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Yanming Liu, Xinmao Liu & Meng Guan

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Adoption of Generative AI in Academic Writing Among Chinese University Students: An Extended UTAUT Model Incorporating Trust, Moral Obligation, and Perceived Risk

Abstract

This study extends the Unified Theory of Acceptance and Use of Technology (UTAUT) by incorporating moral obligation, trust, and perceived risk to examine the adoption of generative artificial intelligence (GAI) for academic writing among Chinese university students. Data were collected through an online survey of 486 undergraduate, master's, and doctoral students and analyzed using partial least squares structural equation modeling (PLS-SEM). The results show that trust was the strongest predictor of behavioral intention, whereas perceived risk had a direct negative effect on behavioral intention. However, the hypothesized link between trust and perceived risk, as well as the mediating role of perceived risk, was not supported. Performance expectancy and social influence positively affected behavioral intention, while moral obligation had a negative effect. Facilitating conditions positively predicted use behavior, whereas effort expectancy was not significant. Multigroup analysis showed no significant gender differences across comparable paths, but the negative effect of moral obligation on behavioral intention was stronger among doctoral students than among undergraduates. These findings advance current understandings of GAI adoption in academic writing, offering valuable implications for ethical governance and instructional support in higher education.

Keywords: Generative AI, UTAUT, Academic writing, Trust, Perceived risk, Moral obligation, China

Introduction

The rapid adoption of generative AI (GAI) across sectors such as finance, healthcare, and manufacturing has received increasing scholarly attention (Kar et al., 2023; Al Naqbi et al., 2024). Unlike conventional AI, which primarily analyzes existing data, GAI is trained on large-scale datasets to generate new text, images, or code in response to user prompts (Dwivedi et al., 2023). This capacity has made GAI well suited to tasks involving content generation and idea development.

In educational settings, tools such as ChatGPT and Claude, along with Chinese-language platforms such as Doubao, Kimi, and DeepSeek, are increasingly used for academic writing. In this study, academic writing refers to the structured production of evidence-based scholarly texts, including essays, theses, and research papers (Bailey, 2022). Prior research suggests that GAI can assist with content development, argument organization, and language refinement, while

also supporting the editing and revision stages of writing (Mahapatra, 2024; Zou and Huang, 2024). Studies have also shown that students may view AI-assisted writing tools as helpful for feedback, engagement, and confidence in the writing process (Song and Song, 2023; Teng, 2024b).

At the same time, the use of GAI in academic writing raises ethical and practical concerns (Rudolph et al., 2023; Gallent Torres et al., 2023). One major concern is academic integrity, as GAI-generated content may facilitate plagiarism and weaken originality (Teng, 2024a; Rentier, 2024; Batista et al., 2024). Other concerns include hallucinated content, privacy and data security risks, and over-reliance on AI-assisted output, which may reduce students' independent engagement in writing and their opportunities for critical reflection (Alkaissi and McFarlane, 2023; Teng, 2024a; Rana et al., 2024; Nugroho et al., 2024; Kim et al., 2025). In response, countries and institutions have introduced AI-detection software and policy frameworks (e.g., European Parliament and Council of the European Union, 2024) to promote ethical practices, although implementation remains uneven across contexts (Cotton et al., 2024).

For university students in China, these issues arise within a particular socio-educational context. One relevant feature of this context is "involution" (neijuan), a form of intensified competition in which increasing effort does not necessarily produce proportional returns. In such an environment, students face sustained academic pressure, and GAI is perceived as a means of improving efficiency and performance (Chen and Hu, 2022; Si, 2022; Yang et al., 2023; Yi et al., 2022). At the same time, institutional guidance on the use of GAI remains limited or ambiguous in many settings, leaving students uncertain about acceptable boundaries of use (Zhou et al., 2024). These conditions intensify the ethical tension between the practical benefits of technology and the traditional Confucian emphasis on authenticity and diligence.

Although research on GAI in writing has expanded, its ethical and psychological dimensions remain insufficiently examined. In particular, the roles of trust, moral obligation, and perceived risk in shaping adoption within high-pressure and culturally specific settings require further investigation. Few studies have examined GAI adoption in academic writing among university students in Mainland China. While Lai et al. (2024) integrated ethical constructs into the Unified Theory of Acceptance and Use of Technology (UTAUT) to study ChatGPT adoption in the Hong Kong Special Administrative Region (SAR), China, their focus was primarily on assessment support. This leaves academic writing underexplored and differences between the Hong Kong and Mainland China contexts insufficiently addressed.

To address these gaps, this study adopts UTAUT (Venkatesh et al., 2003) as its theoretical framework. The original UTAUT was selected instead of UTAUT2 (Venkatesh et al., 2012) because academic writing in Chinese universities is primarily a mandatory and performance-oriented activity rather than a voluntary consumer behavior. Although the core UTAUT constructs—performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC)—are useful for explaining utilitarian technology adoption, they do not fully capture the ethical and psychological conditions surrounding GAI use in academic writing. Accordingly, this study extends the model by incorporating moral obligation (MO), trust (TR), and perceived risk (PR) to better account for the ethical tensions, reliability concerns, and associated risks in Mainland China's academic environment. The following research

questions are developed:
(1) How do the core UTAUT factors (PE, EE, SI, and FC) affect behavioral intention (BI) and use behavior (UB) of GAI in academic writing among Chinese university students?
(2) What roles do trust, moral obligation, and perceived risk play in shaping these adoption patterns?
(3) How do GAI adoption patterns differ by gender and academic level among Chinese university students?

This study contributes to both theory and practice. Theoretically, it extends UTAUT by incorporating ethical and psychological constructs and by testing the framework in a specific academic domain and culturally distinctive context. Practically, the findings can inform institutional policy and educational interventions for responsible GAI use in academic writing. They may also support the development of clearer usage guidelines and more targeted GAI literacy training.

Literature Review

Benefits of GAI in Academic Writing

The use of GAI in academic writing has received increasing attention in recent research. Existing studies generally identify two broad categories of benefits: performance-related benefits, such as improvements in writing quality and efficiency, and affective benefits, such as increased motivation and confidence.

With respect to performance-related benefits, prior research suggests that GAI may support students in several aspects of the writing process. It may help with idea development, organization, and language refinement in writing tasks (Mahapatra, 2024). It may also help reduce time spent on drafting and revision (Teng, 2024a). In addition, doctoral students in Zou and Huang (2024) reported using ChatGPT across multiple stages of writing, from pre-writing to post-writing, and viewed it as potentially supportive of the writing process.

GAI may also influence the affective dimension of writing, particularly among non-native English speakers working in competitive academic settings. Studies across Asian contexts have reported gains in motivation and confidence. For example, Indian students reported increased confidence and reduced anxiety after GAI-supported writing activities (Mahapatra, 2024), while students in Macau described GAI as a non-judgmental companion that helped sustain motivation and reduce writer's block (Teng, 2024b). Similar patterns have been reported in Mainland China, where improvements in motivation and self-efficacy following AI-assisted instruction (Song and Song, 2023). For students facing both linguistic demands and academic pressure, GAI may provide not only language support but also a degree of emotional reassurance. These findings suggest that the adoption of GAI in academic writing may be shaped by both utilitarian considerations and psychological needs.

Issues with GAI in Academic Writing

Although GAI may offer clear benefits, its use in academic writing also raises concerns that are likely to shape students' perceptions and adoption decisions.

Academic integrity remains a central issue. The possibility that GAI-generated content may facilitate plagiarism and weaken originality has been widely discussed in the literature (Rudolph

et al., 2023; Gallent Torres et al., 2023). Studies from the United States (Golding et al., 2024), Europe (Arowosegbe et al., 2024), Turkey (Bozkurt, 2024), and China (Lo, 2023) have highlighted ongoing challenges in understanding and addressing GAI-related plagiarism and originality norms. As a result, concerns about unintended violations of originality norms may discourage some students from using these tools, suggesting that moral obligation is central to how integrity-related risks are interpreted in this context (Zou and Huang, 2024).

Content reliability is another critical consideration. The phenomenon of large language models producing "hallucinations" places a verification burden on users. Nugroho et al. (2024) found that students spent considerable time checking for problems such as inappropriate word choice, grammatical errors, and non-existent references. Such reliability issues can reduce trust, which has been identified as an important predictor of GAI adoption in higher education (Lai et al., 2024). Moreover, reliability concerns are closely related to perceived risk: when students doubt the factual legitimacy and academic acceptability of GAI outputs, the likelihood of unintended errors increases, thereby weakening students' willingness to use GAI in writing tasks.

These concerns further extend to data privacy and security. While scholars call for structured governance frameworks (Chan, 2023), empirical work in Pakistan (Rana et al., 2024) and Australia (Zhou et al., 2024) suggests that fears of data misuse can negatively affect adoption intentions. More broadly, these reliability and transparency concerns are magnified in contexts with weaker infrastructure and policies, where both the risks of misuse and the verification burden tend to be higher (Prakash et al., 2025).

In addition, over-reliance becomes more likely when students face time pressure and use GAI-generated content without sufficient evaluation, potentially constraining independent judgment and critical thinking (Kim et al., 2025; Rentier, 2024; Batista et al., 2024). Qualitative evidence also indicates that some students worry about losing their authorial voice and experiencing learning loss, as well as lack of human touch in GAI feedback (Zou and Huang, 2024; Teng, 2024b).

