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Influencing Factors of Business College Students' AIGC Model Usage Behavior

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ABSTRACT

In recent years, Artificial Intelligence Generated Content (AIGC) large models have become a fundamental production tool for empowering the development of various industries in the new era. In the textile and garment industry, for instance, AIGC is emerging as a critical tool for digital fashion design and intelligent supply chain management. Integrating business education with AIGC models represents an essential approach for cultivating business talents in the new era. Based on the simplified Unified Theory of Acceptance and Use of Technology (UTAUT) framework, this study employs questionnaire surveys and structural equation modeling to explore the influencing factors of AIGC model usage behavior among business students. Empirical research indicates that four major factors—performance expectancy, effort expectancy, social influence, and facilitating conditions—all significantly promote the use of AIGC models among business students. Among these factors, facilitating conditions have the greatest impact on AIGC model adoption, followed by effort expectancy, while the effects of social influence and performance expectancy are sequentially weaker. During the current transitional period of AI models gradually being implemented, particularly in technology-intensive sectors like modern textiles, universities should actively improve facilitating conditions, enhance the perceived ease of use of tools, foster a supportive environment, and strengthen performance expectancy guidance to accelerate the adoption of AIGC technological tools among business students.

KEYWORDS

AIGC model, business students, usage behavior, UTAUT

INTRODUCTION

As the foundational technology underpinning the latest scientific and technological revolution, AIGC (Artificial Intelligence Generated Content) large models are progressively becoming a central driver of industrial transformation and a fundamental production tool that empowers the development of various industries, thanks to their robust capabilities in data processing, language comprehension, and content generation. In the context of the textile trade, these capabilities are increasingly applied to market trend forecasting and the optimization of cross-border e-commerce operations. In the history of Homo sapiens, the innovation of production tools has been a crucial benchmark for measuring the advancement of social productive forces. Only when laborers closely integrate with these new tools can transformative productivity be cultivated within society. The value of information technology is only fully realized when it is accepted and utilized by laborers [1]. Business disciplines are applied-oriented fields within the humanities and social sciences. Integrating business education with AIGC models to cultivate business students' ability to collaborate with AI tools is essential for talent cultivation in the new era. This is particularly vital for students entering the textile and apparel business, where the “Industrial Intelligence” shift demands a high level of human-AI collaboration. Currently, Chinese society is in a transitional period where AIGC large models are shifting from specialized to general-purpose applications and from niche to mainstream adoption. Business disciplines have strong practical social attributes, and business students are a group within the humanities that shows greater interest and willingness to adopt emerging intelligent tools. The deep integration of AIGC models with university business education has become a strategic imperative for cultivating new business talents. Based on this, this paper explores the internal and external driving factors behind business students' usage behaviors of AIGC models. This holds practical guiding value for promoting the transformative development of business education empowered by artificial intelligence technology in the new era and for accelerating the adoption and utilization of AIGC technological tools in humanities departments of higher education institutions. Furthermore, it provides a practical reference for the digital transformation of talent training in the textile and garment business sectors.

As the implementation and application of AIGC technology progress, there has been a growing academic interest in research on users' acceptance and usage behaviors towards AIGC models. Current studies primarily analyze user acceptance and usage behaviors of AIGC models across various application scenarios and theoretical frameworks. For instance, some research, situated within consumption contexts, compares the efficacy of frameworks such as TAM, TPB, UTAUT, and VAM in assessing user acceptance of AI-powered products [2]. Other studies, within higher education settings, investigate factors that influence college students' willingness to adopt AI-assisted learning environments [3], as well as their intentions and behaviors concerning the use of large AIGC models like ChatGPT [4-6]. More detailed examinations explore specific functionalities of large AI models, including information exploration [7,8], various academic disciplines [9,10], diverse student demographics [11,12], and applications in library settings [13,14]. From the viewpoint of university disciplinary education, existing research has predominantly focused on foreign language learners and students in art and design disciplines [9,10], with relatively little attention given to business students. As a result, the behavioral motivations behind their use of AIGC models are not well understood. This study aims to further enrich the research on AIGC user behaviors.

