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Explaining Undergraduate Students' Acceptance of Generative Artificial Intelligence in Higher Education: An Extended TAM Approach

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Abstract: To examine the acceptance mechanism of generative artificial intelligence (GenAI) among undergraduate students in higher education, this study extends the Technology Acceptance Model (TAM) by incorporating two additional variables, personal innovativeness and trust, and proposes eight hypotheses. Based on 353 valid questionnaires, SPSS 27.0 and Mplus 8.3 were employed to conduct common method bias tests, confirmatory factor analysis, and structural equation modeling. The results indicate that perceived ease of use has a significant positive effect on perceived usefulness. Perceived usefulness, perceived ease of use, personal innovativeness, and trust all have significant positive effects on behavioral intention, which in turn significantly and positively influences actual acceptance. The reliability and validity of the measurement scales, as well as the model fit, meet the required statistical standards. The findings suggest that the classical TAM retains strong explanatory power in the context of undergraduate students' acceptance of GenAI, and that personal innovativeness and trust serve as important complementary variables in promoting the formation of behavioral intention.

Keywords: Generative artificial intelligence (GenAI); Undergraduate students; Technology Acceptance Model (TAM); Personal innovativeness; Trust

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1. Introduction

The deep integration of digital technologies with higher education is reshaping university students' learning modes and pathways to knowledge acquisition. Represented by tools such as ChatGPT, Claude, and DeepSeek, generative artificial intelligence (GenAI) has rapidly entered undergraduate learning practices due to its capabilities in content generation, intelligent question answering, and learning support. It has demonstrated clear advantages in information retrieval, text refinement, idea generation, and problem-solving [1–3]. However, in practical application, significant differences exist in students' levels of acceptance. Some students are able to leverage GenAI to enhance learning efficiency and academic performance, whereas others adopt a more cautious attitude due to insufficient perceived value, operational barriers, ethical concerns, and data privacy issues. Therefore, systematically identifying the key factors influencing undergraduate students' acceptance of GenAI holds clear theoretical and practical significance.

Existing studies have largely drawn on the Theory of Planned Behavior (TPB), the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT), and Diffusion of Innovation Theory to explain students' adoption of artificial intelligence technologies from perspectives such as perceived usefulness, perceived ease of use, and behavioral intention [4–6]. In general, perceived usefulness, perceived ease of use, and learning motivation are regarded as facilitating factors, whereas perceived risk, negative attitudes, and uncertainty tend to inhibit usage intentions [2,5]. Nevertheless, empirical research focusing on the use of GenAI among Chinese undergraduate students remains relatively limited, particularly with regard to localized examinations of personal innovativeness, technological trust, and the mechanisms through which behavioral intention translates into actual use.

Based on the above, this study focuses on undergraduate students in Chinese universities. By incorporating personal innovativeness and trust into the classical TAM framework, it constructs an analytical model of "individual traits–technology perceptions–behavioral intention–actual acceptance" and examines the relationships among variables using 353 valid samples [7]. This study aims to explain the formation mechanism of undergraduate students' acceptance of GenAI and to provide empirical evidence for promoting digital literacy education, optimizing educational applications of GenAI, and improving risk governance in higher education.

2. Theoretical background and research hypotheses

2.1. Theoretical background

2.1.1. Technology Acceptance Model (TAM)

The Technology Acceptance Model, proposed by Davis, is a classical framework for explaining individuals' acceptance and use of new technologies [7,8]. The model posits that perceived usefulness and perceived ease of use are the core variables influencing attitudes toward technology and behavioral intention, which ultimately affect actual usage behavior. Owing to its parsimonious structure and robust explanatory power, TAM has been widely applied in research on educational technology, mobile learning, and intelligent systems. In the context of GenAI, the more students perceive that the technology enhances learning efficiency, academic performance, and task quality—and the more they consider it easy to operate and master—the more likely they are to develop a sustained intention to use it.

2.1.2. Personal innovativeness (PIN)

Personal innovativeness refers to an individual's tendency to actively experiment with and adopt new technologies ahead of others [9,10]. In information technology contexts, individuals with high personal innovativeness are generally more willing to take risks in trying new technologies, more capable of identifying their potential value, and quicker to form positive usage judgments. Therefore, personal innovativeness may not only directly enhance students' intention to use GenAI, but also indirectly promote acceptance by strengthening positive evaluations of its usefulness.

