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Perceived Ease of Use and Usefulness in AI-Generated Content Adoption: Gender as a Moderator

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Abstract

Artificial Intelligence generated content (AIGC) is rapidly reshaping higher education. Guided by the Technology Acceptance Model (TAM), this study examines how perceived ease of use (PEOU) and perceived usefulness (PU) predict Chinese faculty members' AIGC use behaviour, with perceived self-efficacy (PSE) and institutional support (IS) modelled as external variables. Survey data from 295 faculty members was analysed and structural equation modelling was employed to test the hypothesized relationships. The results reveal that both PEOU and PU are critical predictors of AIGC adoption, while PSE and IS significantly enhance faculty perceptions of ease of use and usefulness, thereby facilitating actual usage behaviour. The model accounted for 55.2% of the variance in AIGC adoption. Furthermore, gender differences emerged as a significant moderating factor, where female faculty members were more strongly influenced by PEOU, whereas male faculty members with PU. These findings highlight the importance of strengthening faculty confidence and digital competence through differentiated training and institutional support mechanisms. The study extends TAM in an AIGC context and offers practical guidance for inclusive AIGC adoption strategies in higher education.

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Practitioner Notes

1. Faculty adoption of AI-generated content depends strongly on perceptions of ease of use and usefulness.
2. Institutions should provide training and support to enhance faculty confidence and digital competence.
3. Differentiated strategies are needed, as female faculty respond more to ease of use and male faculty to usefulness.
4. Strengthening self-efficacy and institutional support can significantly increase effective use of AI-generated content.

Keywords

Artificial intelligence generated content, technology acceptance model, higher education, faculty adoption, gender differences

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Introduction

Recent scholarly investigations into the deployment of Artificial Intelligence (AI) within higher education (HE) have been pervasive (Hartley et al., 2024). Equally, the proliferation of generative AI (GenAI) technologies, exemplified by applications such as ChatGPT, has significantly accelerated this trajectory by facilitating the development of Artificial Intelligence-Generated Content (AIGC). AIGC is the use of AI technologies, such as deep learning, to automatically generate different modalities of content, such as text, images, audio, video, etc (Yusuf et al., 2024). To date, China has released 79 large language models (LLMs) (as of March 2025, per national industry reporting) with over 1 billion parameters (Zhang, 2025) through applications such as Kimi-Chat (Beijing Moonshot Technology Co., Ltd., 2023), DeepSeek (DeepSeek AI, 2025), ERNIE Bot (Baidu, Inc., 2023), and Doubao (Beijing Chuntian Zhiyun Technology Co., Ltd., 2023). These advancements have laid a robust foundation for applying AIGC in China's education system. Equally, AIGC is increasingly viewed as a crucial tool for driving digital transformation in higher education, attracting growing interest from educators seeking to enhance teaching and learning processes (Zhu et al., 2024). Specifically, educators in China have begun to apply AIGC to their teaching practices to automate the generation of personalized materials, design interactive content, and innovate their curriculum, instructional, and assessment models (Lu et al., 2024). Educators generally agree that AIGC significantly enhances instructional creativity, simplifies task flow, and improves the teacher-student interaction experience (Yang et al., 2024). For example, at Zhejiang University and the Communication University of China, AIGC utilization has been found to successfully improve students' classroom participation and accounting skills (Wei et al., 2024; Wei & Qi, 2024). Hence, in order to promote innovation in teaching and learning, numerous universities in China have initiated systematic efforts to enhance educators' proficiency in and application of AIGC tools through collaboration with AI industries (Lu et al., 2024).

Equally, the 2025 Digital Education Strategic Action Plan was launched to define strategies for deeper AI integration into China's education system, backing national initiatives to develop a world-class educational framework by 2035 ((Ministry of Education of the People's Republic of China, 2025)). The development of China's education informatisation, from Informatisation 1.0 to 2.0, and then to the "Internet+," "blockchain+," "meta-universe" and "intelligent education" stages (Lu et al., 2024) is expected to drive changes in teaching methods, processes, and evaluations (AlAli et al., 2024; Mittal et al., 2024). Hence, institutions of HE, as key entities, play an essential role in integrating AIGC into educational practices and exploring ways for educators and faculty members to effectively utilize this technology to drive digital transformation within the educational landscape (Lu et al., 2024). However, these developments have equally introduced new challenges and opportunities (Yusuf et al., 2024). According to Li et al. (2024) and Ren et al. (2023) empirical studies on AIGC frequently neglect higher educators' motivations for utilizing these tools, as the research focus predominantly concentrates on model performance and students' use. Therefore, given the AI goal of China's education system, we theorized that there is an urgent need to explore the motivation and acceptance of AIGC for teaching among HE educators.