In sum, the interplay among academic integrity (conceptualized here as moral obligation), content reliability (central to trust), and user vulnerability (linked to perceived risk) suggests that traditional technology acceptance models, primarily oriented toward utilitarian factors, may be insufficient for understanding GAI adoption in academic writing. These models do not adequately capture the ethical tensions and psychological uncertainties central to this context. Moreover, few studies have examined GAI adoption in highly competitive environments such as Mainland China, where moral obligation and other ethical constructs may exert distinct influences. Given that much of the existing work remains qualitative, quantitative validation is still needed. Therefore, a broader framework that integrates ethical and psychological elements—moral obligation, trust, and perceived risk—is necessary to better explain GAI adoption behaviors.

Theoretical Framework

The UTAUT is adopted as the theoretical framework for this study. Developed by Venkatesh et al. (2003), UTAUT synthesizes eight prior models and explains user adoption through four core constructs: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC). The model's predictive power and validity have been demonstrated

across diverse educational technology contexts, ranging from e-learning systems to contemporary AI-powered tools (Abbad, 2021; Bilquise et al., 2023; Hsu, 2023). UTAUT also accounts for individual differences such as age, gender, experience, and voluntariness of use (Abbad, 2021), enabling predictions that vary across users and contexts.

At the same time, the original UTAUT framework does not fully account for the socio-cognitive conditions surrounding GAI use in academic writing. To address this limitation, this study extends UTAUT by incorporating three additional constructs: moral obligation (MO), trust (TR), and perceived risk (PR).

MO becomes salient in a context of intense academic competition, which can create temptations to misuse GAI and conflict with pedagogical values that emphasize personal effort and integrity. MO captures this internal ethical self-regulation.

TR, defined as the willingness to be vulnerable to another party (Mayer et al., 1995), is critical in academic settings where reliance on GAI outputs may occur. However, TR in GAI may be undermined by the well-documented issue of AI hallucinations.

PR, drawing on Bauer (1960), is amplified in the Chinese context. The combination of mandatory academic assessment and a relatively sparse governance environment surrounding GAI use can generate uncertainty and potential negative consequences for adopters.

This approach of extending UTAUT with MO, TR, and PR aligns with a scholarly consensus that traditional models are insufficient for understanding GAI adoption (Budhathoki et al., 2024; Parveen et al., 2024; Rana et al., 2024). Specifically, Lai et al. (2024) integrated MO, TR, and PR into the UTAUT framework to investigate GAI use in assessments among Hong Kong university students, providing empirical evidence for the model's relevance.

Building on the model validated by Lai et al. (2024), this study applies the framework to academic writing, a context that requires sustained engagement with ideas and authorial ownership. In this context, the use of GAI may create tension between commitments to authentic authorship and the efficiency gains associated with GAI assistance. Accordingly, moral obligation, trust, and perceived risk function as relevant predictors in this setting. This study therefore contributes to the literature by adapting Lai et al.'s framework to Mainland Chinese university students at the undergraduate, master's, and doctoral levels.

Hypothesis Development

By extending the UTAUT model, this study examines the factors associated with GAI adoption in academic writing among Chinese university students. The hypotheses are developed from the core UTAUT constructs and the extended socio-cognitive factors of moral obligation (MO), trust (TR), and perceived risk (PR).

Performance Expectancy (PE)

PE is defined as "the degree to which individuals believe that using a system will help them attain gains in job performance or enhance their performance in learning processes" (Venkatesh et al., 2003). Recent studies indicate that the perceived usefulness of GAI positively predicts adoption intention (Lai et al., 2024; Strzelecki, 2024). In this study, PE centers on the perceived advantages

of GAI in improving writing quality, boosting research productivity, and facilitating overall writing outcomes. Therefore:

H1: PE positively influences students' behavioral intention (BI) to use GAI in academic writing.

Effort Expectancy (EE)

EE refers to "the degree of ease or effort associated with the use of technology" (Venkatesh et al., 2003). Although many studies report a positive association between EE and GAI adoption in academic contexts (Parveen et al., 2024), the empirical evidence remains mixed (Strzelecki and ElArabawy, 2024). In this study, EE refers to the perceived ease of learning, using, and mastering GAI tools for academic writing tasks. Therefore:

H2: EE positively influences students' BI to use GAI in academic writing.

Social Influence (SI)

SI refers to the degree "to which an individual perceives that important others believe he or she should use the new system" (Venkatesh et al., 2003). In educational settings, SI and peer recognition have been identified as important predictors of technology adoption (Strzelecki and ElArabawy, 2024; Rana et al., 2024). In this study, SI refers to the influence of teachers, peers, and academic institutions on students' decisions to use GAI. Therefore:

H3: SI positively influences students' BI to use GAI in academic writing.

Facilitating Conditions (FC)

FC is defined as "the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system" (Venkatesh et al., 2003). Prior research has shown that technical and institutional support is associated with technology adoption (Abbad, 2021). In this study, FC refers to students' perceived access to resources, relevant knowledge, technical compatibility, and support for using GAI in academic writing. Therefore:

H4: FC positively influences students' use behavior (UB) of GAI in academic writing.

Behavioral Intention (BI)

BI refers to "a user's plan to incorporate a new technology into their daily activities" (Venkatesh et al., 2003). In technology acceptance research, BI is commonly treated as a direct predictor of actual use behavior, reflecting the intention–action link in technology adoption. Therefore:

H5: BI positively influences students' UB of GAI in academic writing.

Moral Obligation (MO)

MO is defined as "the feeling of guilt or the personal obligation to perform or not perform an act" (Beck and Ajzen, 1991). Following Lai et al. (2024), MO refers to students' ethical concerns about the use of GAI in academic writing, including perceptions of moral impropriety, guilt, and the need for transparent disclosure. In the Chinese academic context, where academic integrity is strongly emphasized (Hu and Lei, 2015), students with higher MO may be more reluctant to adopt GAI. Therefore:

H6: MO negatively influences students' BI to use GAI in academic writing.

Trust (TR)

TR refers to "the trustworthiness (i.e., integrity, ability, and benevolence) and reliability of the technology" (Alalwan et al., 2017). Recent research has identified TR as an important predictor of technology acceptance among university students (Lai et al., 2024; Albayati, 2024; Jo, 2023; Rahman et al., 2023). In this study, TR refers to students' confidence in GAI with respect to the reliability and quality of its outputs, the transparency of its provider, and its capacity to perform writing-related tasks appropriately. Therefore:

H7: TR positively influences students' BI to use GAI in academic writing.

In addition, TR has been theorized to reduce PR in technology adoption contexts (Mou et al., 2017; Pavlou, 2003). Therefore:

H8: TR negatively influences students' PR of using GAI in academic writing.

Perceived Risk (PR)

PR refers to "the potential for loss in the pursuit of a desired outcome" (Featherman and Pavlou, 2003). Empirical evidence demonstrates that privacy risks associated with GAI technologies can substantially impact users' BI. In academic contexts, students may hesitate to use GAI due to concerns about data misuse, unauthorized access to their work, or potential academic integrity violations (Albayati, 2024; Cheng and Jiang, 2020; Ikkatai et al., 2022; Rahman et al., 2023). These concerns become particularly salient when students submit sensitive academic materials or personal information to GAI platforms. Such concerns may become more relevant when students submit sensitive academic materials or personal information to GAI platforms. Therefore:

H9: PR negatively influences students' BI to use GAI in academic writing.

Mediating Role of PR

TR has been shown to reduce PR, which in turn facilitates technology adoption (Cheung and Lai, 2022; Pavlou, 2003). In the context of GAI use for academic writing, higher TR in GAI systems may lower perceived risks such as privacy breaches, data security concerns, or potential academic integrity violations, thereby increasing students' BI. However, empirical findings are context-dependent. Lai et al. (2024) reported that, although TR directly influenced adoption intentions for ChatGPT, PR did not mediate that relationship in Hong Kong. Given the distinct characteristics of Mainland China's higher education context, further investigation is warranted. Therefore:

H10: PR mediates the relationship between TR and BI to use GAI in academic writing.

Control Variables

Following prior research (Venkatesh et al., 2003; Strzelecki, 2024), gender and academic level were included as control variables in the structural model.

Figure 1 presents the conceptual framework in which the core UTAUT constructs (PE, EE, SI, and FC) and the extended factors (MO, TR, and PR) are linked, with PR hypothesized to mediate the relationship between TR and BI.

[Insert Fig. 1 here]

Methodology

Participants and Data Collection

This study was conducted at a Chinese "Double First-Class" university with a strong engineering profile. The institution enrolls more than 40,000 students, including about 25,000 undergraduates and 15,000 graduate students, making it a suitable setting for examining GAI adoption among students in an engineering-oriented, research-intensive university in China.

To reflect the university's disciplinary composition, we used a stratified sampling approach based on academic discipline (Figure 2). The strata followed the university's official enrollment distribution: approximately 80% engineering, 11% management, 4% humanities, and 5% other fields, including sciences and arts. Within each stratum, students were randomly selected from student lists provided by faculty administrative offices.

Data were collected between December 2024 and January 2025 through Wenjuanxing, a widely used online survey platform in China. With support from faculty offices, the survey link was distributed to selected students through class group chats. Participation was voluntary, and no financial or material incentives were provided.

A total of 523 questionnaires were returned. After data screening, 486 valid responses were retained for analysis, yielding a valid response rate of 92.9%. Responses were excluded if they were incomplete or failed data-quality checks, such as attention-check items or excessively short completion times. The sample size was adequate according to the guidelines for PLS-SEM (Hair et al., 2022).

[Insert Fig. 2 here]

The demographic characteristics of the final sample are presented in Table 1. To evaluate whether the stratified sample reflected the disciplinary composition of the target population at the university, we conducted a chi-square goodness-of-fit test comparing the sample distribution with the population distribution. The test showed no significant difference between the two distributions ($\chi^2(3) = 0.547$, $p = 0.908$), indicating that the sample adequately reflected the population across academic disciplines.