2.1.3. Trust (TRST)

Trust is a critical psychological prerequisite for users' acceptance of new technologies, particularly in the context of generative artificial intelligence, where data interaction is frequent, algorithmic processes are opaque, and outputs may be uncertain [11,12]. For undergraduate students, if they perceive GenAI as stable in operation, reliable in content, and capable of protecting personal data, they are more likely to reduce concerns, enhance perceived ease of use, and ultimately strengthen their intention to use it.

2.1.4. Perceived usefulness (PU)

Perceived usefulness refers to an individual's subjective evaluation of whether a technology can enhance task performance [7,13]. In the context of higher education, it primarily reflects students' overall assessment of GenAI's value in improving learning efficiency, supporting research, optimizing learning experiences, and enhancing digital

competencies. Previous studies have shown that perceived usefulness is one of the most stable and direct predictors of behavioral intention.

2.1.5. Perceived ease of use (PEOU)

Perceived ease of use refers to the degree to which an individual believes that a technology is easy to learn, understand, and operate [14,15]. When a system features a user-friendly interface, smooth interaction, and low learning costs, students are more likely to form positive usage evaluations. At the same time, ease of use can enhance perceived usefulness, thereby indirectly promoting usage intention.

2.1.6. Behavioral intention (BI)

Behavioral intention is a key variable for measuring the strength of an individual's willingness to perform a behavior in the future, and it serves as a central construct in models such as TAM, the Theory of Reasoned Action (TRA), and TPB [16]. In this study, behavioral intention mainly reflects students' subjective tendencies to try, continuously use, and recommend GenAI to others.

2.1.7. Artificial Intelligence Acceptance (AAI)

Artificial intelligence acceptance refers to the extent to which users translate their subjective intention to use into actual adoption behavior. It encompasses aspects such as actual usage frequency, continued usage intention, and subjective endorsement [17]. Existing research suggests that stronger behavioral intention is associated with a higher likelihood of actual adoption and continued use.

2.2. Research hypotheses

2.2.1. Perceived usefulness and behavioral intention

In UTAUT and related studies, performance expectancy or perceived usefulness has been consistently identified as a key determinant of behavioral intention [18]. In the context of GenAI, the more students recognize its contribution to learning tasks and academic performance, the more likely they are to develop a positive intention to use it. Accordingly, the following hypothesis is proposed:

H1: Perceived usefulness has a significant positive effect on behavioral intention to use AI.

2.2.2. Perceived ease of use, behavioral intention, and perceived usefulness

Perceived ease of use not only directly influences behavioral intention but also enhances perceived usefulness by improving individuals' evaluation of a system's practical value [14,19]. In generative AI applications, the simpler the operation and the smoother the interaction, the more easily students recognize its value in supporting learning. Accordingly, the following hypotheses are proposed:

H2a: Perceived ease of use has a significant positive effect on behavioral intention to use AI.

H2b: Perceived ease of use has a significant positive effect on perceived usefulness.

2.2.3. Personal innovativeness, behavioral intention, and perceived usefulness

Personal innovativeness enhances individuals' willingness to explore new technologies and their ability to identify technological value [20,21]. For undergraduate students, higher innovativeness increases the likelihood of actively experimenting with GenAI and facilitates the perception of its practical usefulness in learning contexts. Accordingly, the following hypotheses are proposed:

H3a: Personal innovativeness has a significant positive effect on behavioral intention to use AI.

H3b: Personal innovativeness has a significant positive effect on perceived usefulness.

2.2.4. Trust, behavioral intention, and perceived ease of use

Systematic reviews and studies on ChatGPT indicate that trust is a crucial antecedent of AI adoption [22,23]. In higher education contexts, the greater students' trust in the reliability, effectiveness, and security of GenAI, the more likely they are to perceive it as usable, easy to use, and worth using. Accordingly, the following hypotheses are proposed:

H4a: Trust has a significant positive effect on behavioral intention to use AI.

H4b: Trust has a significant positive effect on perceived ease of use.

2.2.5. Behavioral intention and artificial intelligence acceptance

Behavioral intention is a direct antecedent of actual technology use behavior, and this relationship has been validated in studies on educational technology and AI adoption [17,24]. Therefore, when undergraduate students develop stronger intentions to use GenAI, their actual level of acceptance is also expected to be higher. Accordingly, the following hypothesis is proposed:

H5: Behavioral intention to use AI has a significant positive effect on actual AI acceptance.