MATERIALS AND METHODS

Model construction

This paper utilizes the Unified Theory of Acceptance and Use of Technology (UTAUT) as the theoretical framework to analyze business students' usage behavior of AIGC models. The theoretical model encompasses four primary explanatory variables: performance expectancy, effort expectancy, social influence, and facilitating conditions. Performance expectancy pertains to users' anticipated evaluations of whether adopting an emerging technology can improve their work or academic performance. Effort expectancy reflects users' perceived ease or difficulty in mastering the technology. Social influence assesses the extent to which users' adoption of technology is influenced by their social circles and organizational factors. Facilitating conditions refer to the array of "external supports" that users receive from their organizations or technological environments when adopting the technology. In the original UTAUT framework, performance expectancy, effort expectancy, and social influence impact usage behavior via the mediating variable of behavioral intention, whereas facilitating conditions directly affect usage behavior[15].

This study investigates the usage behavior of contemporary business students with respect to AIGC models. Since 2023, China's artificial intelligence sector has witnessed robust development and fierce competition among various AI models across application domains. Following 2024, these AI models have increasingly embraced free strategies, removing economic barriers for users of AIGC technology and diminishing their sensitivity to "cost." Research on current university students indicates that they possess traits of "strong self-awareness" and a "desire for immediate experiences." For free AIGC services, most students engage with them out of "curiosity," "alignment with personal interests," or "peer recommendations." "Cognitive" factors, such as performance expectancy and social influence, more directly motivate "usage behavior," thereby diminishing the mediating role of usage intention. A substantial body of research literature refers to contemporary youth born between 1995 and 2009 as "Generation Z." Studies indicate that young students of Generation Z have grown up in an era characterized by the rapid proliferation of the internet and digital technologies. They exhibit distinct core traits such as being digital natives, prioritizing experiential engagement, and embracing individualized value orientations. [16,17] In view of this, this study omits the mediating variable of behavioral intention, enabling the four core variables to directly act on usage behavior. In comparison to the traditional UTAUT model, this study streamlines the model by reducing mediating variables, constructing a more streamlined framework that reflects the technological usage patterns of contemporary students. This approach zeroes in on the theoretical logic of the direct driving mechanisms of core factors on students' AIGC usage behavior. Based on empirical research outcomes from the simplified UTAUT model (Figure 1), we can clearly discern the influence of various factors on contemporary business students' usage behavior of AIGC models, thus identifying effective entry points for integrating business education with AIGC models during the current transitional period. To this end, this paper utilizes questionnaire surveys and structural equation modeling to examine the effective factors influencing business students' AIGC tool usage behavior. Theoretically, all four core variables of the model exert significant positive effects on business students' AIGC model usage behavior.

