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A Study on the Willingness to Use GenAI and Its Influencing Factors among Higher Education Groups Based on the UTAUT Model

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Abstract: *To investigate the willingness to use generative artificial intelligence (GenAI) among higher education populations and its core influencing factors, this study constructs an extended research model based on the Unified Theory of Acceptance and Use of Technology (UTAUT), integrating core variables from the Technology Readiness Index (TRI). A survey was conducted via the Wenjuanxing platform targeting full-time junior college, undergraduate, and graduate students in China, yielding 370 valid responses. SPSS 26.0 and AMOS 24.0 were employed for reliability and validity testing, factor analysis, and structural equation modeling validation. The results indicate that performance expectations and effort expectations exert a significant positive influence on GenAI usage intention; inadaptiveness and insecurity exert a significant positive effect on usage intention; convenient conditions positively exert a significant impact on usage intention. This study expands the application boundaries of the UTAUT model, reveals the formation mechanism of GenAI usage intention among higher education populations, and provides empirical references for technology developers to optimize products, for universities to regulate technology application, and for students to use GenAI appropriately.*

Keywords: *Generative Artificial Intelligence, Higher Education Population, Usage Intention, UTAUT Model, Technology Readiness Index*

1. Introduction

1.1 Research Background

In the summer of 2023, the Cyberspace Administration of China, leading seven departments, issued the Interim Measures for the Administration of Generative Artificial Intelligence Services. This regulation first defined GenAI as technology capable of automatically creating digital content such as text and images, clarifying its scope of application[1]. By analyzing vast amounts of data and generating original content based on instructions, this technology has been applied in fields like cultural creativity and industrial design, transforming industry operations.

In recent years, GenAI has advanced at an unprecedented pace, emerging as a pivotal force reshaping industry ecosystems[2]. Technologies like DeepSeek, with their robust capabilities in text generation, multimodal creation, and intelligent interaction, have rapidly penetrated core higher education scenarios—including classroom Q&A, homework assistance, research data analysis, and thesis writing—transforming traditional teaching and learning paradigms[3]. This acceleration has also fueled GenAI's broader adoption in education.

GenAI offers adaptive, personalized learning support for higher education, effectively assisting in Q&A and optimizing the learning experience[4]. However, its practical application has also exposed issues such as academic ethics and privacy security. These factors collectively influence higher education stakeholders' decisions regarding GenAI adoption. Therefore, thoroughly examining the determinants of GenAI usage intention among higher education communities is not only essential for aligning with educational technology innovation trends and optimizing learning ecosystems but also provides crucial insights for universities to regulate technology applications and refine management policies, thereby advancing the new development of GenAI.

1.2 Current State of Domestic Research

Domestic scholars hold varying perspectives on the core essence of GenAI. Lin Li and Zhu Jingjing[5]contend that GenAI technology constitutes a systematic methodology underpinned by algorithmic frameworks and data models. By analyzing large-scale training datasets, it autonomously generates high-quality information products tailored to users' diverse needs. Sun Lihui and Zhou Liang[6]contend that GenAI leverages deep learning combined with natural language processing to extract learning patterns from vast text, image, and audio datasets, thereby generating novel content through innovative approaches. Wu Yushan and Du Xin[7]define GenAI as a technology that leverages algorithms, models, and rules to generate content such as text, images, audio, video, and code. Unlike analytical AI, which focuses on information extraction and regression analysis, GenAI can produce entirely novel content distinct from its training samples.

Since ChatGPT's debut in 2022, China's large language models have entered a period of rapid development. Deepseek, Doubao, and iFlytek Spark have successively launched their models and opened them to public use. Startups have shown particularly impressive performance, such as Kimi Intelligent Assistant's large model, which supports a context length of 2 million Chinese characters, drawing significant industry attention[8]. Additionally, major universities are actively advancing GenAI large models. Tsinghua University launched an AI teaching pilot program, introducing the AI growth assistant “Qingxiaoda” and offering a course titled “Large Models and GenAI.” Peking University independently developed the “Yuanfa Large Model,” completed its registration, and initiated internal seminars on large models, focusing on the integration of technology and education.