Based on the above, this study establishes a comprehensive analytical framework covering the pathway from "individual traits–psychological perceptions–behavioral intention–actual acceptance." Accordingly, the research model is constructed as shown in **Figure 1**.

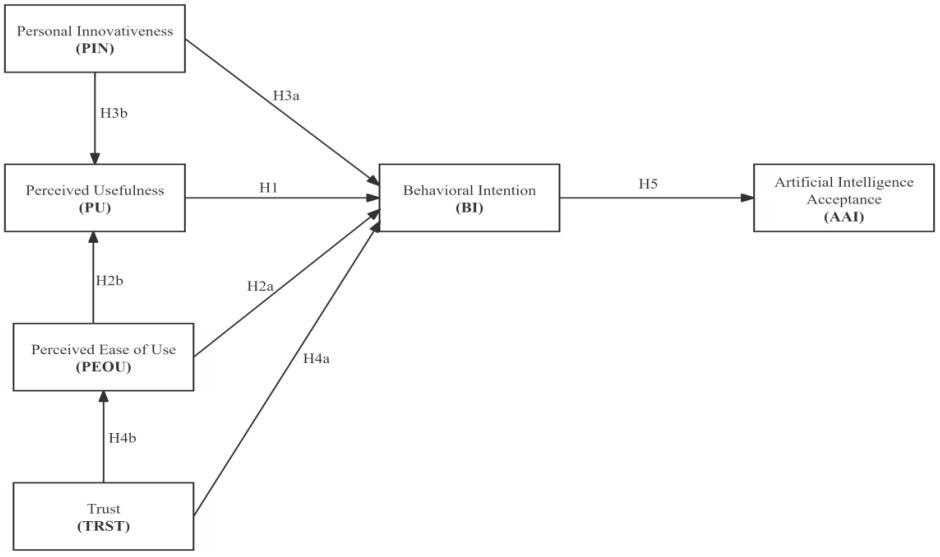


Figure 1. Research model.

3. Research design

3.1. Measurement of variables

The questionnaire consists of two parts: demographic variables and research variables. Demographic variables include gender, grade level, age, university type, and major. All research variables are measured using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). Specifically: Personal Innovativeness (PIN): measured using a scale adapted from Muqing Ma, with 3 items [1]; Trust (TR): measured using a scale adapted from Muqing Ma, with 3 items [1]; Perceived Usefulness (PU): measured using a scale adapted from Bablu et al., with 5 items [6]; Perceived Ease of Use (PEOU): measured using a scale adapted from Bablu et al., with 4 items [6]; Behavioral Intention (BI): measured using a scale adapted from Kang Li, with 4 items [20]; Artificial Intelligence Acceptance (AAI): measured using a scale adapted from Bablu et al., with 4 items [6].

3.2. Data collection and sample description

This study employed an online questionnaire survey targeting undergraduate students (first-year students to seniors) in China. A total of 360 questionnaires were collected, and after removing invalid responses, 353 valid samples were retained, yielding an effective response rate of 98.1%. In the sample: Males accounted for 53.54% and females for 46.46%; Participants aged 21–23 accounted for 54.67%; Students from "Double First-Class" universities accounted for 35.69%, while those from non-elite universities accounted for 64.31%; Students majoring in science, engineering, agriculture, and medicine accounted for 52.41%, while those in humanities and social sciences accounted for 47.59%. The sample structure is presented in **Table 1**.

Table 1. Descriptive statistics of the survey sample

Category	Group	Frequency	Percentage (%)
Gender	Male	189	53.54
	Female	164	46.46
Grade	Freshman	81	22.95
	Sophomore	95	26.91
	Junior	92	26.06
	Senior	85	24.08
Age	18–20	160	45.33
	21–23	193	54.67
University Type	"Double First-Class"	126	35.69
	Non-elite universities	227	64.31
Major	Humanities & Social Sciences	168	47.59
	Science, Engineering, Agriculture & Medicine	185	52.41

3.3. Analytical methods

This study employed SPSS 27.0 and Mplus 8.3 for statistical analysis. First, common method bias was examined, followed by descriptive statistics and correlation analysis. Second, confirmatory factor analysis (CFA) was conducted to assess the reliability and validity of the measurement scales. Finally, structural equation modeling (SEM) was used to test the proposed hypotheses.

4. Data analysis

4.1. Common method bias test

The results of Harman's single-factor test indicate that the variance explained by the first unrotated factor is 33.17%, which is below the critical threshold of 50%. Further, the CFA comparison method shows a significant chi-square difference between the single-factor model and the multi-factor model, suggesting that no serious common method bias exists in the sample. The results are presented in **Table 2**.

