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Research on Factors Influencing University Students' Continuance Intention to Use Generative Artificial Intelligence

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Abstract: To investigate university students' continuance intention regarding the use of generative artificial intelligence (Gen AI) in academic paper writing and to promote the sustained and healthy development of Gen AI, this study constructs a model of factors driving university students' continuance intention towards Gen AI. The study integrates the Stimulus-Organism-Response (SOR) framework and the Technology Acceptance Model (TAM). Valid data from 397 questionnaires were collected and analyzed using Smart-PLS software to test the theoretical model. The findings reveal that perceived usefulness, satisfaction, and subjective norms are the primary factors influencing university students' continuance intention to use Gen AI. Furthermore, perceived usefulness, perceived ease of use, and perceived risk are identified as the main factors affecting university students' satisfaction with leveraging Gen AI.

Keywords: Generative artificial intelligence; Continuance intention; Paper writing; Stimulus-organism-response framework; Technology acceptance model

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1. Introduction

Generative artificial intelligence (Gen AI), represented by ChatGPT, has brought unprecedented, profound transformations to fields such as teaching and learning due to its powerful data analysis and model generation capabilities [1]. Within academic paper writing, Gen AI has been widely adopted and applied [2]. This research constructs a model to study university students' continuance intention towards adopting Gen AI, specifically from the perspective of paper writing, to provide reference and guidance for the scientific and standardized use of Gen AI by university students in their academic writing endeavors.

2. Theoretical foundation

2.1. Stimulus-organism-response framework

The stimulus-organism-response (S-O-R) framework was derived by Woodworth from stimulus-response theory, emphasizing the subjective role of the organism [3]. This framework has been widely applied in studies on users' continuance intention. Wentao Wang et al. explored the impact of changes in user experience on continuance intention in social media based on an extended S-O-R framework [4]. Hongcan Zhu et al. integrated flow experience with the S-O-R framework, demonstrating the influence of functional attributes, social attributes, and perceived privacy on continuance intention [5]. Therefore, this study constructs a structural equation model from the three dimensions of stimulus, organism, and response, providing a fundamental theoretical framework for the research.

2.2. Technology acceptance model

The technology acceptance model (TAM), proposed by Davis in 1989, explains and predicts users' acceptance and usage behavior of information technology [6]. TAM has been extensively applied in research on users' information technology usage behavior. Hong et al. confirmed that TAM has strong explanatory power for continuance usage behavior [7]. Premkumar et al. found that perceived usefulness significantly influences users' attitudes and actual usage behavior [8]. Thong et al. discovered that users' perception of ease of use affects their initial expectations and subsequent usage intention [9]. Bhattacherjee demonstrated that satisfaction has a significant positive impact on users' continuance intention [10]. When explaining users' intention in complex environments, reorganizing and adjusting the influencing factors in TAM can effectively address issues of low reliability and validity [11]. Therefore, this study combines TAM with the S-O-R framework while further introducing perceived risk and subjective norm variables to achieve a more robust model.

2.3. Perceived risk theory

Perceived risk theory (PRT), proposed by Bauer in 1960, analyzes the impact of uncertain outcomes on consumer behavior. With technological advancements and interdisciplinary integration, PRT has gradually been applied in communication, management, and economics [12]. Chi et al. found that privacy risk exerts the strongest negative influence on users' usage intention [13]. Yali Liu et al. revealed that users' risk perception affects their usage intention, particularly as perceived privacy risk intensifies negative states, thereby leading to continuance intention [14]. As a new generation of AI technology, Gen AI is characterized by radicalness, uncertainty, and ambiguity, which may lead users to perceive risks during usage [15]. Thus, incorporating perceived risk into the research framework enables a more objective and accurate understanding of the relationships among factors shaping university students' continuance intention.

2.4. Subjective norm

The concept of subjective norm first appeared in Ajzen and Fishbein's Theory of Reasoned Action (TRA), referring to an individual's perception of significant others' expectations regarding specific behaviors and their willingness to comply, primarily encompassing perceived social pressure and social expectation dynamics [16]. Ajzen further refined subjective norm in the Theory of Planned Behavior (TPB), listing it as one of three core variables explaining behavioral intention [17]. Venkatesh expanded subjective norm into social influence in the Unified Theory of Acceptance and Use of Technology (UTAUT) [18]. In continuance intention research, Chunhui Tan et al. confirmed that subjective norm exerts the most significant influence on users' continuance intention [19]. Therefore, introducing subjective norm as a supplementary variable helps better identify and explain the influence of external factors such as significant others.

