated model, brand perception is a factor of perceived value and enjoyment, which in turn influences users' purchase intention. Based on the above research findings, the following hypotheses are proposed:

- **H5a** Brand perception has a positive effect on perceived value towards using AIGT educational products.
- **H5b** Brand perception has a positive effect on enjoyment towards using AIGT educational products.

According to the VAM, users' adoption decisions are influenced by their perceived value, which is shaped by factors such as enjoyment, brand perception, and perceived fee, and serves as a direct predictor of purchase intention. Furthermore, based on the TPB, users' behavioral intentions are jointly influenced by behavioral attitudes, subjective norms, and perceived behavioral control. Unlike TAM and VAM, which emphasize individual evaluations, TPB incorporates social and control-related factors that affect intention formation. Subjective norms reflect perceived social pressure, while perceived behavioral control relates to users' confidence in their ability to adopt the technology. This theoretical framework has been widely applied in various fields such as education (Wang et al., 2020), smart homes (H. Yang et al., 2017), mobile data services (K. Yang & Jolly, 2009), wearable devices (Lunney et al., 2016), and intelligent transportation systems (Larue et al., 2015), with its universal applicability having been fully demonstrated. By integrating TAM, VAM, and TPB, the model captures technological perceptions, value appraisals, and social-cognitive factors that jointly shape users' intention to adopt AIGT products. Based on the above research findings, the following hypotheses are proposed:

H6 Perceived value has a positive effect on purchase intention towards using AIGT educational products.
H7 Subjective norms have a positive effect on purchase intention towards using AIGT educational products.
H8 Perceived behavioral control has a positive effect on purchase intention towards using AIGT educational products.
H9 Attitude has a positive effect on purchase intention towards using AIGT educational products.