Table 2. Changes between model 1 and model 2 (CFA comparison method)

Model	χ^2	DF	$\triangle\chi^2$	$\triangle$DF	*P*
Single-factor model	1879. 039	230	1606. 259	15	0. 000
Multi-factor model	272. 780	215			

4.2. Reliability and validity testing of the measurement scales

The results of confirmatory factor analysis (CFA) show that Cronbach's α and composite reliability (CR) for all constructs

exceed 0.70. Standardized factor loadings are high, and all average variance extracted (AVE) values exceed 0.50, indicating satisfactory internal consistency and convergent validity. Furthermore, the square roots of AVE for all latent variables are greater than their correlations with other constructs, demonstrating good discriminant validity. The results are shown in **Table 3** and **Table 4**.

Table 3. Reliability and validity of the measurement scales

Dimension	Item	Unstandardized Estimate	Standard Error	Z-value	P-value	Standardized Estimate	Reliability (Cronbach's α)	Composite Reliability (CR)	Convergent Validity (AVE)
PIN	PIN1	1.000	-	-	-	0.733	0.791	0.791	0.558
	PIN2	1.101	0.091	12.092	***	0.770			
	PIN3	1.032	0.090	11.481	***	0.738			
TR	TR1	1.000	-	-	-	0.818	0.825	0.825	0.611
	TR2	0.926	0.065	14.173	***	0.780			
	TR3	0.880	0.066	13.364	***	0.746			
PU	PU1	1.000	-	-	-	0.757	0.879	0.879	0.593
	PU2	1.008	0.072	14.055	***	0.753			
	PU3	1.113	0.077	14.439	***	0.779			
	PU4	1.075	0.075	14.386	***	0.775			
	PU5	1.136	0.077	14.769	***	0.787			
PEoU	PEoU1	1.000	-	-	-	0.748	0.848	0.848	0.583
	PEoU2	1.040	0.076	13.747	***	0.781			
	PEoU3	1.042	0.073	14.224	***	0.799			
	PEoU4	0.925	0.072	12.868	***	0.725			
BI	BI1	1.000	-	-	-	0.761	0.839	0.839	0.567
	BI2	0.950	0.075	12.681	***	0.730			
	BI3	0.928	0.073	12.753	***	0.744			
	BI4	0.971	0.069	14.113	***	0.776			
AAI	AAI1	1.000	-	-	-	0.812	0.853	0.853	0.593
	AAI2	0.922	0.060	15.273	***	0.780			
	AAI3	0.896	0.062	14.480	***	0.758			
	AAI4	0.839	0.060	13.904	***	0.728			

Table 4. Discriminant validity of latent variables

Latent Variable		SD	PIN	TR	PU	PEoU	BI	AAI
PIN	3.431	0.920	0.747					
TR	3.329	0.993	0.363	0.782				
PU	3.355	0.915	0.334	0.356	0.770			
PEoU	3.372	0.897	0.306	0.343	0.367	0.764		
BI	3.371	0.970	0.351	0.323	0.935	0.337	0.753	
AAI	3.362	0.937	0.307	0.359	0.404	0.347	0.351	0.770

Note: Bold values represent the square roots of AVE; other values are Pearson correlation coefficients.

4.3. Model fit assessment

The structural model fit indices are as follows: χ^2/df = 1. 495, TLI = 0. 966, CFI = 0. 971, RMSEA = 0. 037, and SRMR =

0. 066. All indices meet the recommended thresholds, indicating a good fit between the theoretical model and the sample data. The results are shown in **Table 5**.

Table 5. Model fit indices

Fit Index	χ^2	df	χ^2/df	TLI	CFI	RMSEA	SRMR
Recommended Value	—	—	< 3	> 0.900	> 0.900	< 0.080	< 0.080
Observed Value	330.287	221	1.495	0.966	0.971	0.037	0.066

4.4. Hypothesis testing

The structural equation modeling results indicate that all hypotheses (H1, H2a, H2b, H3a, H3b, H4a, H4b, and H5) are supported. Specifically: Perceived usefulness significantly positively affects behavioral intention (β = 0.238, $P < 0.001$); Perceived ease of use significantly positively affects both behavioral intention (β = 0.176, $P < 0.05$) and perceived usefulness (β = 0.452, $P < 0.001$); Personal innovativeness significantly positively affects behavioral intention (β = 0.198, $P < 0.01$) and perceived usefulness (β = 0.226, $P < 0.001$); Trust significantly positively affects behavioral intention (β = 0.198, $P < 0.01$) and perceived ease of use (β = 0.449, $P < 0.001$); Behavioral intention significantly positively affects actual AI acceptance (β = 0.515, $P < 0.001$). The detailed results are presented in **Table 6** and **Figure 2**.