3. Research hypotheses and model construction

3.1. Perceived usefulness

Perceived usefulness refers to university students' belief that using Gen AI in paper writing can improve paper quality and enhance writing efficiency. In the expectation-confirmation model, Bhattacherjee demonstrated that user expectations significantly and positively influence perceived usefulness [10]. Chunhui Tan et al. confirmed the significant positive effects of user expectations and information quality on perceived usefulness, with these factors indirectly affecting satisfaction through perceived usefulness [20]. In the context of paper writing, user expectations reflect the alignment between students' writing needs and Gen AI-provided information. Information quality refers to the quality of content students obtain via Gen AI, while economic efficiency indicates effective reductions in time and financial costs through Gen AI usage. Thus, the following hypotheses are proposed:

H1: User expectations have a significant positive effect on university students' perceived usefulness of Gen AI.

H2: Information quality has a significant positive effect on university students' perceived usefulness of Gen AI.

H3: Economic efficiency has a significant positive effect on university students' perceived usefulness of Gen AI.

Perceived ease of use significantly and positively influences perceived usefulness [6]. When students find Gen AI's interface user-friendly, operation convenient, and information easily accessible, they are more likely to perceive higher usefulness. Thus, the following hypotheses are proposed:

H4: Perceived ease of use has a significant positive effect on university students' perceived usefulness of Gen AI.

3.2. Perceived ease of use

Perceived ease of use refers to university students' perception that utilizing Gen AI for paper writing is effortless. Jianxia Li et al. verified that platform features and information supply significantly and positively affect users' perceived ease of use [21]. Jinfen Xu et al. confirmed that self-efficacy significantly and positively influences perceived ease of use [22]. Fan Zhe et al. demonstrated the significant positive effects of platform quality and self-efficacy on perceived ease of use [23]. For academic paper writing, application features encompass students' perception of how Gen AI's functional design, interface, and technical performance facilitate ease of use. Self-efficacy reflects students' confidence in their ability to use Gen AI for paper writing. Information supply refers to Gen AI's capacity to provide accurate, authoritative, comprehensive, and academically compliant content. Thus, the following hypotheses are proposed:

H5: Application features have a significant positive effect on university students' perceived ease of use of Gen AI.

H6: Self-efficacy has a significant positive effect on university students' perceived ease of use of Gen AI.

H7: Information supply has a significant positive effect on university students' perceived ease of use of

Gen AI.

3.3. Perceived risk

Perceived risk refers to university students' assessment of potential negative consequences when using generative artificial intelligence (Gen AI) for academic writing. Wang et al. found that privacy risk significantly and positively influences perceived risk [24]. Yali Liu et al. identified time-related and ethical risks as key dimensions shaping users' risk perception toward Gen AI [14]. In academic writing scenarios, privacy risk reflects students' concerns about unauthorized use, leakage, or misuse of personal data or paper content, along with resultant negative impacts. Time risk denotes perceived inefficiency or time wastage when leveraging Gen AI. Ethical risk involves potential violations of social norms or personal values through Gen AI usage. Thus, the following hypotheses are proposed:

H8: Privacy risk has a significant positive effect on university students' perceived risk of Gen AI.

H9: Time risk has a significant positive effect on university students' perceived risk of Gen AI.

H10: Ethical risk has a significant positive effect on university students' perceived risk of Gen AI.

3.4. Satisfaction

Satisfaction represents the positive affective state derived from leveraging Gen AI for academic writing. Huang et al. demonstrated that perceived usefulness and ease of use most significantly influence positive affect [25]. Shahrabani et al. revealed that perceived risk substantially affects attitudes, where higher risk perception correlates with more negative attitudes [26]. Thus, the following hypotheses are proposed:

H11: Perceived usefulness has a significant positive effect on university students' satisfaction with Gen AI.