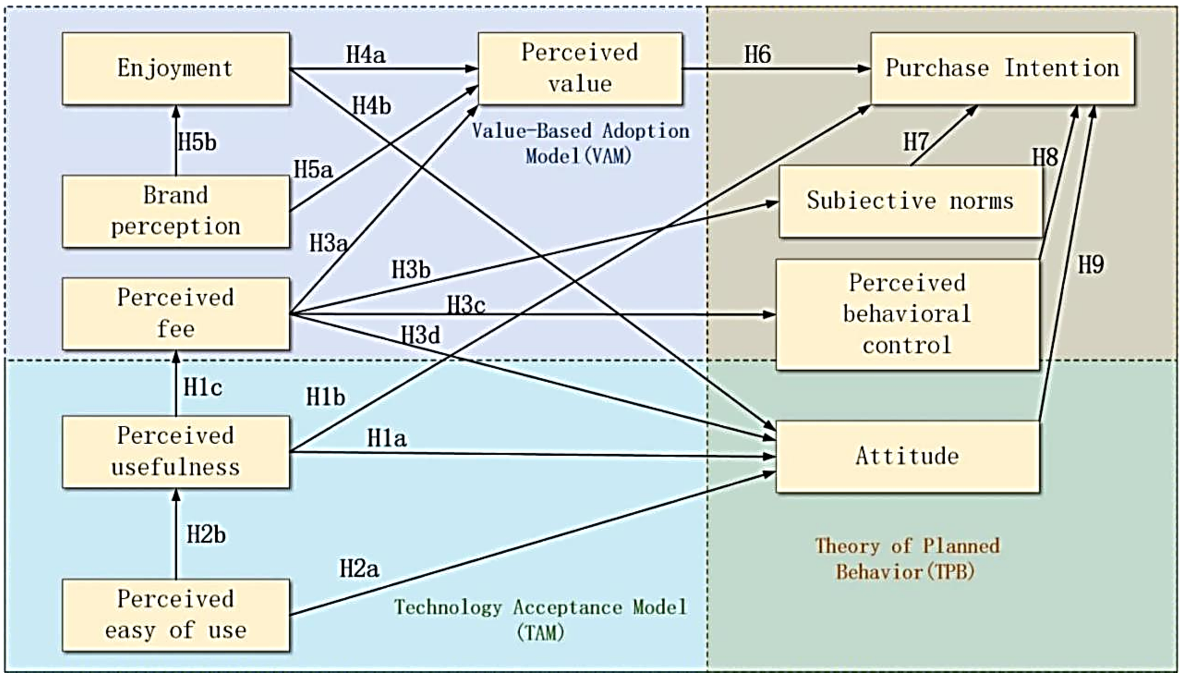

Figure 1. Conceptual model

METHODOLOGY

QUESTIONNAIRE DESIGN AND DATA COLLECTION

Data collection was conducted in December 2024 and January 2025 with a focus on undergraduate students at universities across China's diverse regions. An anonymous questionnaire developed on the "Questionnaire Star" platform (https://www.wjx.cn/), a widely used online survey tool in China, was used to conduct a three-week online survey. Before proceeding to the questionnaire, participants were presented with an informed consent statement outlining the purpose of the study, voluntary participation, anonymity, and data confidentiality. The study was conducted in accordance with the ethical guidelines of Jilin Normal University and was approved by the university's academic ethics committee. Participants were recruited via university learning platforms and student WeChat groups to ensure geographic and disciplinary diversity, with the survey link accompanied by a brief description and eligibility criteria.

Prior to filling out the formal questionnaire, a screening survey was conducted to determine whether respondents had used AIGT educational products (e.g., Have you ever used AIGT educational products in your research/studies? Yes/No), and only those who answered "Yes" could proceed. To prevent duplicate participation, IP address restrictions and cookie tracking functions provided by the platform were enabled, ensuring that each participant could only submit the survey once. Each participant in the survey received a reward of 5 RMB, thereby ensuring the relevance and validity of the survey data.

The formal questionnaire is divided into three parts. The first part collects basic personal information, including gender, grade, major, and region, which also serves to verify participants' eligibility as undergraduate students. The second part presents statements related to the variables in this study (measurement is carried out using a 5-point Likert scale, with 1 representing "strongly disagree" and 5 representing "strongly agree"), namely: perceived usefulness, perceived ease of use, perceived fee, enjoyment, brand perception, perceived value, subjective norms, perceived behavioral control, attitude, purchase intention, detailed statements and sources can be found in the Appendix. The third part consists of three open-ended questions, each provided with an open text box for participants to enter their responses. These questions focus on AIGT education products and services in terms of meeting learning needs, factors influencing purchase decisions, and users' suggestions and expectations. These are all voluntary and not mandatory.

The app research team collected a total of 638 questionnaires and excluded 115 incomplete responses. Ultimately, 523 valid questionnaires were used for subsequent analysis, with an effective response rate of 81.97%. The demographic characteristics of the samples are presented in Table 1.

Table 1. Demographic characteristics of participants

Demographics	Categories	N	%
Gender	Male	195	37.28
	Female	328	62.72
Educational level	Freshman	75	14.34
	Sophomore	124	23.71
	Junior	159	30.4
	Senior	165	31.55
Field of study	Humanities and social sciences	209	39.96
	Natural sciences	187	35.76
	Engineering discipline	127	24.28
Participants by region	East China	134	25.62
	North China	115	21.99
	South China	132	25.23
	Southwest China	78	14.91
	Northeast China	64	12.24
Total		523	100

DATA ANALYSIS

Structural Equation Modeling (SEM) is a multivariate statistical analysis technique used to verify and explore complex relationships among variables by constructing and testing models that include latent and observed variables (Bowen & Guo, 2012). SEM encompasses two statistical approaches: variance-based SEM (PLS-SEM) and covariance-based SEM (CB-SEM) (Dash & Paul, 2021). In the data analysis section of this study, SPSS and AMOS software were used, following the two-step approach proposed by Anderson and Gerbing (1988), which includes the measurement model and structural model. For data analysis using CB-SEM, the measurement model was first employed to assess the reliability and validity of the model. Subsequently, the structural model was utilized to find the best-fitting model to test the causal relationships between the independent and dependent variables.

In the model evaluation process, different fit indices are utilized to comprehensively assess the goodness of fit of a model. Each fit index has its specific acceptable value range, which helps determine whether the model performs well. In this study, we adopted three absolute fit indices, including the Root Mean Square Error of Approximation (RMSEA), the Chi-square to Degrees of Freedom Ratio (χ^2/df), and the Goodness of Fit Index (GFI), as well as two relative fit indices, namely the Comparative Fit Index (CFI) and the Incremental Fit Index (IFI). The model is considered to have good fit when the RMSEA is less than 0.08 (Hair et al., 1998), the χ^2/df is less than 3 (Bentler & Bonett, 1980), the GFI is greater than 0.8 (Hsu & Lin, 2008), the CFI is greater than 0.9 (Hsu & Lin, 2008), and the IFI is greater than 0.9 (Bentler, 1990). In addition, to ensure the validity of the measurement model, construct reliability (C.R.) is greater than 0.6 (Bagozzi & Yi, 1988), and AVE is greater than 0.5 (Fornell & Larcker, 1981a).