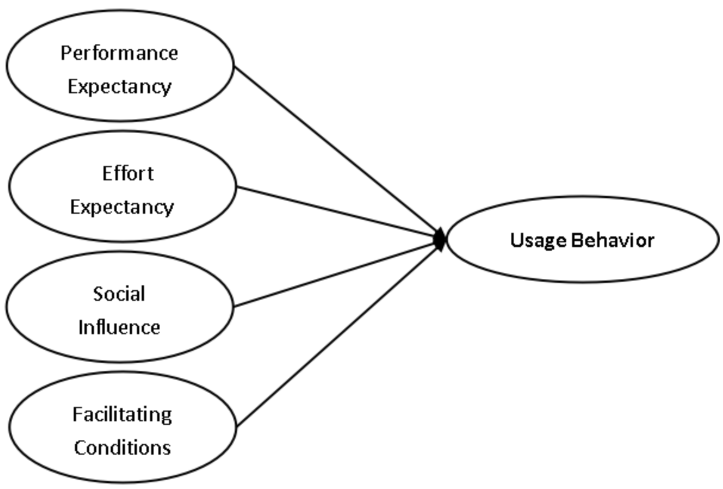

Figure 1. Simplified UTAUT Model

Measurement Indicators

This study developed a questionnaire consisting of six sections: basic information, performance expectancy, effort expectancy, social influence, facilitating conditions, and usage behavior. The basic information section primarily gathers foundational data on business students' gender, academic year, and major. Performance expectancy focuses on business students' expectations regarding the information richness and improvements in learning efficiency offered by AIGC models. Effort expectancy collects evaluations from business students on the ease of use and operational convenience of AIGC models. Social influence measures the extent to which business students are influenced by environmental factors such as peers, teachers, and institutions. Facilitating conditions assesses business students' satisfaction with the hardware and software infrastructure provided by their schools. The usage behavior module of AIGC models primarily measures the breadth and depth of business students' engagement with AIGC models. Specifically, the "frequency of use" item primarily measures the breadth of students' AI model usage, while the "willingness to purchase membership services" item mainly investigates the depth of students' AI model utilization. It should be noted that adopting "willingness to purchase membership services" as a proxy indicator for "the depth of students' AI model usage" is consistent with the service models of Chinese AI platforms. Currently, leading Chinese AI platforms such as ERNIE Bot and Tongyi Qianwen all adopt a hierarchical model of "free basic functions + paid value-added services." The core differences of paid services lie in supporting complex tasks such as professional data visualization and in-depth long-text analysis, as well as lifting restrictions on usage frequency and content length, which are highly aligned with the core demand for "in-depth usage". Relevant details of the measurement items are presented in Table 1.

Table 1. Measurement items and reference sources

Variable	Serial number	Measurement item	Reference source
Performance expectancy	A1	The abundant information provided by AIGC models is helpful to me.	VENKATESH, et al. [15]; ANDREWS, et al. [18]
	A2	The use of AIGC models has enhanced my efficiency in learning, work, and daily life.	
	A3	The content generation quality of AIGC models is excellent.	
	A4	AIGC models provide me with many conveniences in my study and work.	
	A5	Through human-computer interaction, AIGC models can provide me	

		with emotional value.	
Effort expectancy	B1	AIGC models are very easy to get started with.	VENKATESH, et al. [15]; ANDREWS, et al. [18]
	B2	I am proficient in using AIGC models.	
	B3	I can freely switch between different AIGC models.	
	B4	I can flexibly draw upon content generated by different AIGC models.	
	B5	I am capable of conducting in-depth learning and research utilizing AIGC models.	
Social influence	C1	Students freely share their experiences in using AIGC models among peers.	VENKATESH, et al. [15]; ANDREWS, et al. [18]; Zhang, H., et al. [6]
	C2	Course instructors encourage students to utilize AIGC models to assist in learning.	
	C3	The school provides students with an AI learning assistant.	
	C4	The major offers relevant courses in AI applications.	
	C5	My family encourages me to utilize AIGC large language models.	
Facilitating conditions	D1	The hardware infrastructure provided by the school (such as computers, computer labs, etc.) can support the use of AIGC models.	VENKATESH, et al [15]; MENON, et al [4]
	D2	The software infrastructure provided by the school (such as networks, operating systems, etc.) can support the use of AIGC models.	
	D3	The user interface design of the AIGC models I have interacted with is intuitive and easy to operate.	
	D4	In terms of AIGC model usage, I can relatively easily obtain guidance from classmates and teachers around me.	
	D5	The school's teaching management system supports students in using AIGC models.	
Usage behavior	E1	The frequency of my using AIGC model	VENKATESH, et al [15]
	E2	My willingness to purchase AIGC model membership services	