H12: Perceived ease of use has a significant positive effect on university students' satisfaction with Gen AI.

H13: Perceived risk has a significant negative effect on university students' satisfaction with Gen AI.

3.5. Continuance intention

Continuance intention refers to students' willingness to persistently use or recommend Gen AI for academic writing. The positive effects of perceived usefulness and satisfaction on continuance intention have been empirically validated. Zhou et al. confirmed the significant impact of perceived usefulness on behavioral intention [27]. Hong et al. identified satisfaction as a critical determinant of continuance usage [7]. Within academic writing contexts, subjective norm captures social expectations and pressures from significant others regarding Gen AI usage. Both the Theory of Planned Behavior and Unified Theory of Acceptance and Use of Technology empirically validate their influence on usage intention [18, 28]. Thus, the following hypotheses are proposed:

H14: Perceived usefulness has a significant positive effect on university students' continuance intention to use Gen AI.

H15: Satisfaction has a significant positive effect on university students' continuance intention to use Gen AI.

H16: Subjective norm has a significant positive effect on university students' continuance intention to use Gen AI.

Building upon the Stimulus-Organism-Response Framework and Technology Acceptance Model, this study develops a research model (**Figure 1**) to examine factors shaping university students' continuance intention toward Gen AI in academic writing contexts.

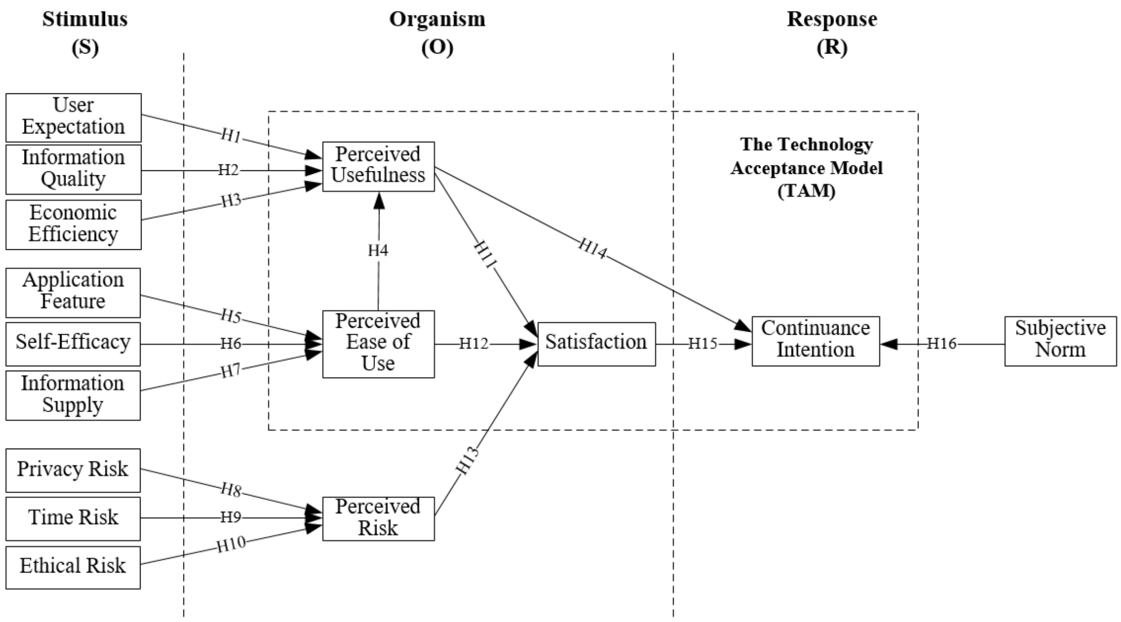

Figure 1. Research model of university students' continuance intention toward Gen AI

4. Research design and data processing

4.1. Questionnaire design

The questionnaire was developed based on established instruments, consisting of two parts: basic information and variable measurement, totaling 49 items. The measurement section employed a 5-point Likert scale. Table 1 presents the measurement items and relevant sources.