RESULTS

MEASUREMENT MODELS: RELIABILITY AND VALIDITY

In CB-SEM, the first step is to evaluate the reliability and validity of the model. To pass this step, two reliability conditions and two validity conditions need to be met. Following the recommendation of Hair et al. (1998), all items with loadings less than 0.6 should be removed before proceeding. Therefore, four items, namely perceived usefulness 4 (PU4), perceived ease of use 3 (PEOU3), perceived fee 1 (PF1), and brand perception 3 (BP3), were deleted. According to Hair et al. (1998), a Cronbach's alpha coefficient above 0.7 indicates good reliability. In this study, the values ranged from 0.735 to 0.932. Construct reliability (C.R.) was measured using composite reliability, which reflects the degree of consistency among multiple items measuring the same construct. In this study, the values ranged from 0.827 to 0.926, far exceeding the benchmark of 0.6 suggested by Bagozzi and Yi (1988).

Validity assessment includes convergent validity and discriminant validity. Convergent validity assesses the consistency among different measurement indicators of the same construct, based on factor loading and average variance extracted (AVE). In this study, the factor loading values ranged from 0.762 to 0.908, all exceeding the 0.6 criterion proposed by Chin et al. (1997). The AVE reached the 0.5 threshold and above suggested by Fornell and Larcker (1981b). Discriminant validity examines the degree of differentiation among measurement indicators of different constructs. According to the relevant criteria proposed by Fornell and Larcker (1981b), sufficient discriminant validity is achieved when the correlation coefficients between factors are below 0.9. This study's values ranged from 0.784 to 0.871, meeting the relevant criteria. In summary, the theoretical model demonstrates adequate validity and reliability. Table 2 provides the value of reliability and validity, and Table 3 provides the value of discriminant validity.

Table 2. Reliability and validity

Construct	Items	Factor loading	Cronbach's alpha	C.R.	Ave
Perceived ease of use	PEOU1	.798	.863	.862	.677
	PEOU2	.841			
	PEOU4	.829			
Perceived usefulness	PU1	.807	.879	.876	.703
	PU2	.854			
	PU3	.853			
Perceived fee	PF2	.801	.849	.836	.629
	PF3	.816			
	PF4	.762			
Enjoyment	EN1	.788	.882	.882	.652
	EN2	.820			
	EN3	.797			

Construct	Items	Factor loading	Cronbach's alpha	C.R.	Ave
	EN4	.824			
Brand perception	BP1	.813	.785	.827	.616
	BP2	.776			
	BP4	.764			
Perceived value	PV1	.890	.920	.912	.723
	PV2	.834			
	PV3	.852			
	PV4	.826			
Subjective norms	SN1	.904	.911	.914	.726
	SN2	.824			
	SN3	.835			
	SN4	.845			
Perceived behavioral control	PBC1	.903	.905	.908	.714
	PBC2	.809			
	PBC3	.816			
	PBC4	.849			
Attitude	ATT1	.832	.912	.899	.692
	ATT2	.839			
	ATT3	.827			
	ATT4	.830			
Purchase intention	PI1	.908	.932	.926	.759
	PI2	.855			
	PI3	.883			
	PI4	.838			

Note: C.R.-Composite Reliability, AVE-Average Variance Extracted, PEOU-Perceived ease of use, PU-Perceived usefulness, PF-Perceived fee, EN-Enjoyment, BP-Brand perception, PV-Perceived value, SN-Subjective norms, PBC-Perceived behavioral control, ATT-Attitude, PI-Purchase intention.

Table 3. Correlation between the constructs and descriptive statistics

	BP	PEOU	PU	EN	PF	PV	ATT	SN	PBC	PI
BP	.784									
PEOU	.210**	.822								
PU	.123	.585**	.838							
EN	.197**	.041	.024	.807						
PF	.076	.362	.619**	.015	.793					
PV	.151	.179	.279	.327**	.436**	.850				
ATT	.140	.429**	.546**	.284**	.447	.287	.855			
SN	.037	.176	.301	.007	.487**	.212	.218	.852		
PBC	.038	.182	.312	.008	.504**	.220	.225	.246	.845	
PI	.082	.280	.447**	.096	.449	.326**	.387**	.342**	.397**	.871

Note: Significance at: $^{*}p < 0.05$ and $^{**}p < 0.01$. The diagonal values mentioned in bold represent the square root of AVE.