For that reason, the Technology Acceptance Model (TAM) (Davis, 1989) was utilised to provide a clear framework for explaining such behaviours, as it has been extensively validated, particularly in the field of education (Bamansoor et al., 2018). Based on TAM, perceived usefulness (PU) and perceived ease of use (PEOU) are the two core factors determining technology adoption behaviour (Davis, 1989). However, we remove "attitude" as suggested by ~~Davis (1989)~~, Kim et al. (2009), and Venkatesh and Davis (2000) as they explained that in contexts where technology adoption decisions predominantly emphasize external factors (e.g., PU and PEOU), the mediating role of attitude typically weakens and becomes less relevant. Additionally, educators’ views on adopting new technologies are predominantly driven by practical utility and operational ease rather than by subjective attitude (Zhao et al., 2024). Nevertheless, while TAM's simplicity and focus make it a particularly suitable tool for examining faculty members' utilization of emerging technologies, such as AIGC (Kavitha & Joshith, 2025), we theorized that perceived self-efficacy (PSE) may have a significant influence on such adoption, as also suggested by Venkatesh and Davis (2000). In the Chinese educational environment, educators not only have to fulfil their teaching tasks but also face the pressure of strict performance appraisal and evaluation (Chang et al., 2024). Furthermore, this includes lesson preparation, delivering lectures, correcting assignments, and simultaneously undertaking scientific research and various administrative tasks, all while managing multiple responsibilities. Consequently, both time and energy are often constraints (Chen & Zhao, 2022) that hinder their ability to learn, navigate, and use emerging technologies confidently. Hence, as proposed by Bandura (1977), we defined PSE in this study as educators' beliefs about their ability to navigate new tools. Numerous studies indicate that educators with higher PSE exhibit greater initiative, sustained engagement, and a higher willingness to embrace technology, which consequently promotes instructional innovation (Ge, 2022; Yang, 2021). Therefore, PSE serves as a crucial antecedent variable that enables educators to overcome the "fear of technology" and effectively utilize AIGC in high-pressure task and performance situations.

Additionally, several studies have demonstrated that institutional support (IS) also plays a crucial role in facilitating educators' effective use of technology. Research indicates that educators' adoption of educational technology depends not only on their own perceived efficacy but is also significantly influenced by the support conditions, training opportunities, and resource guarantees provided by their institutions. For example, a study based on university faculty in Beijing found that IS significantly enhanced educators' behavioural intention and actual adoption of technology. Convenient access to teaching platforms, resource sharing, and technical guidance were identified as key drivers of technology adoption (Wang & Wang, 2024). Another study found that policy guidance and professional development support provided by universities exert a significant positive influence on faculty members' career optimism and participation in continuing education, underscoring the importance of institutional incentive mechanisms (Scott et al., 2023).

Furthermore, we also theorised that, given China’s cultural dynamic, gender differences may play a significant role in the adoption of AIGC. Globally, male users have often exhibited a more receptive attitude towards new technology and are generally more motivated to utilize it in comparison to female users (Alenezi, 2024; Nyaaba et al., 2024; Zhang, 2025); empirical findings have also indicated no significant difference in willingness to use technology (Dong & Zhang, 2011). However, traditionally, women have been found to be more cautious when evaluating new technologies (Fan & Zhao, 2023; Yi et al., 2024), which further impacts their assessment of accuracy, trust levels, and readiness to embrace AIGC-generated content (Damiano et al., 2024). In China, deeply rooted gender roles and patriarchal structures have been known to influence how various genders engage with technology (Qiu, 2023; Yang, 2023). Equally, the "digital divide" in access to information and technological skills, which is exacerbated by gender disparities, persists, potentially worsening the inequality faced by female educators in their teaching practices (Li et al., 2024; Lu et al., 2024). Hence, in light of China's unique cultural and social context, this investigation examines the moderating influence of gender on relevant pathways, as also suggested by Zhang et al. (2023). Concurrently, while existing research has concentrated on the prevalence of gender disparities in technology usage, empirical studies evaluating potential gender differences in AIGC utilization among faculty members remain limited. Therefore, this study aims to provide empirical evidence regarding HE's teaching practices influenced by AIGC by addressing the following research questions (RQs):

RQ 1: To what extent does educators' PEOU and PU affect AIGC usage behaviour (UB)?

RQ 2: To what extent does PSE and IS influence PEOU, PU, and UB?