Table 1. Measurement scale for factors influencing university students' continuance intention toward Gen AI

Latent variable	Measurement items	Reference sources
User Expectation (UE)	UE1: I think my experience and gains from Gen AI exceeded my expectations	[24]
	UE2: I think the quality of content generated by Gen AI exceeded my expectations	
	UE3: I think the functional level of Gen AI exceeded my expectations	
Information Quality (IQ)	IQ1: I think the information provided by Gen AI is authentic and reliable	[20]
	IQ2: I think the information provided by Gen AI demonstrates strong theoretical professionalism	
	IQ3: I think the information generated by Gen AI is highly relevant to academic research	
Economic Efficiency (EE)	EE1: I think Gen AI to be cost-effective	[29, 30]
	EE2: I think Gen AI can reduce my paper writing costs	
	EE3: I think Gen AI is more convenient than other paper writing assistance methods	
	EE4: I think Gen AI provides more comprehensive content than other assistance methods	

Table 1 (Continued)

Latent variable	Measurement items	Reference sources
Application Feature (AF)	AF1: I think Gen AI responses is very quick	[21–22]
	AF2: I think Gen AI is easy to operate and use	
	AF3: I think the interface design of Gen AI is very user-friendly	
Self-Efficacy (SE)	SE1: I believe I can independently use and master Gen AI	[24]
	SE2: I think I can solve problems encountered during usage	
	SE3: I believe I can use various Gen AI tools	
Information Supply (IS)	IS1: I think the information provided by Gen AI is standardized and authoritative	[22]
	IS2: I think the sources of information provided by Gen AI are accurate	
	IS3: I think the information descriptions provided by Gen AI are correct and complete	
Privacy Risk (PR)	PR1: I think Gen AI excessively collects my personal information without my knowledge	[31–32]
	PR2: I think my personal information has been leaked	
	PR3: I feel service providers are inappropriately using my personal information	
Time Risk (TR)	TR1: Installing and learning to use Gen AI took considerable time	[31]
	TR2: I need to continuously follow Gen AI developments to ensure continued usage	
	TR3: I spend time verifying the accuracy of content generated by Gen AI	
Ethical Risk (ER)	ER1: I think research institutions and governments haven't established effective measures for AI ethical risk control	[25]
	ER2: I think adopting Gen AI for paper writing constitutes academic misconduct	
Satisfaction (S)	S1: I'm very interested in Gen AI	[26]
	S2: Using Gen AI makes me happy	
	S3: I'm satisfied with my decision to use Gen AI	
Perceived Usefulness (PU)	PU1: I think Gen AI helps me complete paper writing	[21, 24]
	PU2: I think utilizing Gen AI for paper writing meets my expectations	
	PU3: I think utilizing Gen AI improves my writing efficiency	
Perceived Ease of Use (PEOU)	PEOU1: Learning to use Gen AI for paper writing is very easy	[21, 27]
	PEOU2: I'm proficient in adopting Gen AI for paper writing	
	PEOU3: Papers generated by AI are easily understandable	
Perceived Risk (PRQ)	PRQ1: I feel uneasy adopting Gen AI for paper writing	[26, 32]
	PRQ2: I think adopting Gen AI for paper writing brings uncertain risks	
	PRQ3: I think adopting Gen AI for paper writing is risky	
Subjective Norm (SN)	SN1: I think important people (tutors/friends/family) expect me to use Gen AI for paper writing	[16]
	SN2: I think important people want me to continue leveraging Gen AI for paper writing	
	SN3: I care about others' opinions regarding my use of Gen AI for paper writing	
Continuance Intention (CI)	CI1: I will continue leveraging Gen AI for paper writing	[10]
	CI2: I will frequently use Gen AI for paper writing in the future	
	CI3: I will recommend others to use Gen AI for paper writing	

4.2. Data collection

The study distributed questionnaires through online platforms, collecting 397 valid responses. Subsequently, statistical analysis of the sample data was conducted using SPSS, with results presented in **Table 2**.