STRUCTURAL MODELS: GOODNESS OF FIT STATISTIC AND HYPOTHESIS TESTING

Based on confirmatory factor analysis results, the proposed theoretical framework meets the criteria for reliability and validity. Subsequently, structural analysis was employed to test its goodness of fit statistically. Initially, the structural analysis indicated a relatively poor model fit. After applying modification indices, the model fit was improved, and the results demonstrated that the proposed theoretical framework exhibited good model fit ($\chi^2/df = 2.910$, GFI = 0.853, CFI = 0.918, IFI = 0.919, RMSEA = 0.060).

Figure 2 shows the results regarding the postulated hypothesis. Perceived value (β=.142, p=.01), perceived usefulness (β=.209, p=.01), attitude (β=.146, p=.01), subjective norm (β=.161, p=.01) and perceived behavioral control (β=.228, p=.01) were significantly related to the university student intention to buy AIGT education products, which supported the hypotheses H1b, H6, H7, H8, and H9, respectively. Perceived ease of use (β=.155, p=.01), perceived usefulness (β=.340, p=.01), and enjoyment (β=.267, p=.01) had a significant positive influence on the attitude, which supported the hypotheses H1a, H2a, and H4b, respectively. Perceived ease of use (β=.585, p=.01) had a significant positive influence on the perceived usefulness, which supported the hypothesis H2b. Perceived usefulness (β=.619, p=.01) had a significant positive influence on the perceived fee, which supported the hypothesis H1c.

Perceived fee had a significant negative influence on the perceived value (β=.427, p=.01), attitude (β=.176, p=.01), subjective norm (β=.487, p=.01), and perceived behavioral control (β=.504, p=.01), which supported the hypotheses H3a, H3b, H3c, and H3d, respectively. Enjoyment (β=.309, p=.01) had a significant positive influence on the perceived value, which supported the hypothesis H4a. Brand perception (β=.197, p=.01) had a significant positive influence on the enjoyment, which supported the hypothesis H5b. Brand perception (β=.197, p=.01) had no significant positive influence on the perceived value, which rejected the hypothesis H5a. To improve clarity, the results for each hypothesis are summarized in Table 4.