Sample Data Collection

The study measures five research variables using corresponding questions, with options designed according to a Likert 5-level scale. A preliminary survey was conducted among a small group of students using the initial questionnaire. Based on respondents' feedback on the measurement items, appropriate modifications were made before conducting reliability and validity tests. Items with low factor loadings were excluded to ensure the scientific rigor of the questionnaire, ultimately forming the final version. The formal questionnaire was then distributed to a large sample of business students for data collection. Subsequent data processing included hypothesis testing and correlation analysis, among other procedures. This study selected Fujian Business University as the research site. As the only provincial public undergraduate institution named after "business" in Fujian Province, it possesses the basic characteristics of a typical Chinese business university: Centered on business education, the university enrolls students nationwide, with its disciplinary offerings covering mainstream business majors. It is highly consistent with most local business universities in China in terms of talent training objectives and curriculum systems, thus boasting industry representativeness. The structure of the research sample from this university can reflect the characteristics of AI technology usage among business students from diverse backgrounds. During the current transitional period of AI technology implementation, the university's digital infrastructure and AI-related teaching policies are in line with the general level of similar domestic business universities. Data collection was facilitated through the Wenjuanxing platform and various WeChat groups from December 2024 to January 2025, with 600 questionnaires distributed. During data cleaning, students who had no exposure to large AI models were excluded, resulting in 576 valid questionnaires and an effective response rate of 96%.

RESULTS AND DISCUSSION

Sample Characteristics

The formal questionnaire data were analyzed using descriptive statistics with SPSS 27.0 software. In terms of gender distribution, female students accounted for 54.7%, slightly higher than male students at 45.3%, indicating a relatively balanced gender representation. Regarding grade distribution, freshmen constituted 25%, sophomores 30.2%, juniors 22.4%, and seniors 22.4%, demonstrating that the sample covered students across different academic stages. By discipline, economics and trade-related majors represented 31.6% ((a relatively higher proportion), while other business specialties showed a balanced distribution, confirming comprehensive coverage of various business academic backgrounds. For monthly expenditure levels, the 1001-2000 RMB range showed the highest proportion (39.3%), followed by 2001-3000 RMB (19%), 3001-4000 RMB (14.6%), and over 4001 RMB (14.3%), aligning with typical student consumption patterns. Regarding household registration origins, students from third- and fourth-tier cities constituted the largest group (32.3%), followed by rural areas (18.9%), county towns and townships (16.8% each), and first- and second-tier cities (15.3%), reflecting broad geographical representation in the sample.

Reliability and Validity Analysis

The internal consistency of each dimension was evaluated using Cronbach's alpha reliability test method; the analysis results indicated that the coefficients for all dimensions were above 0.6, and the overall coefficient exceeded 0.8, demonstrating that the adopted scale possesses good internal consistency and reliability (see Table 2).

Table 2. Reliability Analysis

Variable	Item No.	CITC	Cronbach's alpha after item deletion	Alpha coefficient
	Q1	0.697	0.839	
Performance expectancy	Q2	0.681	0.843	
	Q3	0.701	0.838	0.868
	Q4	0.701	0.838	
	Q5	0.679	0.844	
Effort expectancy	Q6	0.691	0.865	
	Q7	0.709	0.861	
	Q8	0.741	0.853	0.884
	Q9	0.731	0.856	
	Q10	0.726	0.857	
Social influence	Q11	0.694	0.84	
	Q12	0.716	0.835	
	Q13	0.699	0.839	0.868
	Q14	0.686	0.842	
	Q15	0.664	0.847	
Facilitating conditions	Q16	0.728	0.824	
	Q17	0.697	0.831	
	Q18	0.699	0.831	0.863
	Q19	0.714	0.827	
	Q20	0.584	0.86	

In terms of validity, the sample's KMO value is 0.918, which exceeds 0.7, and the Bartlett's test of sphericity yields a p-value of 0.000, indicating that the scale data is suitable for factor analysis.

Factor Analysis

Based on the results of the Kaiser-Meyer-Olkin (KMO) and Bartlett's sphericity test, principal component factor analysis was conducted. As indicated in Table 3, a total of four factors with eigenvalues greater than 1 were extracted, with explanatory powers of 17.306%, 16.612%, 16.583%, and 16.303%, respectively. The cumulative variance explanation reached 66.804%, meeting the 60% standard, indicating that the four selected factors possess good representativeness.