To assess potential non-response bias, we compared early respondents ($N = 43$) and late respondents ($N = 59$), following the common practice of treating late respondents as a proxy for non-respondents (Armstrong and Overton, 1977). Independent samples *t*-tests showed no significant differences between the two groups across all main constructs (all $p > 0.05$). These results suggest that non-response bias is unlikely to be a major concern in this study (Table 2).

Table 1. Demographic characteristics of respondents ($N = 486$)

Demographic characteristics	Categories	N	Percentage
Gender	Male	327	67.28%
	Female	159	32.72%
Age	18-22	151	31.1%
	23-25	167	34.4%
	26-29	99	20.4%
	≥30	69	14.2%
Academic level	Undergraduate	106	21.81%
	Master	193	39.71%
	Doctoral	187	38.48%

Discipline	Engineering	389	80.04%
	Management	55	11.32%
	Humanities	20	4.12%
	Others	22	4.52%

Table 2. Non-response bias assessment

Construct	Group	N	M	SD	*t* value	*p* value
PE	Early	43	2.740	0.920	-1.366	0.175
	Late	59	3.020	1.090		
EE	Early	43	2.910	0.970	-0.012	0.990
	Late	59	2.920	1.010		
SI	Early	43	2.900	1.060	-0.595	0.553
	Late	59	3.030	1.090		
FC	Early	43	2.950	0.930	0.108	0.914
	Late	59	2.930	1.020		
BI	Early	43	3.010	0.950	-0.894	0.373
	Late	59	3.170	0.820		
UB	Early	43	2.850	1.020	0.333	0.740
	Late	59	2.790	0.980		
MO	Early	43	2.890	0.890	0.021	0.983
	Late	59	2.890	0.940		
TR	Early	43	2.630	1.010	-0.553	0.581
	Late	59	2.740	0.880		
PR	Early	43	2.550	0.960	-1.849	0.067
	Late	59	2.900	0.940		

Ethical Considerations

This study followed established ethical principles for research involving human participants. The research protocol, including the survey instrument and informed-consent procedures, was reviewed and formally approved by the Institutional Review Board of the School of Foreign Studies at China University of Mining and Technology. Before starting the survey, participants were shown an electronic informed-consent form describing the study purpose, the voluntary nature of participation, confidentiality protections, and the right to withdraw at any time without penalty. Participants could proceed to the questionnaire only after providing consent. To protect anonymity, no personally identifying information was collected.

Instruments

We developed a questionnaire to test the proposed hypotheses and examine the use of GAI tools (e.g., ChatGPT, Doubao, and Kimi) in academic writing among Chinese university students. The instrument consisted of two sections: (1) demographic information, including gender, age, academic level, and discipline, and (2) measures of the nine constructs in the research model.

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Following common practice in technology acceptance research, all constructs were modeled as reflective.

The measurement items were adapted from validated scales reported in Lai et al. (2024) and Abbad (2021). The final instrument contained 36 items, with four items for each construct: Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Behavioral Intention (BI), Use Behavior (UB), Moral Obligation (MO), Trust (TR), and Perceived Risk (PR). The full list of items and their sources is presented in Table 3. Items MO1, MO2, and MO3 were reverse-coded before analysis. Therefore, a higher MO score indicates a stronger sense of moral obligation, consistent with the conceptual definition of the construct and Hypothesis 6.

Table 3. Measurement items and sources

Construct	Code	Item	Source
Performance Expectancy	PE1	I find GAI useful in my academic writing.	Adapted from Lai et al. (2024) and Venkatesh et al. (2012)
	PE2	Using GAI helps me accomplish academic writing more quickly.	
	PE3	Using GAI increases my academic writing productivity.	
	PE4	Using GAI increases my chances to improve my academic writing quality.	
Effort expectancy	EE1	Learning how to use GAI is easy for me.	Adapted from Lai et al. (2024) and Venkatesh et al. (2012)
	EE2	I find GAI easy to use in academic writing.	
	EE3	I find it easy to become skillful at using GAI in academic writing.	
	EE4	My interaction with GAI is clear and understandable.	
Social Influence	SI1	People who are important to me think that I should use GAI in academic writing.	Adapted from Lai et al. (2024) and Venkatesh et al. (2012)
	SI2	People who influence my writing think that I should use GAI in academic writing.	
	SI3	My peers think I should use GAI in academic writing.	
	SI4	My academic advisors recommend that I use GAI in academic writing.	
Facilitating Conditions	FC1	I have the resources necessary to use GAI.	Adapted from Abbad (2021) and Venkatesh et al. (2012)
	FC2	I have the knowledge necessary for GAI use.	
	FC3	GAI is compatible with other academic writing tools I use.	
	FC4	A specific person (or group) is available for assistance with GAI difficulties.	
Behavioral Intention	BI1	I intend to use GAI in my future academic writing.	Adapted from Lai et al. (2024) and Venkatesh et al. (2012)
	BI2	I predict I will use GAI in my future academic writing.	
	BI3	I plan to use GAI frequently in my future academic writing.	
	BI4	I will recommend using GAI for academic writing to my colleagues.	Adapted from Abbad (2021)
Use Behavior	UB1	I consider myself a regular user of GAI for academic writing.	Adapted from Abbad (2021)
	UB2	I prefer using GAI for academic writing whenever available.	

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	UB3	I use GAI to assist with most of my academic writing tasks.	
	UB4	I tend to use GAI for academic writing whenever possible.	
Moral Obligation	MO1	It would not be morally wrong for me to use GAI for academic writing.	Adapted from Lai et al. (2024)
	MO2	I would not feel guilty using GAI content in my academic writing.	
	MO3	Using GAI for academic writing does not conflict with my moral principles.	
	MO4	Not disclosing GAI use in academic writing is morally wrong.	
Trust	TR1	I believe GAI is trustworthy for completing my academic writing tasks.	Adapted from Lai et al. (2024)
	TR2	I trust the quality of GAI's academic writing outputs.	
	TR3	I am confident that the technology provider of GAI is honest.	
	TR4	Even if not monitored, I would trust high-quality academic writing could be done right with the GAI function.	
Perceived Risk	PR1	I might be accused of academic dishonesty if I use GAI for my academic writing.	Adapted from Lai et al. (2024)
	PR2	I would probably be detected for plagiarism if I use GAI for my academic writing.	
	PR3	I might be disappointed if I use GAI for academic writing.	
	PR4	I think using GAI for academic writing puts my privacy at risk.	

A multi-stage procedure was used to support the validity of the instrument. First, to strengthen content validity and linguistic equivalence, the initial item pool was reviewed by three experts in digital learning and higher education, and the wording was refined accordingly. A standard back-translation procedure was then applied to ensure equivalence between the Chinese and English versions.

Second, a two-stage pilot study was conducted. The questionnaire was first administered to 30 students to assess readability and completion experience, and minor wording revisions were made accordingly. A larger pilot study (N = 114) was then conducted to examine the instrument's factor structure (Johanson & Brooks, 2010). The results showed that the data were suitable for factor analysis (KMO = 0.67; Bartlett's test of sphericity, $p < 0.001$). Using principal component extraction with varimax rotation, nine factors were identified, accounting for 71.89% of the total variance. All items loaded on their intended constructs, with loadings above recommended thresholds. Detailed EFA results, including the total variance explained and the rotated component matrix, are reported in Tables 4 and 5.

Table 4. Explained variance ratio

	Initial eigenvalue			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	5.821	16.169	16.169	5.821	16.169	16.169	3.085	8.57	8.57
2	3.907	10.853	27.022	3.907	10.853	27.022	3.055	8.487	17.057
3	3.044	8.455	35.477	3.044	8.455	35.477	2.999	8.329	25.386

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4	2.898	8.051	43.528	2.898	8.051	43.528	2.909	8.081	33.467
5	2.493	6.925	50.453	2.493	6.925	50.453	2.899	8.052	41.519
6	2.382	6.615	57.068	2.382	6.615	57.068	2.843	7.898	49.417
7	1.931	5.363	62.431	1.931	5.363	62.431	2.794	7.761	57.178
8	1.862	5.174	67.604	1.862	5.174	67.604	2.776	7.712	64.89
9	1.544	4.289	71.893	1.544	4.289	71.893	2.521	7.003	71.893

Table 5. Coefficient after rotation

	component								
	1	2	3	4	5	6	7	8	9
PE1				0.9					
PE2				0.756					
PE3				0.785					
PE4				0.779					
EE1					0.868				
EE2					0.843				
EE3					0.754				
EE4					0.721				
SI1									0.896
SI2									0.741
SI3									0.732
SI4									0.64
FC1								0.901	
FC2								0.773	
FC3								0.778	
FC4								0.771	
BI1	0.861								
BI2	0.771								
BI3	0.822								
BI4	0.842								
UB1							0.899		
UB2							0.784		
UB3							0.734		
UB4							0.808		
MO1						0.873			
MO2						0.79			
MO3						0.796			
MO4						0.782			
TR1			0.862						
TR2			0.707						
TR3			0.863						

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TR4		0.827
PR1	0.924	
PR2	0.834	
PR3	0.802	
PR4	0.802	

Data Analysis

Data were analyzed using partial least squares structural equation modeling (PLS-SEM) in SmartPLS 4. We adopted a two-stage approach recommended for PLS-SEM, assessing the measurement model and the structural model (Hair et al., 2019, 2022).

First, the measurement model was assessed. Internal consistency reliability was evaluated using Cronbach's alpha and composite reliability (CR > .70). Convergent validity was assessed using indicator loadings (> .70) and average variance extracted (AVE > .50). Discriminant validity was examined using the heterotrait-monotrait (HTMT) ratio, the Fornell–Larcker criterion, and cross-loadings (Fornell and Larcker, 1981; Henseler et al., 2015). Indicator collinearity was also checked using outer variance inflation factor (VIF) values. Potential common method bias was assessed using Harman's single-factor test and a common method factor (CMF) approach (Kock, 2015; Podsakoff et al., 2003, 2012).