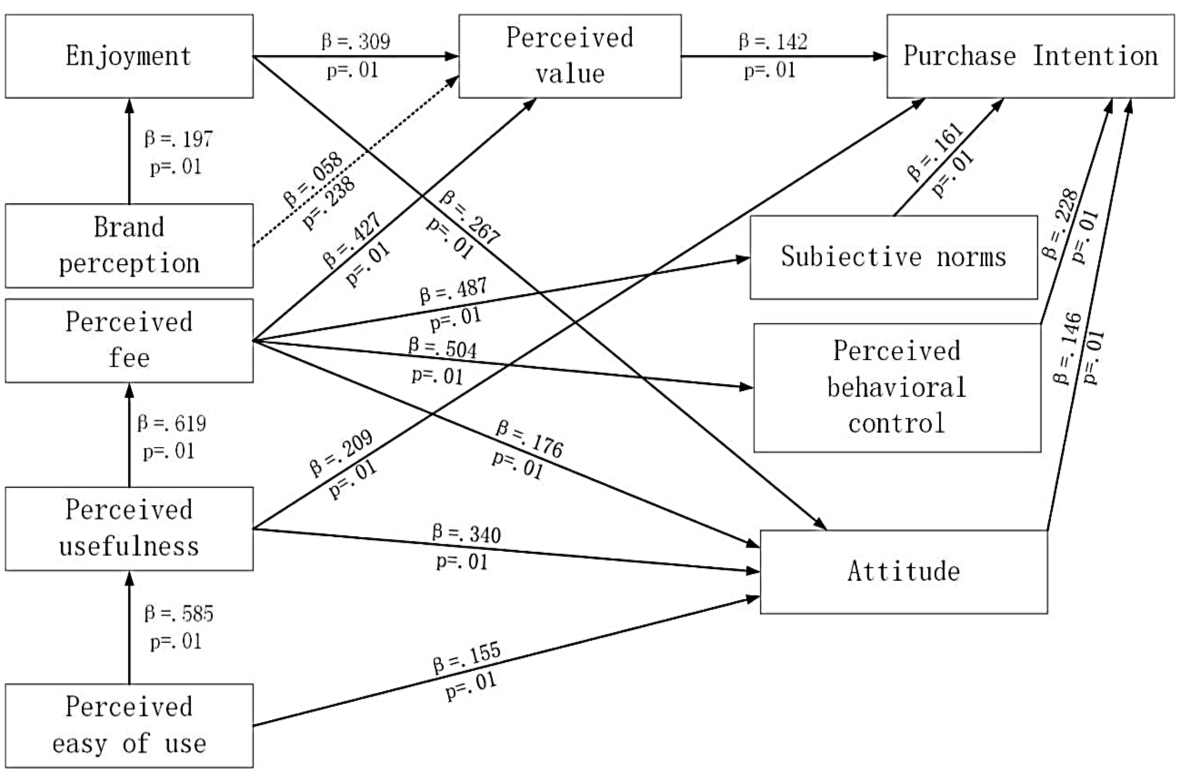

Figure 2. Structural model

Table 4. Summary of hypothesis testing results

Hypothesis	Result	Path and significance	Interpretation
H1a	Supported	PU → ATT (β = .340, p < .01)	Students who find AIGT useful are more likely to develop positive attitudes toward its use.
H1b	Supported	PU → PI (β = .209, p < .01)	Perceived usefulness directly increases students' intention to purchase AIGT products.
H1c	Supported	PU → PF (β = .619, p < .01)	Students who find AIGT useful are more tolerant of its cost.
H2a	Supported	PEOU → ATT (β = .155, p < .01)	Ease of use positively shapes students' attitudes toward AIGT.
H2b	Supported	PEOU → PU (β = .585, p < .01)	If AIGT is easy to use, it is more likely to be perceived as useful.
H3a	Supported	PF → PV (β = .427, p < .01)	High perceived fees reduce students' perceived value.
H3b	Supported	PF → SN (β = .487, p < .01)	High perceived fees negatively affect subjective norms.
H3c	Supported	PF → PBC (β = .504, p < .01)	High perceived fees weaken perceived behavioral control over purchasing AIGT products.
H3d	Supported	PF → ATT (β = .176, p < .01)	High perceived fees reduce students' positive attitudes toward AIGT.
H4a	Supported	EN → PV (β = .309, p < .01)	Enjoyable user experience enhances perceived value.
H4b	Supported	EN → ATT (β = .267, p < .01)	Students who enjoy using AIGT are more likely to view it positively.
H5a	Not supported	BP → PV (β = .058, p=.238)	Brand perception does not directly affect perceived value.
H5b	Supported	BP → EN (β = .197, p < .01)	Positive brand perception enhances the enjoyment of using AIGT.
H6	Supported	PV → PI (β = .142, p < .01)	Greater perceived value leads to stronger purchase intention.
H7	Supported	SN → PI (β = .161, p < .01)	Subjective norms contribute to students' purchase intention.
H8	Supported	PBC → PI (β = .228, p < .01)	Students with higher perceived behavioral control are more likely to buy AIGT products.
H9	Supported	ATT → PI (β = .146, p < .01)	Positive attitudes directly increase intention to purchase.

Text Content Analysis

The third part of the questionnaire contains three open-ended questions; the specific questions are provided in the Appendix. This study extracted words that appeared more than 30 times in each question, and the results are presented in Figure 3. For the first question, which asks about the aspects of AIGT educational products that best meet learning needs, the word frequency analysis showed that "Knowledge" appeared 104 times, accounting for 23.06% of the total, followed by "Resources", "Personalization", and "Thesis", which appeared 83 times, 47 times, and 42 times respectively, accounting for 18.4%, 10.42%, and 9.31% of the total. For the second question, which asks about the factors that influence the use or purchase of AIGT educational products, the word frequency analysis showed that “Price” appeared 124 times, accounting for 20.87% of the total, followed by “Usage”, “Reputation”, and “Functionality”, which appeared 93 times, 55 times, and 49 times respectively, accounting for 15.66%, 9.26%, and 8.25% of the total. For the third question, which asks for suggestions or expectations regarding AIGT educational products, the word frequency analysis showed that “Lower cost” appeared 57 times, accounting for 22.62% of the total, followed by “Enhance cost-effectiveness”, “Personalization”, and “Content accuracy”, which appeared 53 times, 41 times, and 38 times respectively, accounting for 21.03%, 16.27%, and 15.08% of the total.