Table 3. Total Variance Explained

Component	Initial eigenvalue			Square sum of extracted loads			Square sum of rotational loads		
	Total	Variance percentage	Accumulated %	Total	Variance percentage	Accumulated %	Total	Variance percentage	Accumulated %
1	7.136	35.678	35.678	7.136	35.678	35.678	3.461	17.306	17.306
2	2.565	12.827	48.505	2.565	12.827	48.505	3.322	16.612	33.918
3	1.885	9.426	57.931	1.885	9.426	57.931	3.317	16.583	50.5
4	1.774	8.872	66.804	1.774	8.872	66.804	3.261	16.303	66.804
5	0.701	3.505	70.308						
6	0.511	2.553	72.861						
7	0.5	2.502	75.363						
8	0.471	2.354	77.717						
9	0.47	2.351	80.068						
10	0.44	2.202	82.27						
11	0.433	2.167	84.437						
12	0.407	2.037	86.475						
13	0.396	1.98	88.454						
14	0.383	1.914	90.369						
15	0.352	1.759	92.128						
16	0.343	1.713	93.841						
17	0.335	1.675	95.516						
18	0.305	1.523	97.038						
19	0.303	1.514	98.552						
20	0.29	1.448	100						

Extraction method: Principal component analysis.

This study utilized the varimax method for orthogonal rotation (as illustrated in Table 4), extracting four principal factors from 20 items, which corresponded with the pre-established latent variables. Specifically, Component 1 corresponded to items Q6, Q7, Q8, Q9, and Q10, representing the factor "Effort Expectancy"; Component 2 comprised items Q1, Q2, Q3, Q4, and Q5, indicating the factor "Performance Expectancy"; Component 3 included items Q11, Q12, Q13, Q14, and Q15, reflecting the factor "Social Influence"; and Component 4 consisted of items Q16, Q17, Q18, Q19, and Q20, denoting the factor "Facilitating Conditions". Within each factor domain, the factor loadings of the corresponding items all exceeded 0.6, demonstrating a high correlation among items within the same dimension and significant explanatory power for that dimension. In contrast, factor loadings in other factors were below 0.4, suggesting distinctiveness among dimensional factors, which reflects reasonable construct validity of the scale.

Table 4. Rotated component matrix

Item No.	Component			
	1	2	3	4
Q1		0.766		
Q2		0.777		
Q3		0.756		
Q4		0.774		
Q5		0.751		
Q6	0.787			
Q7	0.800			
Q8	0.792			
Q9	0.791			
Q10	0.781			
Q11			0.726	
Q12			0.77	
Q13			0.761	
Q14			0.811	
Q15			0.816	
Q16				0.789
Q17				0.797
Q18				0.776
Q19				0.755
Q20				0.694

Note: The rotation has converged after 6 iterations.

Correlation Analysis

The Pearson correlation analysis results (as presented in Table 5), reveal significant positive correlations among the variables. These correlations are statistically significant at the 1% level, with correlation coefficients indicating positive values.

Table 5. Results of Pearson correlation analysis among variables

Variable	Performance expectancy	Effort expectancy	Social influence	Facilitating conditions
Performance expectancy	1			
Effort expectancy	0.402**	1		
Social influence	0.471**	0.440**	1	
Facilitating conditions	0.410**	0.446**	0.401**	1

**. The correlation is significant at the 0.01 level (two-tailed).

Structural equation test

The structural equation model's fitness and path relationships were tested using AMOS 26.0 software. As indicated in Table 6, which presents the model fitness test results, the CMIN/DF (chi-square to degrees of freedom ratio) value is 2.054, which falls within the acceptable range of 1 to 3. Additionally, the RMSEA (root mean square error of approximation) is 0.043, which is below the threshold of 0.05, indicating a good level of fit. The post-test results for the fit indices IFI, TLI, and CFI all exceeded 0.9, demonstrating high-quality performance. The constructed model achieved a good fit with the sample data, confirming the reliability of the analysis results.