Second, the structural model was evaluated. Collinearity among predictors was assessed using inner VIF values. Model fit was examined using the standardized root mean square residual (SRMR) and the normed fit index (NFI). Explanatory power was evaluated using R^2 and adjusted R^2, and predictive relevance was assessed using the Stone–Geisser Q^2 statistic obtained through blindfolding; out-of-sample predictive performance was further examined using the PLSpredict procedure (Shmueli et al., 2019). The proposed direct effects were tested using bootstrapping with 5,000 resamples (Hair et al., 2019). The indirect effect of TR on BI through PR was also examined using bootstrapping with bias-corrected 95% confidence intervals.

Finally, multigroup analysis was conducted by gender and academic level after measurement invariance was assessed using the MICOM procedure (Henseler et al., 2015).

Results

Descriptive Statistics

Descriptive statistics were calculated for all constructs. As shown in Table 6, mean scores ranged from 2.74 for TR to 3.03 for BI, and standard deviations ranged from 0.911 to 1.011. These results indicate that the construct means were generally close to the midpoint of the scale.

Table 6. Descriptive statistics ($N = 486$)

	N	Min	Max	Mean	SD
PE	486	1	4.75	2.92	0.960
EE	486	1	5	2.81	0.964
SI	486	1	5	2.97	0.964
FC	486	1	5	3.01	1.011
BI	486	1	5	3.03	0.918

UB	486	1	5	2.82	0.982
MO	486	1	5	2.97	0.970
TR	486	1	5	2.74	0.911
PR	486	1	5	2.77	0.955

Notes: SD = Standard Deviation.

Common Method Bias (CMB) Assessment

To assess potential common method bias, two procedures were applied (Kock, 2015; Podsakoff et al., 2003, 2012). First, Harman's single-factor test was conducted using an unrotated exploratory factor analysis in which all indicators were constrained to load on a single factor. As shown in Table 7, the first factor accounted for 18.4% of the total variance, which is below the 50% threshold commonly used to indicate serious common method bias (Podsakoff et al., 2003).

Second, a common method factor (CMF) approach was used by estimating models with and without a latent CMF. The CMF was specified to load on all 36 indicators, and the CMF-inclusive model is shown in Figure 3. Comparison of the two models showed only negligible differences in model fit (ΔSRMR < 0.01) and path coefficients ($|\Delta\beta| < 0.01$; Table 8). Overall, these results indicate that common method bias was unlikely to materially influence the findings.

Table 7. Harman's single-factor test results

	Initial eigenvalue			Extraction Sums of Squared Loading		
	Total	% of variance	Cumulative %	Total	% of variance	Cumulative %
1	6.624	18.4	18.4	6.624	18.4	18.4

Table 8. Common method factor analysis: Path Coefficients

Hypothesis	Path	Coefficient (β)	*p* value	f^2 value	Results
H1	PE→BI	0.200	0.000	0.057	consistent
H2	EE→BI	0.007	0.833	0.000	consistent
H3	SI→BI	0.200	0.000	0.060	consistent
H4	FC→UB	0.384	0.000	0.180	consistent
H5	BI→UB	0.197	0.000	0.047	consistent
H6	MO→BI	-0.175	0.000	0.044	consistent
H7	TR→BI	0.303	0.000	0.146	consistent
H8	TR→PR	-0.068	0.128	0.005	consistent
H9	PR→BI	-0.200	0.000	0.060	consistent

[Insert Fig. 3 here]

Measurement Model Assessment

Reliability and Convergent Validity

Internal consistency reliability was assessed using Cronbach's alpha and composite reliability (CR). As shown in Table 9, Cronbach's alpha ranged from 0.841 to 0.877, and CR ranged from 0.894 to 0.914, exceeding the recommended threshold of 0.70 (Nunnally and Bernstein, 1994).

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Convergent validity was assessed using indicator loadings and average variance extracted (AVE). All indicator loadings were significant and ranged from 0.722 to 0.939, exceeding the recommended threshold of 0.70. AVE values ranged from 0.680 to 0.726, exceeding the 0.50 criterion (Fornell and Larcker, 1981). Outer variance inflation factor (VIF) values ranged from 1.766 to 4.011 (Table 9), indicating no evidence of problematic indicator collinearity.

Table 9. Reliability and convergent validity assessment

Construct	Item	Factor loading	Cronbach's alpha	Composite Reliability	AVE	VIF
Performance Expectancy	PE1	0.912	0.858	0.904	0.704	3.334
	PE2	0.812				1.900
	PE3	0.831				2.023
	PE4	0.795				1.892
Effort Expectancy	EE1	0.894	0.877	0.896	0.685	3.495
	EE2	0.722				2.208
	EE3	0.740				2.116
	EE4	0.934				1.965
Social Influence	SI1	0.904	0.872	0.912	0.723	3.178
	SI2	0.839				2.081
	SI3	0.847				2.050
	SI4	0.808				1.942
Facilitating Conditions	FC1	0.920	0.873	0.914	0.726	3.663
	FC2	0.830				2.186
	FC3	0.814				1.998
	FC4	0.840				2.067
Behavioral Intention	BI1	0.915	0.844	0.896	0.684	3.190
	BI2	0.798				1.777
	BI3	0.789				1.850
	BI4	0.799				1.868
Use Behavior	UB1	0.938	0.856	0.903	0.701	4.011
	UB2	0.782				1.919
	UB3	0.828				2.127
	UB4	0.793				1.924
Moral Obligation	MO1	0.920	0.862	0.907	0.709	3.527
	MO2	0.818				2.045
	MO3	0.787				1.940
	MO4	0.836				1.949
Trust	TR1	0.925	0.841	0.894	0.680	3.184
	TR2	0.791				1.846
	TR3	0.785				1.766
	TR4	0.790				1.824
Perceived Risk	PR1	0.939	0.850	0.899	0.692	3.969

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	PR2	0.818	2.085
	PR3	0.766	1.778
	PR4	0.794	2.007

Notes: CR = Composite Reliability; AVE = Average Variance Extracted; VIF = Variance Inflation Factor.

Discriminant Validity

Discriminant validity was assessed using the heterotrait-monotrait (HTMT) ratio, the Fornell–Larcker criterion, and cross-loadings. As shown in Table 10, all HTMT values were below the conservative threshold of 0.85, with the highest value observed for FC and UB (0.494). The Fornell–Larcker criterion was also satisfied (Table 11), as the square root of the AVE for each construct exceeded its correlations with the other constructs. The cross-loadings likewise supported discriminant validity, as each indicator loaded most strongly on its intended construct (Table 12).

Table 10. Discriminant validity - HTMT results

	BI	EE	FC	MO	PE	PR	SI	TR	UB
BI									
EE	0.065								
FC	0.251	0.049							
MO	0.422	0.032	0.062						
PE	0.447	0.112	0.044	0.319					
PR	0.394	0.055	0.067	0.272	0.221				
SI	0.402	0.073	0.072	0.232	0.273	0.209			
TR	0.462	0.037	0.072	0.168	0.182	0.086	0.100		
UB	0.330	0.088	0.494	0.058	0.057	0.045	0.183	0.115	

Notes: BI = Behavioral Intention; EE = Effort Expectancy; FC = Facilitating Conditions; MO = Moral Obligation; PE = Performance Expectancy; PR = Perceived Risk; SI = Social Influence; TR = Trust; UB = Use Behavior.

Table 11. Discriminant validity: Fornell-Larcker criterion

	BI	EE	FC	MO	PE	PR	SI	TR	UB
BI	**0.827**								
EE	0.079	**0.828**							
FC	0.216	-0.007	**0.852**						
MO	-0.361	-0.006	-0.047	**0.842**					
PE	0.381	0.098	0.040	-0.275	**0.839**				
PR	-0.336	-0.050	-0.026	0.232	-0.190	**0.832**			
SI	0.347	0.054	0.058	-0.202	0.238	-0.179	**0.850**		
TR	0.391	0.016	0.061	-0.145	0.157	-0.070	0.086	**0.825**	
UB	0.280	-0.080	0.429	-0.016	0.035	0.010	0.157	0.096	**0.838**

Notes: Bold values on the diagonal are the square root of the AVE.