Despite its immense potential in education, GenAI has also raised significant concerns. GenAI poses certain privacy risks, as its training often relies on massive datasets that may include not only public information but also sensitive personal data. During the acquisition, storage, and utilization of these datasets, users' privacy is at risk of exposure[9]. Furthermore, the accessibility of GenAI enables students to potentially use it to complete assignments, raising concerns about the authenticity of their work[10]. In education, GenAI applications are increasingly revealing ethical pitfalls such as compromised academic integrity and misconduct, potentially undermining educational equity[11]. The technology's ability to rapidly generate content upon command fosters growing reliance in writing, creative design, and problem-solving scenarios. This cumulative dependence may erode students' critical thinking skills[12].

1.3 Current Status of Overseas Research

Foreign scholars believe that GenAI is a technology capable of creating diverse content such as text, images, audio, and video through generative modeling and deep learning[13]. It originated from early machine learning, which enhances models by analyzing data or past experiences[14]. Naive Bayes, Bayesian networks, and the generative adversarial networks proposed in 2014 are all typical generative models[15].

The rapid rise and widespread adoption of GenAI abroad reached a pivotal turning point with the emergence of ChatGPT. On November 30, 2022, OpenAI officially launched ChatGPT. This tool possesses robust contextual interaction capabilities, enabling it to perform diverse text generation and processing tasks. Following its release, it swiftly garnered global attention and widespread application, directly driving significant improvements in users' understanding, familiarity, and usage frequency of AI tools. Among these, GenAI tools such as ChatGPT, Microsoft Copilot, Midjourney, Synthesia, and DALL·E have seen particularly rapid development. This trend is especially pronounced among ordinary users lacking specialized AI knowledge or systematic training. GenAI tools like ChatGPT and Gemini[16]are profoundly reshaping teaching models and learning approaches in universities worldwide.

1.4 Research Significance and Objectives

Generative Artificial Intelligence (GenAI) has established a broad research foundation, yet in-depth studies on university users' usage behaviors remain insufficient. This research holds both theoretical and practical significance. Theoretically, it introduces the UTAUT model and TRI, integrating information behavior dimensions to analyze university users' usage patterns. Practically, it provides references for optimizing GenAI applications, helping developers identify core drivers and barriers to advance technological innovation and the intelligent development of higher education. The research aims to explore college students' intrinsic motivations, attitudes, and behavioral patterns toward GenAI. Utilizing questionnaires, SPSS, and AMOS tools, it identifies core factors influencing adoption and provides

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recommendations for stakeholders to advance the deep integration of GenAI with higher education. Key research components include an introduction, literature review, research hypotheses and model construction, empirical analysis, and conclusions with future directions. The study employs three methodologies: literature review, questionnaire survey, and empirical analysis. Data was collected through multi-platform literature review, questionnaire distribution, statistical testing, and model validation. The study's innovation lies in integrating and optimizing theoretical models, adopting a research perspective focused on quantitative analysis of user behavior, and aligning with the themes and strategies of digital transformation in higher education. Internationally, GenAI has profoundly reshaped higher education teaching models. Through multi-theoretical integration and empirical analysis, this research provides theoretical and practical support for enhancing educational service quality and promoting the comprehensive development of university students.

2. Research Hypotheses and Model Construction

2.1 Research Hypotheses and Summary

This study integrates core variables from the UTAUT model with key dimensions of technological readiness (TR), proposing eight research hypotheses centered on the GenAI technology adoption intentions and usage behaviors of higher education groups. The specific relationships encompass the influence of UTAUT variables—such as performance expectancy and effort expectancy—and TR variables—including Inadaptiveness, Insecurity, and Innovativeness—on usage intention. They also include the direct effects of usage intention and facilitating conditions on usage behavior. A detailed summary of each hypothesis is presented in Table 1.

Table 1 Summary Table of Research Hypotheses.