Table 6. Model goodness-of-fit test

Fitting indicators	Reference standard	Measured results
CMIN/DF	1-3 is excellent, 3-5 is good	2.054
GFI	>0.8	0.941
AGFI	>0.8	0.925
RMSEA	<0.05 is excellent, <0.08 is good	0.043
IFI	0.9 is excellent, >0.8 is good	0.970
TLI	0.9 is excellent, >0.8 is good	0.965
CFI	0.9 is excellent, >0.8 is good	0.970

Table 7 presents the standardized path coefficients and significance test results of the research model. The study indicates that performance expectancy has a positive impact on business students' AIGC model usage behavior (B=0.178, $p<0.05$); effort expectancy significantly positively influences usage behavior (B=0.416, $p<0.001$); social influence significantly positively affects usage behavior (B=0.226, $p<0.05$); and facilitating conditions significantly positively impact usage behavior (B=0.593, $p<0.001$). The empirical research demonstrates that facilitating conditions exert the greatest influence on contemporary business students' usage of AIGC large models, followed by effort expectancy, social influence, and performance expectancy.

Table 7. SEM Path Relationship Test Results

Path relationship			Standardized coefficient	Non-standardized coefficients	S.E.	C.R.	P	Conclusion
Usage behavior	<--	Performance expectancy	0.178	0.111	0.05	2.191	0.028	Support
Usage behavior	<--	Effort expectancy	0.416	0.265	0.049	5.35	0.001	Support
Usage behavior	<--	Social influence	0.226	0.130	0.042	3.07	0.002	Support
Usage behavior	<--	Facilitating conditions	0.593	0.348	0.048	7.295	0.001	Support

The standardized parameter estimates of the output model are shown in Figure 2.