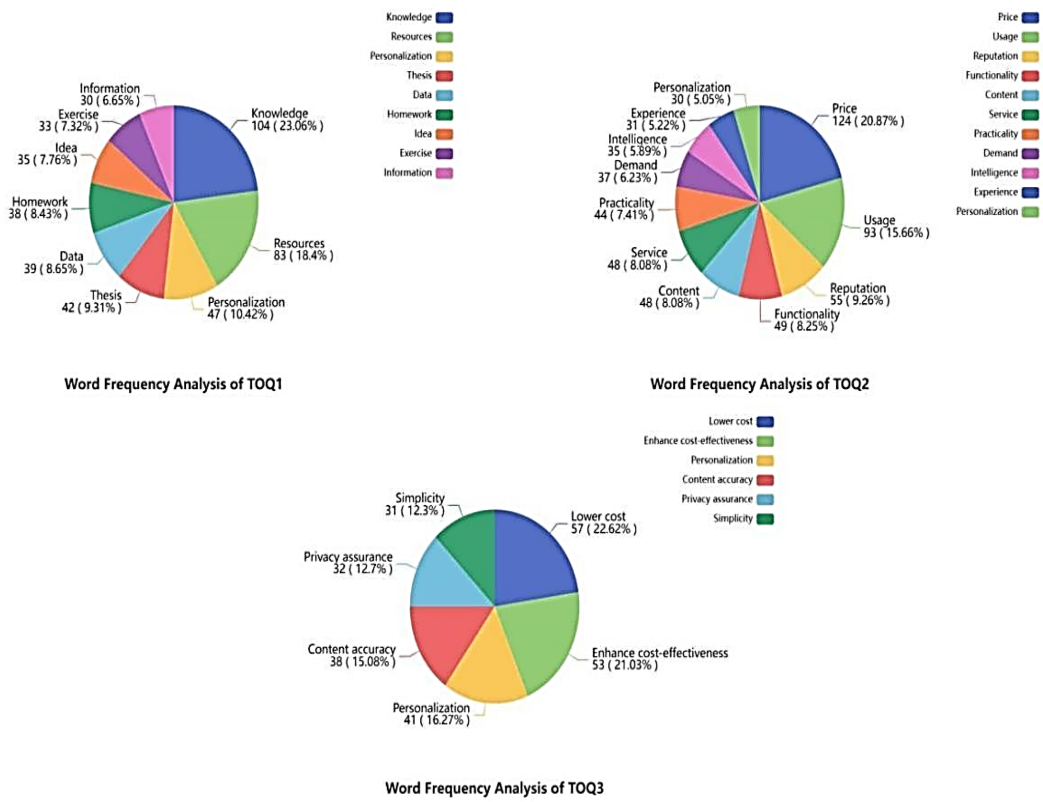

Figure 3. Word frequency analysis

DISCUSSION AND CONCLUSIONS

DISCUSSION

This research sought to explore the key psychological and contextual factors influencing Chinese undergraduate students’ purchase intentions toward AIGT educational products by integrating the Theory of Planned Behavior (TPB), the Technology Acceptance Model (TAM), and the Value-based Adoption Model (VAM). The study aimed to address two central questions: (1) How does the perceived usefulness, perceived ease of use, perceived fee, enjoyment, and brand perception of AIGT educational products influence college students’ perceived value, attitude, subjective norms, and perceived behavioral control? (2) How do college students’ perceived value, attitude, subjective norms, and perceived behavioral control further affect their intention to purchase and use AIGT educational products? The following discussion interprets the empirical findings in light of these research aims.

The study found that perceived usefulness has a significant positive effect on college students' attitudes towards AIGT educational products, purchase intention, and perceived fee. When college students believe that AIGT educational products can improve learning performance and efficiency, they are more inclined to evaluate positively and are willing to pay reasonable fees. Perceived ease of use also has a significant positive effect on attitudes and perceived usefulness, further confirming the importance of technology ease of use in enhancing user acceptance. This result may be related to the intensifying competition in education and increasing academic pressure, as college students are increasingly focusing on improving learning efficiency and effectiveness. AIGT educational products have won favor by providing intelligent and personalized learning aids, which help them better grasp knowledge and improve learning efficiency. These results are consistent with the study by Pillai and Sivathanu (2020) on the willingness to use AI chatbots, as well as the assessment by S. Liu et al. (2023) of foreign language learners' acceptance of ChatGPT in informal digital English learning environments.

Perceived fee exhibits a significant negative impact on perceived value, subjective norms, perceived behavioral control, and attitudes. In the text content analysis, the word "price" appeared most frequently, indicating that high costs may constitute a major obstacle for college students in purchasing AIGT educational products, thereby reducing their perceived value of the product and purchase intention. This result may be related to the relatively limited economic independence and spending power of college students. If the price of AIGT educational products is too high, exceeding their affordability, they are likely to choose not to purchase. Therefore, a reasonable pricing strategy is crucial for increasing purchase intention. These results are consistent with the findings of Chen et al. (2024) and Basri et al. (2016), which highlight the crucial role of perceived price in consumers' purchase decisions.