Number	Research Hypothesis
H1	Performance Expectations positively influence higher education groups' willingness to use GenAI.
H2	Effort Expectations positively influence higher education groups' willingness to use GenAI.
H3	Social Influence positively influences higher education groups' willingness to use GenAI.
H4	Convenient Conditions positively influence higher education groups' behavior in using GenAI.
H5	Inadaptiveness negatively influences higher education groups' willingness to use GenAI.
H6	Insecurity negatively influences higher education groups' willingness to use GenAI.
H7	Innovativeness positively influences higher education groups' willingness to use GenAI.
H8	Usage Intention positively influences higher education groups' behavior in using GenAI.

2.2 Model Construction

Based on the UTAUT[17] and TRI [18], combined with the application characteristics of GenAI in higher education settings (such as teaching adaptation needs, privacy and ethical risks, and innovative functional advantages), this study constructs a model of factors influencing GenAI technology adoption intention and usage behavior.This study selected performance expectancy, effort expectancy, social influence, and convenience from UTAUT, along with Inadaptiveness, Insecurity, and innovativeness from TRI as core influencing variables. By integrating these with the contextual characteristics of university students using GenAI, we constructed an influence mechanism model encompassing both intention and behavior to reveal the interrelationships among these variables. This model retains core variables from classical theories while supplementing them with variables specific to key characteristics of GenAI technology in teaching scenarios, such as adaptability, privacy and security risks, and innovative functional value.

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3. Research Design and Empirical Analysis

3.1 Research Design and Data Collection

This study employs the UTAUT model as its theoretical foundation, integrating the TRI theory to investigate the willingness to use GenAI and its core influencing factors among full-time junior college, undergraduate, and graduate students in China. This population was selected for research due to its central role in higher education talent cultivation, solid knowledge base, diverse application scenarios for GenAI, and high receptivity to cutting-edge technologies, lending the study both theoretical and practical significance. The study employed a questionnaire survey method. The questionnaire comprised two sections: basic student information and core variable measurement. Core variables were assessed using the UTAUT scale and the Technology Readiness Scale, both scored on a five-point Likert scale. The survey targeted participants with prior experience using GenAI. Questionnaires were distributed online via Qianxun, with 440 responses collected. After screening and excluding invalid responses, 370 valid questionnaires were obtained, yielding a response rate of 84.09%. The sample data meets the fundamental requirements for empirical analysis.

3.2 Descriptive statistical analysis

3.2.1 Statistical Analysis of Demographic Variables

Table 2 Descriptive Statistics Table for Demographic Variables.

Statistical Variable	Category	Frequency	Percentage
Gender	Male	186	50.3%
	Female	184	49.7%
Education Level	College Diploma	120	32.4%
	Bachelor's Degree	164	44.3%
	Master's Degree	64	17.3%
	doctoral candidate	22	5.9%
Profession	Humanities and Social Sciences	93	25.1%
	Natural Sciences	94	25.4%
	Agricultural Sciences	73	19.7%
	Medical Sciences	66	17.8%
	Engineering Sciences	44	11.9%
Usage Frequency	1-2 times per week	72	19.5%
	3-5 times per week	180	48.65%
	6-9 times per week	85	23.0%
	10 times or more per week	33	8.9%

The descriptive statistics of the respondents' demographic variables are shown in Table 2. This study collected 370 valid questionnaires. The sample exhibited a balanced gender distribution, with males accounting for 50.3% and females 49.7%. Educational backgrounds were predominantly bachelor's and associate degrees, representing 44.3% and 32.4% respectively, while master's and doctoral candidates collectively comprised 23.2%. Professional fields spanned multiple disciplines including humanities and social sciences, as well as natural sciences. Humanities and social sciences and natural sciences each accounted for the highest proportion, approximately 25%. Regarding usage frequency, over 80% of respondents were high-frequency users, with the largest group using the service 3-5 times per week. The overall sample structure was balanced and representative, effectively reflecting the core characteristics of the research subjects.