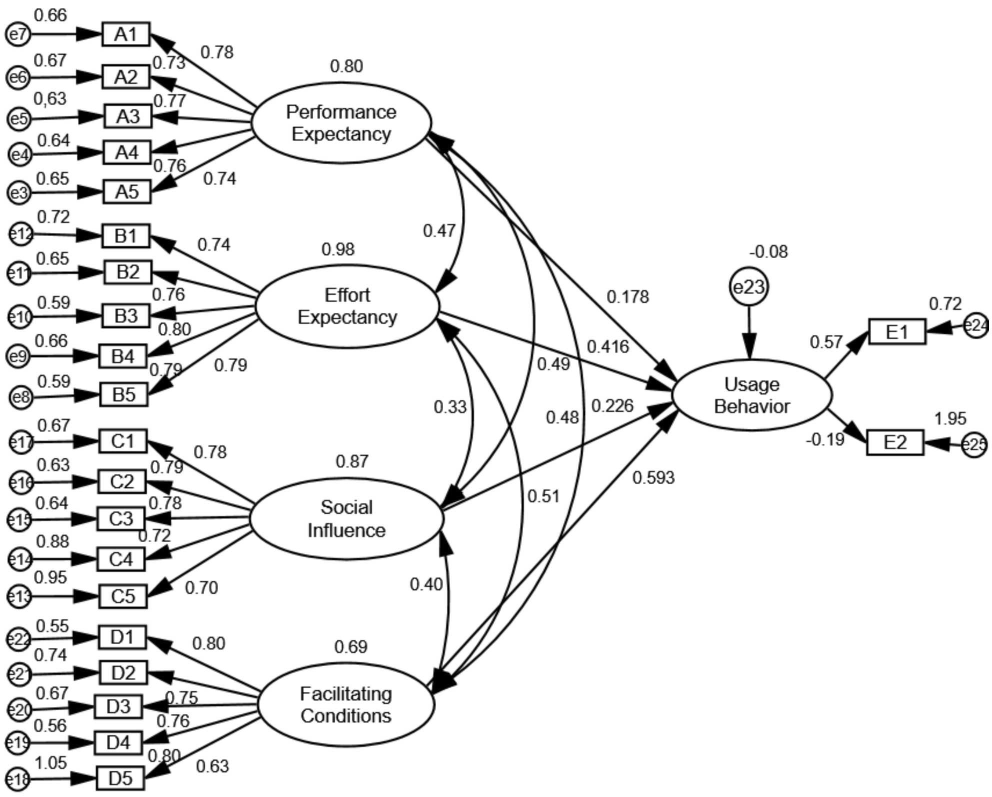

Figure 2. Structural equation model test results

CONCLUSIONS

The research conclusion of this paper indicate that performance expectancy, effort expectancy, social influence, and facilitating conditions all significantly and positively promote their usage behavior. Facilitating conditions have the greatest impact, with a standardized coefficient of 0.593, followed by effort expectancy at 0.416. The influence of social influence (0.226) and performance expectancy (0.178) decreases sequentially. Research findings indicate that during the current transitional period of AI large-scale model implementation, especially within the evolving digital ecosystem of the textile and apparel industry, the external factor of "facilitating conditions" plays a significant promoting role in business students' adoption of AIGC technologies. The Possible reason is that their measurement dimensions (school hardware and software, network support, teacher-student guidance, etc.) directly address the core barrier to students' usage during the transitional period—"whether it can be used smoothly" is a prerequisite for "willingness to use". Combined with Hofstede's Cultural Dimensions Theory, in China's context characterized by high power distance and collectivism, students' adoption of new technologies is highly dependent on the legitimate support provided by schools (e.g., permission from teaching management systems and guidance on usage scenarios from teachers). The constraint of this external environment takes priority over "perceived usefulness" during the transitional period, hence the more prominent impact of facilitating conditions.

The factor of "performance expectations" has the least impact because Questionnaire Items A1 (abundant and helpful information) and A2 (improved efficiency) reflect students' perception of the tool's "potential utility" rather than "performance feedback from actual application." The survey was conducted during the transitional period of AIGC implementation (December 2024-January 2025). While business students acknowledge the theoretical value of the AI tool, they lack specific scenarios and guidance to integrate it into professional learning (e.g., case analysis, data processing, and industry report writing). This leads to insufficient conversion efficiency from "potential utility" to "actual usage behavior," thereby making the impact of performance expectancy weaker than other factors. The questionnaire data shows that the average score of performance expectancy items is 3.72, significantly lower than that of facilitating conditions (4.15) and effort expectancy (4.21), indicating that students' recognition of the tool has not reached a "strong perception" level. Additionally, 52.5% of the samples are students from rural areas, county towns and townships, and some students lack AIGC application scenarios exclusive to business disciplines, which further limits the driving effect of performance expectancy.

To facilitate the swift adoption of AIGC models among business students, universities must implement multi-faceted strategies. On one hand, they should enhance the necessary infrastructure by boosting investments in digital resources to refine network and server setups, streamline localized AIGC implementation, and promote resource sharing. They should also modify teaching management policies to eliminate any usage barriers. Collaborating with AI firms and on-campus educational support entities, universities should offer AIGC application training and AI literacy programs to heighten students' awareness of the tools' utility. For example, training programs could highlight AIGC applications in textile market analysis or intelligent brand management to demonstrate concrete professional benefits. On the other hand, cultivating a supportive environment is essential. Initiatives such as professional contests, study groups, and knowledge-sharing sessions can bolster constructive guidance. Faculty members should incorporate AIGC into their teaching and research methodologies. Moreover, by collaborating with businesses-including those in the textile and garment supply chain— to create industry-specific AIGC models, universities can improve functionality and data security, while also reinforcing students' abilities in innovation and critical thinking. By leveraging the benefits of these tools and the unique capabilities of Homo sapiens, students' confidence and satisfaction with using AIGC can be elevated.

Author Contributions

Hang Lin conducted the study, designed the questionnaire, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Qishan Chen collected and analyzed the data, and drafted the manuscript. Hang Lin participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Conflicts of Interest

The authors declare no conflict of interest.

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Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, author-ship, and/or publication of this article.

Data Sharing Agreement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Human research subjects

The questionnaire used in this study was anonymous, and no personally identifiable information (such as name, contact information, IP address, etc.) was collected. Therefore, this study exempted participants from obtaining informed consent.