Table 12. Discriminant validity: cross-loadings

	BI	EE	FC	MO	PE	PR	SI	TR	UB
BI1	**0.915**	0.062	0.182	-0.317	0.360	-0.311	0.326	0.334	0.204
BI2	**0.798**	0.039	0.219	-0.272	0.296	-0.237	0.297	0.307	0.280
BI3	**0.789**	0.065	0.144	-0.284	0.292	-0.276	0.274	0.318	0.209
BI4	**0.799**	0.096	0.168	-0.320	0.310	-0.284	0.249	0.333	0.235
EE1	0.057	**0.894**	-0.015	-0.006	0.065	-0.027	0.063	0.033	-0.123
EE2	0.010	**0.722**	0.051	-0.016	0.079	-0.052	0.069	0.016	-0.058
EE3	0.021	**0.740**	0.007	0.013	0.087	-0.018	0.044	-0.017	-0.030
EE4	0.096	**0.934**	-0.010	-0.007	0.101	-0.059	0.037	0.010	-0.050
FC1	0.161	-0.021	**0.920**	0.002	0.028	-0.055	0.060	0.033	0.349
FC2	0.163	-0.027	**0.830**	-0.034	0.016	-0.024	0.024	0.062	0.350
FC3	0.224	0.041	**0.814**	-0.048	0.033	-0.053	0.034	0.049	0.372
FC4	0.185	-0.018	**0.840**	-0.076	0.056	0.038	0.078	0.063	0.387
MO1	-0.312	-0.013	-0.046	**0.920**	-0.224	0.229	-0.148	-0.107	0.002
MO2	-0.295	-0.042	-0.024	**0.818**	-0.260	0.193	-0.146	-0.167	0.025
MO3	-0.268	0.004	-0.001	**0.787**	-0.206	0.167	-0.192	-0.083	0.015
MO4	-0.336	0.028	-0.077	**0.836**	-0.235	0.189	-0.194	-0.127	-0.083
PE1	0.307	0.109	0.010	-0.203	**0.912**	-0.125	0.207	0.133	0.038
PE2	0.314	0.053	0.046	-0.196	**0.812**	-0.149	0.165	0.110	0.001
PE3	0.340	0.102	0.054	-0.249	**0.831**	-0.157	0.210	0.156	0.052
PE4	0.314	0.063	0.021	-0.271	**0.795**	-0.205	0.213	0.124	0.026
PR1	-0.322	-0.057	-0.025	0.226	-0.186	**0.939**	-0.167	-0.08	0.015
PR2	-0.288	-0.011	0.018	0.157	-0.186	**0.818**	-0.133	-0.061	0.004
PR3	-0.244	-0.081	-0.022	0.220	-0.153	**0.766**	-0.156	0.009	0.049
PR4	-0.256	-0.022	-0.063	0.173	-0.102	**0.794**	-0.144	-0.09	-0.031
SI1	0.271	0.060	0.054	-0.121	0.180	-0.167	**0.904**	0.059	0.157
SI2	0.303	0.042	0.064	-0.213	0.243	-0.154	**0.839**	0.053	0.112
SI3	0.327	0.071	0.055	-0.168	0.194	-0.155	**0.847**	0.079	0.142
SI4	0.270	0.004	0.021	-0.179	0.187	-0.133	**0.808**	0.103	0.121
TR1	0.384	0.011	0.108	-0.138	0.159	-0.076	0.095	**0.925**	0.107
TR2	0.304	0.049	0.033	-0.139	0.084	-0.024	0.081	**0.791**	0.070
TR3	0.300	-0.003	0.043	-0.073	0.128	-0.035	0.069	**0.785**	0.071
TR4	0.292	-0.002	0.003	-0.125	0.140	-0.093	0.036	**0.79**	0.062
UB1	0.258	-0.075	0.409	-0.013	0.021	-0.007	0.129	0.097	**0.938**
UB2	0.216	-0.063	0.311	-0.007	-0.018	-0.015	0.111	0.107	**0.780**
UB3	0.257	-0.073	0.366	-0.054	0.065	0.040	0.110	0.083	**0.829**
UB4	0.204	-0.055	0.345	0.026	0.046	0.015	0.179	0.034	**0.794**

Structural Model Assessment

The coefficient of determination (R^2) indicates the proportion of variance explained in endogenous constructs. As shown in Table 13, the model explained 39.6% of the variance in BI (R^2 = 0.396; adjusted R^2 =0.389) and 22.4% of the variance in UB (R^2 = 0.224; adjusted R^2 = 0.218). By contrast, the variance explained in PR was very low (R^2 = 0.005; adjusted R^2 = 0.003).

Model fit was assessed using the standardized root mean square residual (SRMR) and the normed fit index (NFI). The SRMR was 0.063, and the NFI was 0.844 (Table 14).

Table 13. Coefficient of Determination

Item	R^2	Adjusted R^2
BI	0.396	0.389
PR	0.005	0.003
UB	0.224	0.218

Note: R^2 = Coefficient of Determination

Table 14. Model fit indices

Index	Value
SRMR	0.063
NFI	0.844

Predictive relevance was assessed using blindfolding and PLSpredict. As shown in Table 15, the Stone–Geisser Q^2 values were positive for BI (Q^2 = 0.264), UB (Q^2 = 0.152), and PR (Q^2 = 0.003). The Q^2predict values were also positive for BI (0.343) and UB (0.184), whereas PR showed a value of 0.000, which is consistent with its low R^2.

Table 15. Predictive relevance

Construct	Q^2	Q^2predict
BI	0.264	0.343
PR	0.003	0.000
UB	0.152	0.184

Notes: Q^2 = Stone-Geisser's predictive relevance; Q^2predict = PLSpredict out-of-sample predictive power.

Multicollinearity was assessed using inner variance inflation factor (VIF) values. As shown in Table 16, the VIF values ranged from 1.000 to 1.161, indicating that multicollinearity was not a concern (Kock, 2015; Hair et al., 2019).

Table 16. Variance inflation factors

Path	VIF
BI → UB	1.049
EE → BI	1.013
FC → UB	1.049
MO → BI	1.152
PE → BI	1.161
PR → BI	1.093

SI → BI	1.100
TR → BI	1.039
TR → PR	1.000

Hypothesis Testing

The hypotheses were tested using bootstrapping with 5,000 resamples (Hair et al., 2019). Table 17 and Figure 4 report the path coefficients, significance levels, and effect sizes. Seven of the nine hypothesized relationships were supported.

For BI, five of the six predictors were significant. TR was the strongest predictor of BI (H7: $\beta = 0.303$, $p < .001$, $f^2 = 0.146$), followed by SI (H3: $\beta = 0.201$, $p < .001$, $f^2 = 0.061$) and PE (H1: $\beta = 0.197$, $p < .001$, $f^2 = 0.055$). PR (H9: $\beta = -0.198$, $p < .001$, $f^2 = 0.060$) and MO (H6: $\beta = -0.177$, $p < .001$, $f^2 = 0.045$) were negatively associated with BI. EE was not significant (H2: $\beta = 0.033$, $p = .555$, $f^2 = 0.002$).

For UB, both hypothesized predictors were significant. FC showed the largest effect on UB (H4: $\beta = 0.387$, $p < .001$, $f^2 = 0.184$), and BI also positively predicted UB (H5: $\beta = 0.198$, $p < .001$, $f^2 = 0.048$). The control variables were not significant (gender: $\beta = 0.012$, $p = .730$; academic level: $\beta = -0.025$, $p = .498$). The hypothesized negative effect of TR on PR was not supported (H8: $\beta = -0.070$, $p = .123$, $f^2 = 0.005$).

Table 17. Hypothesis testing results

Hypothesis	Path	Coefficient (β)	*t* value	*p* value	2.5% CI	97.5% CI	f^2	Results
H1	PE→BI	0.197	5.593	0.000	0.128	0.264	0.055	Supported
H2	EE→BI	0.033	0.591	0.555	-0.152	0.093	0.002	Not supported
H3	SI→BI	0.201	5.945	0.000	0.134	0.266	0.061	Supported
H4	FC→UB	0.387	11.174	0.000	0.314	0.45	0.184	Supported
H5	BI→UB	0.198	5.166	0.000	0.118	0.269	0.048	Supported
H6	MO→BI	-0.177	4.826	0.000	-0.248	-0.105	0.045	Supported
H7	TR→BI	0.303	9.208	0.000	0.236	0.364	0.146	Supported
H8	TR→PR	-0.070	1.542	0.123	-0.152	0.026	0.005	Not supported
H9	PR→BI	-0.198	5.183	0.000	-0.271	-0.120	0.060	Supported

Notes: β = Standardized Path Coefficient; CI = Confidence Interval; f^2 = Cohen's effect size.

[Insert Fig. 4 here]

Mediation Analysis

H10 was tested using bootstrapping with 5,000 resamples. As shown in Table 18, the indirect effect of TR on BI through PR was not significant ($\beta = 0.014$, $t = 1.443$, $p = 0.149$). The total effect of TR on BI was significant ($\beta = 0.317$, $p < .001$) and was largely attributable to the direct effect ($\beta = 0.303$, $p < .001$). Therefore, H10 was not supported.

Table 18. Mediation analysis results

Hypothesis	Path	Effect	Coefficient(β)	SE	*t*-value	*p*-value
	TR→PR→BI	Direct	0.303	0.033	9.208	0.000

Hypothesis	Path	Effect	Coefficient(β)	SE	*t*-value	*p*-value
H10		Indirect	0.014	0.010	1.443	0.149
		Total	0.317	0.032	9.798	0.000

Notes: β = Standardised Path Coefficient; SE = Standard Error.

Multigroup Analysis (MGA)

To examine whether the structural relationships differed across subgroups, multigroup analysis was conducted for gender and academic-level following Henseler et al. (2015). For academic-level comparisons, the MICOM procedure established at least partial measurement invariance for all constructs, allowing valid comparisons of path coefficients (Tables 20–22). For gender, partial measurement invariance was established for all constructs except SI (Table 19). Therefore, male–female comparisons were conducted only for the paths that could be validly compared, and SI→BI was excluded.