Enjoyment has a significant positive effect on perceived value and attitude, indicating that the pleasant experiences college students gain when using AIGT educational products can enhance their perceived value of the product and positive attitudes. Brand perception has a significant positive effect on enjoyment, but its impact on perceived value is not significant. This may be due to the current immaturity of AIGT brands, which lack strong market recognition or credibility, making students more focused on practical experience than brand reputation. Cultural factors may also play a role, as Chinese students tend to adopt a pragmatic, results-oriented attitude when evaluating educational tools, placing less emphasis on brand value (Shen et al., 2023). In addition, many students may still be cautious about emerging AI technologies, leading them to prioritize functionality over branding when assessing value. Therefore, brand image and reputation may need to influence perceived value indirectly through factors like enjoyment, reflecting the importance young users place on usage experience and emotional engagement. If AIGT educational products can be designed to be interesting and enjoyable, allowing students to feel satisfied during the usage process, they are more likely to develop a favorable impression of these branded products and perceive them as having higher value. The findings of this study are consistent with the conclusions of S. Liu et al. (2023), which indicate that enjoyment has a significant impact on perceived value.

Perceived value, attitude, subjective norms, and perceived behavioral control all have a significant positive effect on purchase intention. This indicates that when college students decide to purchase AIGT educational products, they will comprehensively consider the product's value, social pressure, and their own ability to control their purchase behavior. This result may be because personal factors, social environments, and external conditions influence college students' purchase behavior. If AIGT educational products align with their values and needs, are recognized by those around them, and they possess the purchasing power and conditions, they are more likely to make a purchase decision. The findings of this study are consistent with the research conclusions of the thesis (E. Kim et al., 2021; Ma et al., 2024; Youn & Lee, 2019; Zeng et al., 2024), etc.

Text content analysis further confirms the aforementioned quantitative research findings. College students generally believe that AIGT educational products best meet their learning needs in terms of knowledge acquisition, personalized resource customization, and paper writing. These are precisely the key areas of focus for college students during their learning process. Meanwhile, the main factors influencing purchase decisions include price, ease of use, brand reputation, and functional diversity. In terms of suggestions and expectations for AIGT educational products, opinions on reducing costs, improving cost-effectiveness, enhancing personalization, and improving content accuracy are frequently raised. These suggestions and expectations reflect the genuine demands of college students for AIGT educational products, providing directions for AIGT educational product providers to improve and optimize their products.

Enterprises and Universities Implications

Based on the research results, enterprises should focus on improving the perceived usefulness of products. This can be achieved by continuously optimizing the functions of AIGT educational products, such as enhancing the accuracy of content generation, providing more personalized learning plans, and better meeting the diverse learning needs of students. At the same time, improving the user experience and ease of use is also crucial. Simplifying the operation interface and optimizing the interaction process can reduce the learning cost of students and increase their acceptance. In terms of pricing, a reasonable pricing strategy needs to be formulated, considering the economic affordability of students. For example, different pricing packages can be provided to meet the needs of different consumption levels. Strengthening brand building is also necessary. Through improving product quality and service, enhancing brand image and reputation, and increasing students' enjoyment and loyalty.

For universities, they can actively introduce and promote the use of AIGT educational products. Incorporate them into teaching and learning processes, provide guidance and training for students to help them better use these products, and improve learning efficiency. At the same time, universities can cooperate with enterprises to jointly develop AIGT products suitable for the school's teaching characteristics and student needs, as well as promote innovation and the development of education.

Limitations and Future Research Directions

This study has some limitations. First, the sample was only from undergraduate students in Chinese universities, lacking data from other regions and educational levels, which may limit the generalizability of the research results. Future research can expand the sample scope to include students from different countries and educational backgrounds. Second, this study only focused on a few factors influencing purchase intention, and there may be other potential factors that were not considered. Future research can explore more factors, such as cultural background, technological innovation speed, and policy environment. Third, the research method was mainly based on questionnaires and structural equation modeling, and future research can combine multiple research methods, such as interviews, experiments, and longitudinal studies, to obtain more in-depth and comprehensive research results.