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REFERENCES

[1] Venkatesh V, Davis FD. A model of the antecedents of perceived ease of use: Development and test. Decision Sciences. 1996; 27(3):451-481. doi: 10.1111/j.1540-5915. 1996.tb00860.x

[2] Sohn K, Kwon O. Technology acceptance theories and factors influencing artificial intelligence-based intelligent products. Telematics and Informatics. 2020; 47:101324. doi: 10.1016/j.tele.2019.101324

[3] Wu W, Zhang B, Li S, Liu H. Exploring factors of the willingness to accept AI-assisted learning environments: An empirical investigation based on the UTAUT model and perceived risk theory. Frontiers in Psychology. 2022; 13:870777. doi: 10.3389/fpsyg.2022.870777

[4] Menon D, Shilpa K. “Chatting with ChatGPT”: Analyzing the factors influencing users’ intention to use the open AI’s ChatGPT using the UTAUT model. Heliyon. 2023; 9(11):e20962. doi: 10.1016/j.heliyon. 2023.e20962.

[5] Foroughi B, Senali MG, Iranmanesh M, Khanfar A, Ghobakhloo M, Annamalai N, et al. Determinants of intention to use ChatGPT for educational purposes: Findings from PLS-SEM and fsQCA. International Journal of Human-Computer Interaction. 2024; 40(17):4501-4520. doi: 10.1080/10447318.2023.2226495

[6] Zhang H, Liu C, Wang D, Zhao Z. Research on the influencing factors of ChatGPT users’ Intention. Information Studies: Theory & Application. 2023; 46(4):15-22. doi: 10.16353/j.cnki.1000-7490.2023.04.003

[7] Lu X, Zhang J, Lei X. Research on User Information Behavior in the Context of AI-Generated Content: A Case Study of Conversational Search Engines. Information Studies: Theory & Application. 2023; 46(12):84-92. doi: 10.16353/j.cnki.1000-7490.2023.12.012

[8] Zhou T, Li S. Understanding user switch of information seeking: From search engines to generative AI. Journal of librarianship and information science. 2024; 0(0):09610006241244800. doi: 10.1177/09610006241244800

[9] Liu G, Ma C. Measuring EFL learners' use of ChatGPT in informal digital learning of English based on the technology acceptance model. Innovation in Language Learning and Teaching. 2024; 18(2):125-138. doi: 10.1080/17501229.2023.2240316

[10] Li W. A study on factors influencing designers' behavioral intention in using AI-generated content for assisted design: Perceived anxiety, perceived risk, and UTAUT. International Journal of Human-Computer Interaction. 2025; 41(2):1064-1077. doi: 10.1080/10447318.2024.2310354

[11] Huang K, Zhao C, Li H, Li L. Research on the Construction of College Students' AIGC Tools Usage Intention Model in Scientific Research Context. Library and Information Service. 2025; 69(07):53-66. doi: 10.13266/j.issn.0252-3116.2025.07.005

[12] Wan Y, Gu L. Behavioral motivations and influencing factors of graduate students using AIGC tools: An empirical analysis based on questionnaire survey. Journal of Agricultural Library and Information Science. 2024; 36(10):4-22. doi: 10.13998/j.cnki.issn1002-1248.24-0716

[13] Yang X, Ding J, Chen H, Ji H. Factors affecting the use of artificial intelligence generated content by subject librarians: A qualitative study. Heliyon. 2024; 10(8):e29584. doi: 10.1016/j.heliyon. 2024.e29584

[14] Hervieux S, Wheatley A. Perceptions of artificial intelligence: A survey of academic librarians in Canada and the United States. The Journal of Academic Librarianship. 2021; 47(1):102270. doi: 10.1016/j.acalib.2020.102270

[15] Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: Toward a unified view. MIS Quarterly. 2003; 27(3):425-478. doi: 10.2307/30036540

[16] Wang Y. The logic of Z generation's subcultural consumption. China Youth Study. 2021; (11):88-95. doi: 10.19633/j.cnki.11-2579/d.2021.0168

[17] Ao C. The Multiple Characteristics, Realistic Causes, and Subcultural Significance of Z Generation's Consumption Concept. China Youth Study. 2021; (06):100-106. doi: 10.19633/j.cnki.11-2579/d.2021.0092

[18] Andrews JE, Ward H, Yoon J. UTAUT as a model for understanding intention to adopt AI and related technologies among librarians. The Journal of Academic Librarianship. 2021; 47(6):102437. doi: 10.1016/j.acalib.2021.102437