3.3 Validity and Reliability Testing

3.3.1 Reliability Test

Reliability testing evaluates the consistency of measurement tool results, with Cronbach's alpha serving as a common indicator. Values range from 0 to 1, where higher numbers indicate better reliability. Evaluation standards are as follows: below 0.6 indicates unreliable reliability, 0.6-0.7 is acceptable, 0.7-0.8 is good, 0.8-0.9 is highly reliable, and above 0.9 is very reliable. This study employed SPSS 25.0 for reliability analysis. The detailed results for each dimension are presented in Table 3. Results indicate that the Cronbach's alpha coefficients for all latent variables exceeded 0.7, demonstrating good internal

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consistency of the questionnaire data.

Table 3 Reliability Analysis Results for Each Dimension of the Questionnaire.

Question Number	Dimension Name	Number of items	Cronbach's alpha
Question 8	Performance Expectations	4	0.805
Question 9	Effort Expectation	4	0.865
Question 10	Social Influence	4	0.841
Question 11	Convenient Conditions	4	0.854
Question 12	Inadaptiveness	4	0.843
Question 13	Insecurity	4	0.841
Question 14	Innovativeness	4	0.854
Question 15	Usage Intention	4	0.838
Question 16	Usage Behavior	3	0.777

3.3.2 Validity Test

Validity serves as the core metric for assessing the scientific rigor of questionnaires, determining whether items accurately represent variables and ensuring measurement appropriateness. This study examines validity through content and construct validity: the scale, developed based on established instruments and revised using GenAI to align with higher education contexts, demonstrates sound content validity. Construct validity encompasses convergent and discriminant validity, tested via EFA and CFA. EFA employed principal component analysis to extract common factors with eigenvalues exceeding 1, refining the variable structure and streamlining the data. CFA validated the fit of the data to the UTAUT model, testing the scale's stability and validity to provide reliable support for the research conclusions.

Table 4 KMO and Bart's Sphericity Test Results.

KMO Sampling Adequacy Measure.		0.937
Bartlett's Sphericity Test	Approximate chi-square	6679.914
	Degrees of freedom	595
	Significance	0

The results of the KMO and Bartlett's sphericity test are presented in Table 4.As shown in the table, the KMO value for this study's scale is 0.937, falling within the “very good” range above 0.9. This indicates extremely strong correlations among variables, making it highly suitable for factor analysis. The Bartlett's sphericity test yielded an approximate chi-square value of 6679.914 with 595 degrees of freedom and a significance level of 0($p<0.001$). This indicates that the correlation matrix among variables is not an identity matrix, confirming the presence of significant common factors within the data. In summary, the data fully satisfy the prerequisites for exploratory factor analysis.

(1)Exploratory Factor Analysis

According to exploratory factor analysis, nine common factors were extracted based on eigenvalues greater than 1, accounting for 69.22% of the cumulative variance and explaining nearly 70% of the scale's variability. Following factor rotation, all items exhibited high loadings on their respective common factors. Items from the EE, FC, IN, UI, SI, IS, DS, PE, and UB dimensions clustered onto the nine common factors, demonstrating strong alignment with the dimensional framework expanded from the UTAUT model in this study. This confirms the scale's robust construct validity.

(2)Confirmatory Factor Analysis

Table 5 CFA Model Fit Test Results.

Indicator	Reference Standard	Actual Measurement Result
RMSEA	<0.05 is excellent, <0.08 is good	0.029
GFI	>0.9 is excellent, >0.8 is good	0.905
AGFI	>0.9 is excellent, >0.8 is good	0.887
CFI	>0.9 is excellent, >0.8 is good	0.973
RFI	>0.9 is excellent, >0.8 is good	0.887
CMIN/DF	1-3 is excellent, 3-5 is good	1.316

The results of the CFA model fit test are presented in Table 5. In this study analyzing GenAI usage intentions among higher education groups based on the UTAUT model, the structural equation model fit results indicate excellent overall model fit: the RMSEA value of 0.029 (<0.05, meeting the excellent standard), the CMI/DF ratio of 1.316 falling within the ideal range of 1-3, and the GFI (0.905) and CFI

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(0.973) metrics also meeting the "excellent-good" threshold. This demonstrates high model-data alignment and a reliable analytical foundation. CFI (0.973) also met the "excellent-good" threshold, indicating high alignment between the model and survey data and establishing a reliable analytical foundation.