Table 19. Measurement invariance assessment: gender groups

Construct	Step2			Step3a-Equal Mean		Step3b-Equal Variance		Result
	Correlation	5.00%	Result	Difference	97.5% CI	Difference	97.5%CI	
BI	0.999	0.998	√	0.227	[-0.182, 0.180]	-0.054	[-0.190, 0.202]	Partial
EE	0.968	0.128	√	-0.156	[-0.199, 0.188]	-0.008	[-0.188, 0.201]	Complete
FC	0.998	0.997	√	-0.102	[-0.187, 0.205]	0.081	[-0.196, 0.196]	Complete
MO	0.999	0.994	√	-0.185	[-0.176, 0.191]	0.059	[-0.169, 0.209]	Partial
PE	0.999	0.995	√	0.176	[-0.186, 0.192]	0.066	[-0.174, 0.182]	Complete
PR	0.996	0.989	√	-0.958	[-0.201, 0.186]	-0.119	[-0.203, 0.197]	Partial
SI	0.991	0.995	×	-	-	-	-	-
TR	0.999	0.994	√	0.141	[-0.188, 0.19]	0.111	[-0.201, 0.218]	Complete
UB	0.998	0.996	√	-0.189	[-0.187, 0.215]	-0.024	[-0.166, 0.191]	Complete

Table 20. Measurement invariance assessment: undergraduate vs. master's

Construct	Step2			Step3a-Equal Mean		Step3b-Equal Variance		Result
	Correlation	5.00%	Result	Difference	97.5%CI	Difference	97.5%CI	
BI	1	0.997	√	-0.186	[-0.234,0.227]	-0.086	[-0.254,0.225]	Complete
EE	0.916	0.248	√	-0.033	[-0.233,0.262]	-0.032	[-0.26,0.243]	Complete
FC	1	0.996	√	0.058	[-0.237,0.245]	-0.041	[-0.254,0.243]	Complete
MO	0.995	0.988	√	0.208	[-0.237,0.228]	0.034	[-0.223,0.216]	Complete
PE	0.994	0.991	√	-0.647	[-0.233,0.243]	-0.154	[-0.234,0.222]	Partial
PR	0.998	0.984	√	0.098	[-0.253,0.233]	0.033	[-0.251,0.248]	Complete
SI	0.997	0.989	√	-0.267	[-0.252,0.257]	-0.258	[-0.242,0.226]	Partial
TR	0.998	0.992	√	-0.207	[-0.245,0.228]	-0.15	[-0.275,0.27]	Complete
UB	0.999	0.995	√	0.124	[-0.234,0.246]	-0.133	[-0.251,0.215]	Complete

Table 21. Measurement invariance assessment: undergraduate vs. doctoral

Construct	Step2			Step3a-Equal Mean		Step3b-Equal Variance		Result
	Correlation	5.00%	Result	Difference	97.5%CI	Difference	97.5%CI	
BI	1	0.998	√	-0.138	[-0.23,0.227]	-0.146	[-0.255,0.238]	Complete
EE	0.745	0.099	√	-0.045	[-0.224,0.244]	0.061	[-0.272,0.238]	Complete
FC	0.999	0.994	√	-0.027	[-0.237,0.215]	0.152	[-0.259,0.241]	Complete
MO	0.994	0.989	√	0.211	[-0.22,0.24]	0.146	[-0.237,0.227]	Complete
PE	1	0.99	√	-0.457	[-0.22,0.221]	-0.133	[-0.239,0.21]	Partial
PR	0.999	0.979	√	0.094	[-0.244,0.237]	0.009	[-0.256,0.232]	Complete
SI	0.997	0.988	√	-0.226	[-0.229,0.221]	-0.031	[-0.234,0.246]	Complete
TR	0.997	0.99	√	-0.155	[-0.233,0.221]	0.023	[-0.272,0.246]	Complete
UB	1	0.993	√	0.057	[-0.214,0.234]	0.026	[-0.239,0.228]	Complete

Table 22. Measurement invariance assessment: master's vs. doctoral

Construct	Step2			Step3a-Equal Mean		Step3b-Equal Variance		Result
	Correlation	5.00%	Result	Difference	97.5%CI	Difference	97.5%CI	
BI	1	0.999	√	0.046	[-0.207,0.195]	-0.055	[-0.221,0.205]	Complete
EE	0.62	0.045	√	-0.043	[-0.214,0.194]	0.141	[-0.23,0.222]	Complete
FC	0.999	0.996	√	-0.085	[-0.201,0.208]	0.194	[-0.198,0.217]	Complete
MO	0.999	0.995	√	0.005	[-0.208,0.192]	0.103	[-0.183,0.204]	Complete
PE	0.996	0.994	√	0.218	[-0.2,0.191]	0.023	[-0.222,0.196]	Partial
PR	0.999	0.991	√	0.002	[-0.205,0.198]	-0.024	[-0.211,0.215]	Complete
SI	0.999	0.996	√	0.054	[-0.201,0.207]	0.221	[-0.201,0.199]	Partial
TR	0.999	0.992	√	0.06	[-0.195,0.193]	0.167	[-0.225,0.217]	Complete
UB	0.998	0.997	√	-0.07	[-0.184,0.192]	0.151	[-0.206,0.196]	Complete

Gender. As shown in Table 23, no significant differences were found between male and female groups across the comparable hypothesized paths (all $p > .05$). Although the negative effect of MO on BI was larger for males ($\beta = -0.216$) than for females ($\beta = -0.083$), this difference was not statistically significant ($\Delta\beta = -0.133$, $p = 0.084$). These findings indicate that gender does not moderate the proposed relationships that could be validly compared.

Academic level. As shown in Table 24, only one significant difference was found across the academic-level groups. Specifically, the negative effect of MO on BI was larger for doctoral students ($\beta = -0.276$) than for undergraduates ($\beta = -0.045$), and this difference was significant ($\Delta\beta = 0.231$, $p = 0.012$). No other path differences were significant. These findings indicate broad structural stability across undergraduate, master's, and doctoral groups, although moral obligation had a larger negative effect on BI among doctoral students than among undergraduates.

Table 23. Path coefficient comparison: male vs. female

Path	Female		Male		Difference	*p* value
	Original	*p* value	Original	*p* value	(Male - Female)	

BI→UB	0.281	0.000	0.171	0.000	-0.11	0.186
EE→BI	0.018	0.827	0.033	0.632	0.015	0.865
FC→UB	0.371	0.000	0.391	0.000	0.02	0.793
MO→BI	-0.083	0.188	-0.216	0.000	-0.133	0.084
PE→BI	0.238	0.000	0.176	0.000	-0.061	0.415
PR→BI	-0.268	0.000	-0.175	0.000	0.093	0.244
TR→BI	0.279	0.000	0.315	0.000	0.035	0.647
TR→PR	-0.036	0.66	-0.055	0.338	-0.02	0.849

Table 24. Path coefficient comparison: academic-level groups

	Doctoral Original	Master Original	Undergraduate Original	Master vs Doctoral		Master vs Undergraduate		Undergraduate vs Doctoral	
				Difference	*p* value	Difference	*p* value	Difference	*p* value
BI→UB	0.205**	0.233**	0.15	0.028	0.742	0.083	0.458	-0.055	0.628
EE→BI	0.135	0.006	0.108	-0.128	0.461	-0.101	0.419	-0.027	0.771
FC→UB	0.398**	0.402**	0.349**	0.004	0.96	0.053	0.598	-0.049	0.625
MO→BI	-0.276**	-0.177**	-0.045	0.099	0.222	-0.132	0.168	0.231	0.012*
PE→BI	0.179**	0.165**	0.304**	-0.014	0.86	-0.139	0.157	0.126	0.183
PR→BI	-0.144*	-0.232**	-0.162	-0.088	0.294	-0.07	0.529	-0.018	0.852
SI→BI	0.22**	0.224**	0.116	0.003	0.968	0.108	0.258	-0.104	0.258
TR→BI	0.327**	0.265**	0.381**	-0.062	0.401	-0.116	0.206	0.053	0.554
TR→PR	-0.047	-0.064	-0.114	-0.018	0.868	0.05	0.65	-0.067	0.561

Discussion and Implications

This study extends the UTAUT model by incorporating MO, TR, and PR to explain Chinese university students' adoption of GAI for academic writing. Using data from students at the undergraduate, master's, and doctoral levels across multiple disciplines, the study adds to the the literature on technology adoption in higher education. In the context of Chinese higher education, norms related to diligence, authentic authorship, and academic integrity, together with performance pressures and sensitivity to social evaluation (mianzi), may increase attention to both moral expectations and integrity-related risks. Collectivist orientations may also increase responsiveness to prevailing social norms (Hofstede et al., 2010; Chan, 2014; Liang and Matthews, 2023). Against this background, the model captures the combined roles of performance, social, moral, trust, and risk considerations in shaping GAI adoption.

Key Contributions

First, TR and PR functioned as parallel predictors of BI. TR positively predicted BI, but the path from TR to PR was not significant. Accordingly, the indirect effect of TR on BI through PR was not supported. This pattern differs from some prior technology adoption studies (e.g., Venkatesh et al., 2012; Lee and Song, 2013) but is consistent with Lai et al. (2024), who also reported a non-significant TR–PR relationship in a similar academic context.

PR also had a direct negative effect on BI. Concerns about data privacy, output inaccuracy, plagiarism, security, and possible effects on critical thinking therefore appear to operate as independent constraints on adoption (Memarian and Doleck, 2023; Sallam et al., 2024). These findings suggest that, in this setting, TR and PR are better specified as parallel predictors of BI than as elements of a mediated pathway from TR to BI through PR.

Second, MO negatively predicted BI, and this effect was larger among doctoral students than among undergraduates. This result suggests that concerns about academic integrity, originality, and over-reliance on AI reduce willingness to adopt GAI even when students recognize its instrumental benefits. The finding is consistent with prior evidence that moral judgments can inhibit technology adoption (Lai et al., 2024). In this context, MO may reflect norms of effortful learning and authorial ownership, reinforced by institutional integrity expectations and concerns about maintaining academic standing. The larger coefficient among doctoral students is also consistent with their closer identification with norms of original contribution and research integrity.