Table 6. Path analysis results

Hypothesis	Path	Unstandardized Estimate	SE	Z-value	P-value	Standardized Estimate	Result
H1	PU → BI	0.261	0.076	3.431	0.001***	0.238	Strongly supported
H2a	PEOU → BI	0.184	0.075	2.463	0.014*	0.176	Supported
H2b	PEOU → PU	0.431	0.063	6.803	0.000***	0.452	Strongly supported
H3a	PIN → BI	0.224	0.082	2.738	0.006**	0.198	Supported
H3b	PIN → PU	0.233	0.066	3.534	0.000***	0.226	Strongly supported
H4a	TR → BI	0.185	0.069	2.666	0.008**	0.198	Supported
H4b	TR → PEOU	0.401	0.059	6.826	0.000***	0.449	Strongly supported
H5	BI → AAI	0.566	0.070	8.080	0.000***	0.515	Strongly supported

Note: * indicates $P < 0.05$; ** indicates $P < 0.01$; *** indicates $P < 0.001$.

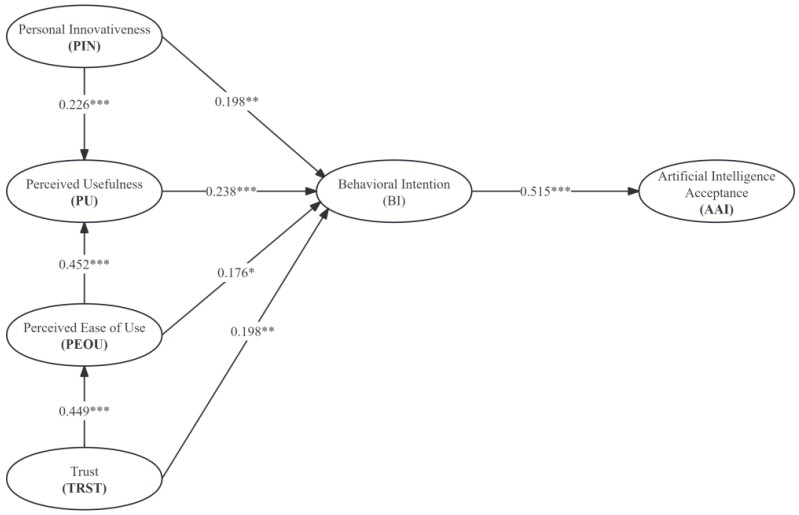


Figure 2. Structural model with standardized path coefficients.

5. Discussion and implications

Based on the TAM, this study used a sample of 353 undergraduate students to construct and empirically test the relationships among personal innovativeness, perceived usefulness, perceived ease of use, trust, behavioral intention, and GenAI acceptance. The results indicate that perceived ease of use significantly enhances perceived usefulness, which in turn strengthens behavioral intention. Personal innovativeness not only directly promotes usage intention but also exerts an indirect effect by increasing perceived usefulness. Trust significantly improves perceived ease of use and positively predicts behavioral intention. Moreover, behavioral intention has the strongest effect on actual acceptance, thereby confirming the applicability of the TAM framework in the context of GenAI use in higher education. From a theoretical perspective, this study extends the technology acceptance framework in the context of GenAI applications in education and enriches empirical evidence regarding the roles of individual traits and psychological factors. From a practical perspective, higher education institutions should focus on improving system usability, enhancing students' perceptions of application value, cultivating innovative competencies, strengthening trust assurance mechanisms, and promoting curriculum integration, so as to facilitate the transformation of usage intention into actual adoption behavior. Nevertheless, several limitations should be acknowledged. First, the sample is geographically limited, which may affect the generalizability of the findings. Second, the cross-sectional design restricts the ability to capture dynamic changes over time. Third, the set of variables may not be sufficiently comprehensive, and differences across application contexts are not fully addressed. Future research could incorporate cross-regional comparisons, longitudinal designs, and mixed-method approaches to enhance explanatory power and applicability further.

Disclosure statement

The author declares no conflict of interest.

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