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APPENDIX: QUESTIONNAIRE

Variables	Items	Source
Perceived ease of use	PEOU1. AIGT educational products are easy to get started with.	(Venkatesh & Davis, 2000)
	PEOU2. The interface design of AIGT educational products is intuitive and easy to understand.	
	PEOU3. It is effortless to locate the required functions.	
	PEOU4(R). I find the operation of AIGT educational products to be complex.	
Perceived usefulness	PU1. Using AIGT educational products can improve learning performance.	(Venkatesh & Davis, 2000)
	PU2. AIGT educational products can enhance learning efficiency.	
	PU3. The content of AIGT educational products highly matches learning needs.	
	PU4(R). AIGT products have no impact on my learning performance.	
Perceived fee	PF1. The cost of AIGT educational products is reasonable.	(Y. Kim et al., 2017)
	PF2. The cost of AIGT educational products is attractive compared to other educational products.	
	PF3. The cost of AIGT educational products is within my economic means.	
	PF4(R). I think the cost of AIGT educational products is too high.	
	EN1. Using AIGT educational products for learning is enjoyable.	

Variables	Items	Source
Enjoyment	EN2. The interactivity and fun of AIGT educational products enhance learning interest.	(Y. Kim et al., 2017)
	EN3. I am very satisfied and enjoy learning with AIGT educational products.	
	EN4(R). Using AIGT educational products for learning is an unpleasant experience.	
Brand perception	BP1. A certain brand makes me more inclined to purchase.	(Coelho et al., 2019)
	BP2. When considering a purchase, a certain brand is my first choice.	
	BP3. The advertisements or reputation of a certain brand have sparked my interest in purchasing.	
	BP4(R). The brand does not motivate me to purchase AIGT educational products.	
Perceived value	PV1. Purchasing AIGT educational products is worth the money.	(Y. Kim et al., 2017)
	PV2. AIGT educational products offer better value for money compared to traditional educational products.	
	PV3. Considering the learning benefits and convenience provided by AIGT educational products or services, the price is fair.	
	PV4(R). I do not believe that AIGT educational products provide any additional value or advantages.	
Subjective norms	SN1. The opinions of family members, teachers, and experts influence my purchasing decisions.	(Ajzen, 1991)
	SN2. The use of AIGT educational products is popular among my peer group.	
	SN3. My friends or classmates support the purchase of AIGT educational products.	
	SN4(R). My friends or classmates do not care whether I purchase AIGT educational products.	
Perceived behavioral control	PBC1. I am capable of selecting and purchasing suitable AIGT educational products.	(Ajzen, 1991)
	PBC2. I can access information about AIGT educational products to make informed decisions.	
	PBC3. I possess the knowledge and skills to use AIGT educational products.	
	PBC4(R). I find it difficult to select and purchase suitable AIGT educational products.	
Attitude	ATT1. I hold a positive attitude towards AIGT educational products.	(Ajzen, 1991)
	ATT2. I believe that AIGT products are helpful for my learning.	
	ATT3. AIGT educational products are more personalized and efficient than traditional resources.	
	ATT4(R). I am concerned that AIGT educational products may not be as good as advertised.	
Purchase intention	PI1. I am considering purchasing AIGT educational products in the future.	(Ajzen, 1991)
	PI2. I will frequently purchase AIGT educational products for my future learning.	

Variables	Items	Source
	PI3. I am willing to recommend AIGT educational products to friends or family.	
	PI4(R). I have no intention of purchasing AIGT educational products.	
Three open-ended questions	TOQ1. In which aspects do you think AIGT educational products and services best meet your learning needs?	Developed by authors
	TOQ2. What other factors influenced your decision when considering the use or purchase of AIGT educational products and services?	
	TOQ3. If you have any suggestions or expectations for AIGT educational products and services, please describe them in detail.	

AUTHORS

Donghe Li is a Master's student in Modern Educational Technology at Jilin Normal University, with three years of teaching experience in higher education. His research focuses on the application of artificial intelligence in education, particularly in the areas of personalized learning, learner behavior, and technology acceptance.

Guijie Zhang has a PhD and is an Associate Professor at Jilin Normal University, where she also serves as the head of the Educational Technology major. With extensive experience in both teaching and research, she has published multiple high-quality research papers in reputable journals and conferences. Her primary research interests include educational technology, personalized learning recommendation systems, and the integration of artificial intelligence to enhance adaptive learning environments.

Xiaowen Liu is a Master's student in Electronic Information at Northeast Normal University, with three years of teaching experience in higher education. She specializes in intelligent learning systems and the analysis of student decision-making behavior. Her research focuses on developing adaptive educational technologies that enhance learning outcomes by modeling and supporting students' cognitive and behavioral processes.