Third, SI positively predicted BI. Recommendations or approval from peers, academic advisers, and other influential referents therefore appear to shape students' willingness to adopt GAI. This result is consistent with studies emphasizing the role of social influence and student networks in technology acceptance (Strzelecki and ElArabawy, 2024; Budhathoki et al., 2024; Rana et al., 2024), but differs from studies reporting a non-significant SI effect (Tian, 2024; Parveen et al., 2024). In this context, adoption may depend in part on whether GAI use is perceived as socially acceptable within students' immediate academic networks.

Fourth, EE did not significantly predict BI. This suggests that ease of use may be less important when students are already familiar with digital tools and when access barriers are low. Under such conditions, effort may shift from learning how to operate the tool to evaluating the quality and acceptability of its outputs.

Fifth, PE and the core UTAUT intention–use relationship were supported. PE positively predicted BI, consistent with UTAUT (Venkatesh et al., 2003) and recent studies of GAI adoption (Budhathoki et al., 2024; Rana et al., 2024). In academic writing, expected gains such as faster drafting, idea generation, and greater efficiency appear to motivate adoption. FC also positively predicted UB, indicating that infrastructure and technical support directly facilitate GAI use (Shahzad et al., 2024; Strzelecki and ElArabawy, 2024). These results suggest that adoption is shaped not only by expected benefits but also by whether students can access and use the technology within their institutional environment.

Sixth, gender did not moderate the comparable structural relationships. No significant gender differences were found across the paths that could be validly compared. This result is consistent with Romero-Rodríguez et al. (2023), although it differs from studies reporting gender-based moderation (Strzelecki and ElArabawy, 2024). One possible explanation is that shared academic pressures and broadly similar levels of digital familiarity reduce gender differentiation in the mechanisms underlying GAI adoption.

Theoretical Implications

The findings extend technology adoption theory in three respects. First, the non-significant TR–PR path, together with the minimal variance in PR explained by TR ($R^2 = 0.005$), suggests

that risk perceptions were not primarily dependent on trust in this context. Students may distinguish between judgments about a tool's reliability and judgments about its integrity-related risks. In settings where institutional expectations remain unsettled, trust and risk may therefore be more appropriately modeled as parallel predictors shaped by different antecedents, including governance arrangements, assessment practices, policy awareness, and prior experience.

Second, the non-significant effect of EE suggests that ease of use may lose explanatory value once a technology becomes widely accessible and familiar. Under such conditions, adoption decisions may depend less on interface-related effort and more on judgments about performance, output quality, and normative acceptability.

Third, FC showed a larger effect on actual use than BI, indicating that institutional infrastructure may function as a direct determinant of behavior rather than only as an enabling condition. This pattern is consistent with accounts in which institutional support complements, and in some cases partly substitutes for, intention in shaping actual use.

Practical Implications

The findings provide an empirical basis for institutions seeking to support responsible GAI use in academic writing. First, trust-building and risk management should be addressed separately. Because the TR–PR relationship was not significant, efforts to strengthen trust are unlikely to reduce perceived risk on their own. Trust-building may involve providing access to vetted tools and clarifying appropriate academic uses. Risk management requires a clearer ethical infrastructure, including disclosure and citation expectations, transparent data-protection practices, and consistent academic integrity procedures.

Second, because EE did not significantly predict adoption, training should move beyond basic tool operation. Instruction should place greater emphasis on higher-order GAI literacy, including how to evaluate generated content for accuracy, bias, and verifiability, and how to document, cite, and disclose GAI use in discipline-appropriate ways. This is particularly relevant given the negative effect of MO on BI, which indicates the need for practical guidance on acceptable and unacceptable uses. Such guidance may be especially important for doctoral students, for whom MO had a larger negative effect.

Finally, institutions should strengthen the structural conditions that support responsible use. Because FC showed the largest effect on UB, resource provision appears to be a direct mechanism shaping behavior. Institutions should therefore ensure equitable access to approved GAI platforms, integrate such tools with library and citation resources where appropriate, and provide accessible support channels to facilitate compliant use.

Conclusion, Limitations, and Future Directions

Conclusion

This study extended UTAUT by incorporating MO, TR, and PR to explain Chinese university students' adoption of GAI for academic writing. The findings indicate that adoption was shaped by multiple considerations. BI was positively predicted by PE, SI, and TR, but negatively predicted by MO and PR. The non-significant path from TR to PR, together with the non-significant indirect effect of TR on BI through PR, suggests that trust and perceived risk functioned as parallel

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predictors rather than as elements of a mediated pathway. FC showed a larger effect on actual use than BI, indicating that institutional infrastructure functioned as a direct determinant of use. EE was not significant, suggesting that ease of use may have limited explanatory value in contexts where students are already familiar with digital tools. The multigroup results further indicated broad structural stability across gender and academic-level groups, although the negative effect of MO on BI was larger for doctoral students than for undergraduates. Overall, the findings extend UTAUT to a setting in which performance expectations, social influence, moral considerations, trust, and perceived risk jointly shape GAI adoption in academic writing.

Limitations

This study has several limitations. First, the data were collected from one university, which may limit the generalizability of the findings to institutions with different student populations, resource conditions, and academic norms. Second, the cross-sectional design captured relationships at a single point in time and does not allow assessment of whether adoption patterns change as GAI technologies and institutional responses evolve. Third, the study relied on self-reported measures, including use behavior and moral obligation, which may be affected by recall error or social desirability bias. Fourth, because both the technological environment and the institutional governance of GAI are changing rapidly, the relative importance of the determinants identified here may also shift over time.

Future Directions

Future research can build on these limitations in several ways. Longitudinal designs would help examine whether the roles of trust, perceived risk, and moral obligation change as students gain more experience with GAI and as institutional expectations become more clearly defined. Studies using behavioral indicators, such as system logs or usage traces, could complement self-reported measures and provide a more direct basis for assessing actual use. Replication across multiple institutions in China and in other national contexts would help assess whether the model remains stable across governance regimes, disciplinary norms, and levels of digital maturity. Future work should also examine newer forms of GAI and their implications for academic work and academic integrity, including discipline-specific uses, expectations, and risks.

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Data Availability Statement

The datasets analyzed in this study are not publicly available due to privacy restrictions but are accessible via the supplementary materials for peer review. Anonymized data, questionnaire, informed consent, ethical approval, and variable coding are provided. Data are also available from the corresponding author upon reasonable request.

Ethical Approval

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Ethical approval was obtained from Institutional Review Board of the School of Foreign Studies at China University of Mining and Technology on 18th December, 2024. This study was conducted in compliance with the 1964 Helsinki declaration and its later amendments or comparable standards.

Informed Consent

Informed consent was obtained from all individual participants included in the study.

Declaration of Competing Interest

The authors declare no competing interests.

Author Contributions

Yanming Liu: conceptualization, methodology and writing- original draft preparation.
Xinmao Liu: conceptualization, methodology, reviewing and editing.
Meng Guan: conceptualization, writing, reviewing and editing.

Figure legends

Figure 1. Conceptual model for testing the hypotheses

Figure 2. Stratified sampling process

Figure 3. PLS-SEM model with common method factor

Figure 4. Path coefficients and results of model estimation

Notes: CVs=control variables; CV1=gender; CV2=education.

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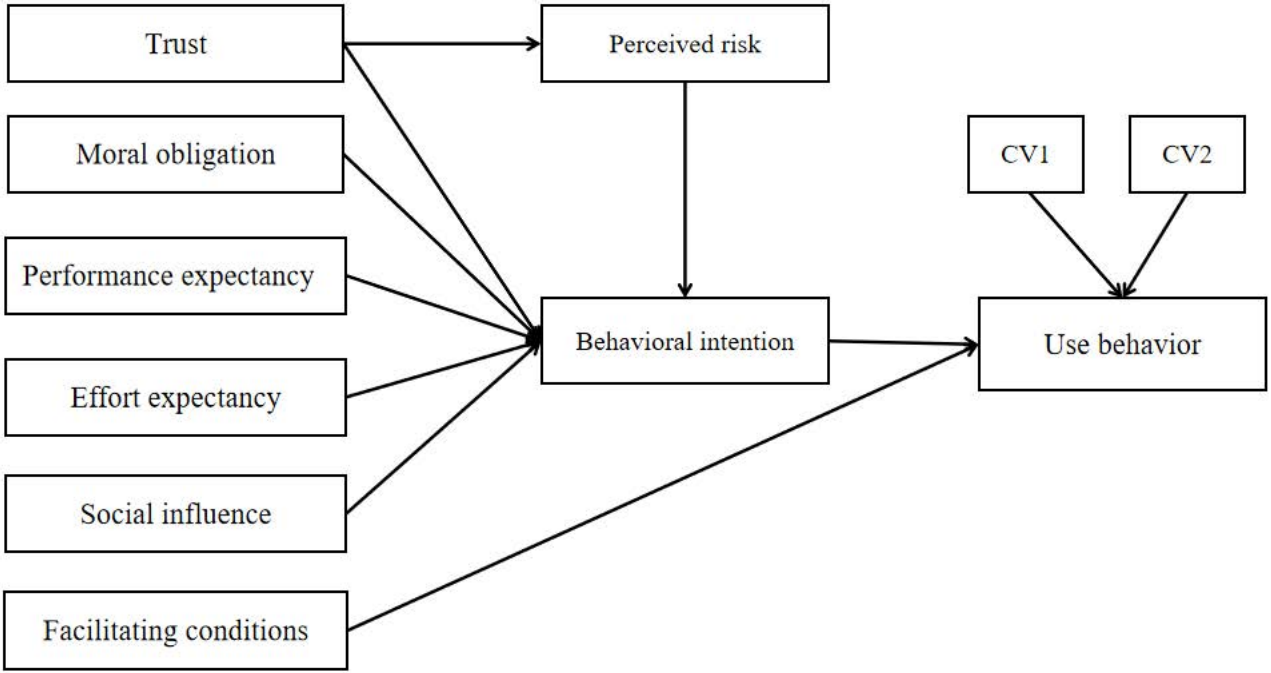
Trust
Perceived risk
Moral obligation
CV1
CV2
Performance expectancy
Behavioral intention
Use behavior
Effort expectancy
Social influence
Facilitating conditions