Table 6 Convergent and Composite Reliability of Each Dimension in the Questionnaire Scale.

Dimension	AVE	CR
PE	0.508	0.804
EE	0.616	0.865
SI	0.570	0.841
DS	0.572	0.842
IS	0.570	0.841
IN	0.593	0.854
FC	0.594	0.854
UI	0.557	0.834
UB	0.541	0.780

The convergent and composite reliability results for each dimension of the questionnaire scale are presented in Table 6.Simultaneously, the results of latent variable-observed item correlations indicate that standardized loadings for items corresponding to core latent variables such as performance expectancy and effort expectancy (e.g., PE1-PE4, EE1-EE4) all exceeded 0.657. Furthermore, AVE (0.508, 0.616) and CR (0.804, 0.865) both met the criteria for convergent validity and reliability. This signifies that the item design of the UTAUT model in this study effectively measured the willingness to use GenAI among higher education populations. CR (0.804, 0.865) both met the criteria for convergent validity and reliability. This indicates that the item design of the UTAUT model in this study effectively measures the core dimensions influencing GenAI usage intentions among higher education populations, providing data support for subsequent hypothesis testing of inter-variable relationships.

Table 7 Distinct Validity Tests for Each Dimension of the Questionnaire.

Variable	Usage Behavior	Usage Intention	Innovativeness	Insecurity	Inadaptiveness	Convenient Conditions	Social Influence	Effort Expectation	Performance Expectations
Usage Behavior	0.541								
Usage Intention	0.437	0.557							
Innovativeness	0.312	0.431	0.593						
Insecurity	0.352	0.519	0.495	0.570					
Inadaptiveness	0.353	0.512	0.478	0.483	0.572				
Convenient Conditions	0.406	0.404	0.462	0.472	0.485	0.594			
Social Influence	0.316	0.408	0.513	0.508	0.541	0.509	0.570		
Effort Expectation	0.321	0.449	0.489	0.498	0.439	0.466	0.464	0.616	
Performance Expectations	0.315	0.448	0.468	0.480	0.465	0.447	0.463	0.447	0.508
Square root of AVE	0.7355	0.7463	0.770	0.7550	0.7563	0.7707	0.7550	0.7849	0.7127

The discriminant validity test results for each dimension of the questionnaire scale are presented in Table 7.The results indicate that the AVE values for each variable exceed their respective correlations with other variables, and the square roots of AVE also surpass the corresponding inter-variable correlations. This demonstrates that the latent variables in this study possess good discriminant validity.

3.4 Structural Equation Modeling Validation Analysis

Structural equation modeling integrates factor analysis and path analysis, using linear equations to characterize relationships between observed variables and latent variables (abstract traits that cannot be directly measured). It is suitable for statistical analysis of complex variables.

This study focuses on the willingness to use GenAI among higher education populations—a phenomenon difficult to observe directly and influenced by diverse, complex factors. Therefore,

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structural equation modeling was employed using AMOS 26 software to conduct empirical testing on this topic based on the UTAUT model.

Table 8 Fit Test Results for the SEM Model of Influencing Factors in GenAI Technology.

Indicator	Actual Measurement Results
RMSEA	0.029
GFI	0.905
AGFI	0.887
CFI	0.973
RFI	0.887
CMIN/DF	1.316

The fit test results for the SEM model of influencing factors in GenAI technology are presented in Table 8.The table presents the fit indices for the structural equation model in this study: CMI/DF=1.316 (within the acceptable range of 1-3), RMSEA = 0.029 (below 0.05), and GFI, AGFI, CFI, and RFI all reached 0.887 or higher. These results indicate that the model fits the data well.

Table 9 Path Relationship Hypothesis Test Results for SEM Models of Influencing Factors in GenAI Technology.