Table 2. Demographic statistics

Category	Option	Frequency	Percentage
Gender	Female	154	38.79
	Male	243	61.21
Education	Bachelor	216	54.41
	Master	158	39.80
	Doctorate	23	5.79
Discipline	Education	24	6.04
	Science	50	12.59
	Engineering	255	64.23
	Management	43	10.83
	Others	25	6.30

4.3. Reliability and validity analysis

The study employed Smart-PLS software to conduct reliability and validity tests on the sample data, with the results presented in **Tables 3** and **4**. The analysis demonstrates strong reliability of the results, with the model data exhibiting high convergent validity. The internal correlations among variables meet established standards, and the discriminant validity between variables is satisfactory.

Table 3. Reliability and convergent validity test results of the sample data

Latent variable	Measurement items	Factor loading coefficients	Cronbach'α	CR	AVE
User Expectation (UE)	UE1	0.866	0.805	0.885	0.719
	UE2	0.858			
	UE3	0.819			
Information Quality(IQ)	IQ1	0.858	0.788	0.876	0.702
	IQ2	0.814			
	IQ3	0.841			
Economic Efficiency (EE)	EE1	0.756	0.835	0.887	0.664
	EE2	0.84			
	EE3	0.821			
	EE4	0.839			
Application Feature (AF)	AF1	0.876	0.828	0.897	0.744
	AF2	0.859			
	AF3	0.852			

Table 3 (Continued)

Latent variable	Measurement items	Factor loading coefficients	Cronbach'α	CR	AVE
Self-Efficacy (SE)	SE1	0.882	0.791	0.877	0.704
	SE2	0.77			
	SE3	0.862			
Information Supply (IS)	IS1	0.873	0.843	0.905	0.762
	IS2	0.858			
	IS3	0.888			
Privacy Risk (PR)	PR1	0.872	0.857	0.913	0.778
	PR2	0.907			
	PR3	0.867			
Time Risk (TR)	TR1	0.763	0.745	0.854	0.662
	TR2	0.835			
	TR3	0.84			
Ethical Risk (ER)	ER1	0.917	0.805	0.911	0.837
	ER2	0.912			
Satisfaction(S)	S1	0.875	0.775	0.87	0.69
	S2	0.793			
	S3	0.822			
Perceived Usefulness (PU)	PU1	0.881	0.828	0.897	0.744
	PU2	0.872			
	PU3	0.835			
Perceived Ease of Use (PEOU)	PEOU1	0.843	0.772	0.868	0.687
	PEOU2	0.814			
	PEOU3	0.83			
Perceived Risk (PRQ)	PR1	0.858	0.842	0.905	0.76
	PR2	0.875			
	PR3	0.883			
Subjective Norm (SN)	SN1	0.893	0.774	0.869	0.691
	SN2	0.883			
	SN3	0.705			
Continuance Intention (CI)	CI1	0.874	0.813	0.889	0.728
	CI2	0.86			
	CI3	0.825			

Table 4. Discriminant validity test results of the sample data

	SN	ER	IS	IQ	AF	PEOU	PU	PRQ	CI	TR	S	UE	EE	SE	PR
SN	0.831														
ER	0.005	0.915													
IS	0.354	0.029	0.873												
IQ	0.283	0.073	0.437	0.838											
AF	0.270	0.018	0.458	0.346	0.862										
PEOU	0.288	0.043	0.534	0.327	0.486	0.829									
PU	0.377	0.032	0.571	0.544	0.484	0.600	0.863								
PRQ	0.073	0.360	-0.211	0.157	0.216	-0.306	0.359	0.872							
CI	0.622	0.052	0.406	0.368	0.338	0.522	0.624	0.252	0.853						
TR	0.079	0.370	0.079	0.034	0.044	-0.092	0.058	0.303	0.154	0.813					
S	0.262	0.035	0.392	0.325	0.282	0.552	0.619	0.367	0.544	0.003	0.831				
UE	0.081	0.086	0.201	0.305	0.179	0.081	0.257	0.001	0.172	0.071	0.175	0.848			
EE	0.135	0.041	0.347	0.467	0.320	0.282	0.516	0.299	0.389	0.039	0.412	0.367	0.815		
SE	0.266	0.120	0.528	0.315	0.455	0.538	0.425	0.168	0.354	0.072	0.365	0.175	0.340	0.839	
PR	0.128	0.307	0.039	0.021	0.021	-0.064	0.029	0.445	0.011	0.447	0.048	0.030	0.105	0.006	0.882

4.4. Model fit and hypothesis testing

Using Smart-PLS software with the Bootstrapping algorithm (5,000 resamples), the path coefficients, *t*-values, F^2, significance levels (*P*-values), and hypothesis testing results are summarized in Table 5. The results indicate that the endogenous variables demonstrate strong explanatory power, the model exhibits good goodness-of-fit, and all hypotheses were supported except for H1 and H9.