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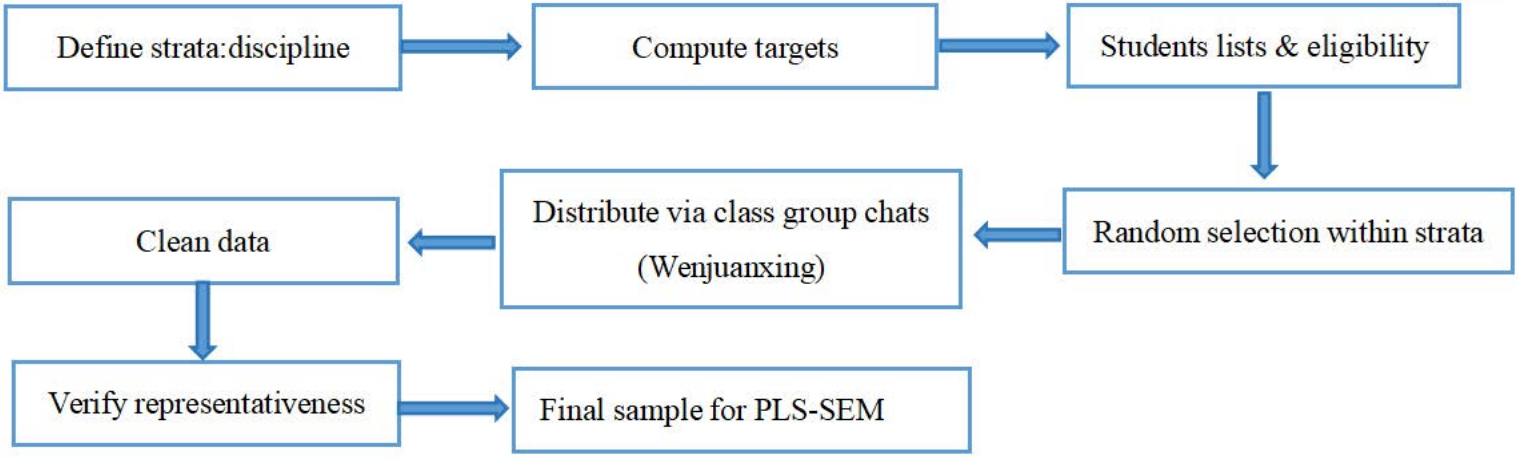

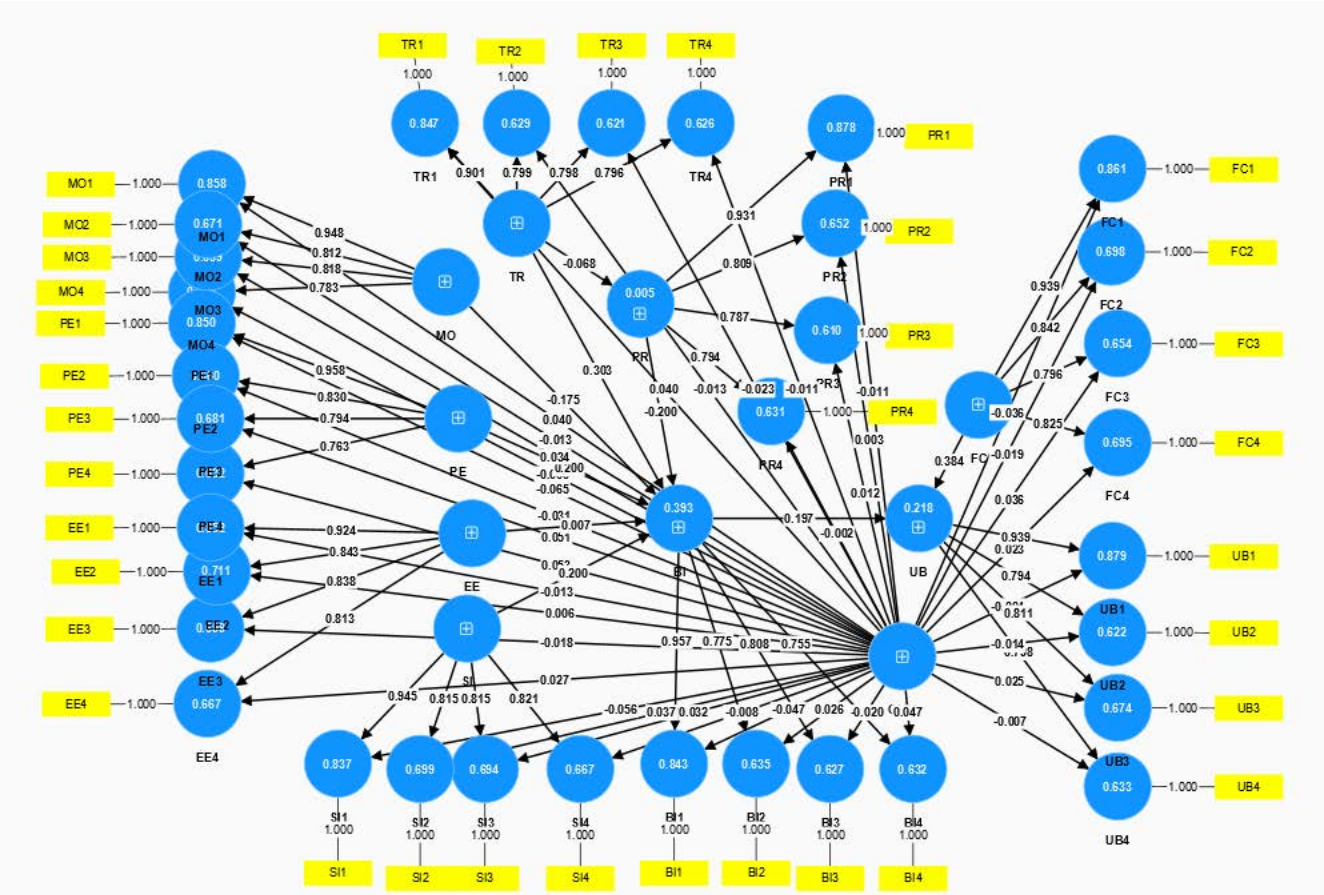
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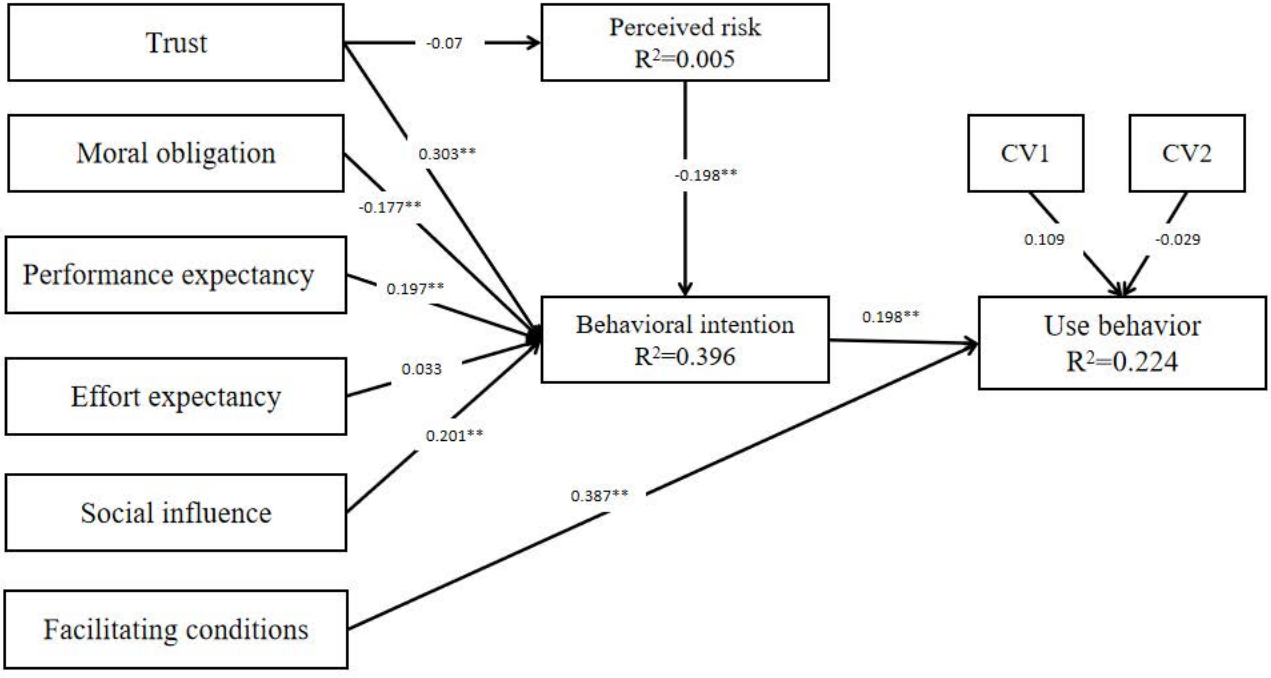
Trust
Moral obligation
Performance expectancy
Effort expectancy
Social influence
Facilitating conditions
-0.07
Perceived risk
R2=0.005
0.303**
-0.177**
0.197**
0.033
0.201**
-0.198**
Behavioral intention
R2=0.396
0.387**
0.198**
CV1
CV2
0.109
-0.029
Use behavior
R2=0.224