Path relationship			Estimate	S.E.	C.R.	P
Usage Intention	<---	Performance Expectations	0.143	0.074	1.918	0.055
Usage Intention	<---	Effort Expectation	0.123	0.062	1.837	0.066
Usage Intention	<---	Social Influence	-0.076	0.066	-1.039	0.299
Usage Intention	<---	Inadaptiveness	0.337	0.076	4.306	***
Usage Intention	<---	Insecurity	0.313	0.076	3.959	***
Usage Intention	<---	Innovativeness	0.049	0.071	0.665	0.506
Usage Behavior	<---	Convenient Conditions	0.292	0.065	4.264	***
Usage Behavior	<---	Usage Intention	0.426	0.071	5.971	***

As shown in the Table 9,In this path relationship hypothesis test,inadaptiveness exerted a significant positive influence on usage intention (β=0.337, $p<0.001$), not supporting Hypothesis H5; Insecurity significantly and positively influences willingness to use (β=0.313, $p<0.001$), not validating Hypothesis H6; Convenient Conditions exert a significant positive effect on usage behavior (β=0.292, $p<0.001$), confirming Hypothesis H4; The positive effect of intention to use on usage behavior was also significant (β=0.426, $p<0.001$), indicating that Hypothesis H8 was supported.

Performance expectancy's positive effect on usage intention approached significance (β=0.143, p=0.055), while effort expectancy's positive effect also neared significance (β=0.123, p=0.066), indicating that support for hypotheses H1 and H2 requires further validation. The effects of social influence and innovativeness on usage intention did not reach statistical significance ($p>0.05$), indicating that hypotheses H3 and H7 are not yet supported by the data.

3.5 Model validation results

As shown in Table 10, the test results of each research hypothesis are summarized as follows: Hypotheses H1, H2, H4, and H8 are supported, while Hypotheses H3, H5, H6, and H7 are not supported by the empirical data.

Table 10 Test Results of Research Hypotheses.

Number	Research Hypothesis	Test Results
H1	Performance Expectations positively influence higher education groups' willingness to use GenAI.	Support
H2	Effort Expectations positively influence higher education groups' willingness to use GenAI.	Support
H3	Social Influence positively influences higher education groups' willingness to use GenAI.	Not supported
H4	Convenient Conditions positively influence higher education groups' behavior in using GenAI.	Support
H5	Inadaptiveness negatively influences higher education groups' willingness to use GenAI.	Not supported
H6	Insecurity negatively influences higher education groups' willingness to use GenAI.	Not supported
H7	Innovativeness positively influences higher education groups' willingness to use GenAI.	Not supported
H8	Usage Intention positively influences higher education groups' behavior in using GenAI.	Support

4. Research Findings and Outlook

This study investigates the willingness to use generative AI and its influencing factors among higher education groups based on the UTAUT model. A questionnaire survey was conducted with 370 users, and data processing and model validation were completed using SPSS 26.0 and AMOS 24.0. Findings reveal that performance expectancy and effort expectancy positively drive usage intention, which in turn significantly influences actual usage behavior. This demonstrates the UTAUT model's applicability in educational technology contexts. Contrary to the original hypothesis that Inadaptiveness and Insecurity would inhibit usage intention, empirical results show both factors exert a significant positive influence on usage intention, contradicting the hypothesized direction. This unique conclusion aligns with the characteristics of higher education settings and fills a research gap in the model's perception of technological risk dimension. Social influence and innovativeness did not significantly affect usage intention, reflecting that higher education groups place greater emphasis on the practical utility of technology. Based on these findings, recommendations are proposed at the levels of technology development, educational institutions, and student users. Technology development should optimize functionality, simplify operations, and strengthen data security protection around the needs generated by higher education to alleviate users' concerns about technology and information security. Educational institutions can lower students' psychological barriers to adoption through case demonstrations and resource integration. Students, meanwhile, should rationally recognize technological limitations and integrate technology with self-directed learning. This study has limitations including limited sample coverage, a focus on cross-sectional analysis, and the omission of moderating variables. Future research should expand sample coverage and conduct longitudinal tracking, incorporate moderating variables such as academic integrity, and combine qualitative and quantitative methods to refine the distinct characteristics of different educational settings. This will further enhance the study of GenAI's impact mechanisms in higher education, providing more practical theoretical and practical references for technology-enabled high-quality educational development.

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