Table 5. Path coefficient test results

Hypotheses	Path	Path coefficients	t-values	F2	P-values	Test results
H1	UE→PU	0.047	1.017	0.004	0.309	Not Supported
H2	IQ→PU	0.270	4.837	0.116	0***	Supported
H3	EE→PU	0.250	4.427	0.098	0***	Supported
H4	PEOU→PU	0.437	8.269	0.368	0***	Supported
H5	AF→PEOU	0.228	3.776	0.064	0***	Supported
H6	SE→PEOU	0.287	5.138	0.093	0***	Supported
H7	IS→PEOU	0.278	5.322	0.087	0***	Supported
H8	PR→PRQ	0.346	5.961	0.125	0***	Supported
H9	TR→PRQ	0.063	1.067	0.004	0.286	Not Supported
H10	ER→PRQ	0.230	4.243	0.060	0***	Supported
H11	PU→S	0.412	6.376	0.188	0***	Supported
H12	PEOU→S	0.262	4.449	0.079	0***	Supported
H13	PRQ→S	-0.139	3.588	0.030	0***	Supported
H14	PU→CI	0.311	4.759	0.137	0***	Supported
H15	S→CI	0.235	3.596	0.085	0***	Supported
H16	SN→CI	0.443	9.464	0.419	0***	Supported

Note: *** indicates $P < 0.001$

5. Conclusions and recommendations

5.1. Conclusions

Perceived usefulness, satisfaction, and subjective norms emerged as primary factors driving university students' continuance intention to use Gen AI. Study results show that subjective norms exhibited the most significant impact, which indicates that social approval from significant others strongly motivates sustained usage. Both perceived usefulness and satisfaction positively affected continuance intention, confirming that utility perceptions and positive affective states drive adoption persistence.

Satisfaction was predominantly shaped by perceived usefulness, perceived ease of use, and perceived risk. Results reveal that perceived usefulness and ease of use exhibit significant positive effects on satisfaction, with perceived usefulness demonstrating the strongest influence. This indicates that students develop more positive affective responses when they explicitly recognize Gen AI's effectiveness in supporting academic writing. Conversely, perceived risk shows a significant negative effect on satisfaction, meaning heightened risk perception during Gen AI usage correlates with increased negative affect toward the application. Additionally, the hypothesis that user expectations would affect perceived usefulness was not supported, indicating that pre-usage expectations do not significantly influence students' perception of Gen AI's utility. The hypothesis that time risk influences perceived risk is also not supported, suggesting that the efficiency of time usage does not significantly affect students' perception of the risks associated with Gen AI.

5.2. Recommendations

For generative AI developers and operators, satisfaction, perceived usefulness, and subjective norm exert significant and direct effects on users' continuance intention. First, developers and operators should continuously optimize user experience to enhance satisfaction—particularly regarding perceived usefulness and ease of use—by actively addressing user feedback, refining product functionalities, and improving interface friendliness to prevent user churn. Second, product usefulness must be prioritized, with generated content quality as the core offering. Continuous improvement of output quality is essential to elevate users' perceived usefulness. Finally, developers should collaborate proactively with regulatory authorities to establish usage guidelines, ensuring generative AI amplifies academic value in paper writing rather than becoming synonymous with academic misconduct.

For higher education administrators, guidance should be provided to ensure students' appropriate and ethical use of Gen AI in academic writing, preventing over-reliance and academic misconduct. While Gen AI undeniably offers tangible efficiency benefits in scholarly writing, educational administrators must leverage its instrumental role through general courses and academic workshops that disseminate standardized application methodologies for research. Concurrently, it is necessary to develop robust usage guidelines for Gen AI, create a positive academic atmosphere, and avoid excessive dependence and academic misconduct.

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