RQ 3: To what extent does gender moderate the relationships between PU, PEOU, and UB?

Hypothesis Development

Perceived Usefulness (PU) and Perceived Ease of Use (PEOU)

Perceived Usefulness (PU) is the extent to which a person believes that the use of a particular system will improve his or her job performance (Davis, 1989). PU is a key factor in determining faculty members' future use of Information and Communication Technology (Kumar et al., 2018). In the context of the AIGC, PU reflects educators' belief that AI-generated content can improve instructional effectiveness by increasing instructional efficiency, personalizing learning materials, and streamlining assessment design (Liu & Liu, 2025). At the same time, the study found that when educators perceived technology to be easy to use, they also perceived it to be more usable (Eze et al., 2021; Huang & Teo, 2020). PEOU is the degree to which a person believes that using a particular system will not require effort (Davis, 1989). For the purposes of this study, PEOU is the level of effort that educators believe is required to use the AIGC. Research suggests that AIGC-like ChatGPT are generally perceived as intuitive and user-friendly, enabling faculty members to adopt them without the need for formal technical training (Adıgüzel et al., 2023). Given the significant variation in digital literacy among faculty members, PEOU becomes a critical factor (Strzelecki, 2024). Prior research has demonstrated that PEOU directly affects UB (Huang & Teo, 2020). In the Chinese HE context, several studies also confirm this relationship. For example, Zhao and Zhao (2021) reported Chinese university faculty members possessing higher levels of computer self-efficacy and ease-of-use perception were significantly more inclined to adopt digital technologies in teaching. Similarly, Lu et al. (2024) reported that when educators perceived GenAI tools as easy to operate, their willingness to integrate them into course design and teaching practice was greatly enhanced. Therefore, we propose the following hypotheses:

H1: PEOU has a positive and significant influence on PU.

H2: PU has a positive and significant influence on UB.

H3: PEOU has a positive and significant influence on UB.

Perceived Self-efficacy (PSE)

Bandura (1986) suggests that PSE reflects an individual's self-beliefs in specific situations. In this study, we defined PSE as educators' confidence in their ability to use AIGC effectively as another key factor. We argue that such beliefs not only enhance educators' evaluations of the PEOU and PU of the tool but may also directly influence their intentions to use it and their actual use behaviour as also reported in previous studies by Menabò et al. (2021) and Usman et al. (2022). Recent research has found that educators with higher PSE are more likely to explore and use the AIGC (Al-Adwan et al., 2024). This was supported by Jatmikowati et al. (2020), who found that educators' self-efficacy directly and indirectly influences their willingness and behaviour to use e-learning systems, mediated by their perceived usefulness and ease of use. In the Chinese HE context, PSE is particularly critical. Zhao and Zhao (2021) further confirmed that computer self-efficacy among Chinese faculty members significantly predicted their technology adoption behaviours, primarily through enhanced perceptions of ease of use and usefulness. Similarly, Ge (2022) found that Chinese educators with higher self-efficacy demonstrated stronger engagement and a greater willingness to integrate digital technologies into their instructional practices. These findings suggest that PSE not only enhances PEOU and PU but also directly influences actual UB. Therefore, the following hypotheses are proposed:

H4: PSE has a positive and significant effect on PEOU.

H5: PSE has a positive and significant influence on PU.

H6: PSE has a positive and significant influence on UB.

Institutional support (IS)

Institutional support (IS) is essential for higher education faculty in adopting emerging technologies, generally offering financial, technical, and policy resources to cultivate a supportive environment (Stumbrienė et al., 2024). Therefore, delivering IT infrastructure, continuous training programs, and precise guidelines for the utilization of AIGC can significantly mitigate the uncertainty and operational challenges encountered by faculty members throughout the technology adoption process. (Yang et al., 2023). For instance, offering reliable technical support and subscription services for resources can significantly enhance faculty members' trust in AIGC and their willingness to use them (Bansah & Darko Agyei, 2022). Simultaneously, HE institutions that provide strong IT support can ease faculty challenges with technology, enabling them to concentrate more on innovative teaching (Yang et al., 2023). In the Chinese HE context, IS plays a particularly fundamental role. Wang and Wang (2024) found that university faculty in Beijing were more likely to adopt educational technology when sufficient institutional resources, platform access, and technical guidance were provided. Similarly, Scott et al. (2023) highlighted that institutional policy support and professional development opportunities significantly influenced Chinese university instructors' continuous learning and optimism, which in turn enhanced their technology adoption. Taken together, these findings suggest that institutional support not only shapes educators' perceptions of ease of use and usefulness but also exerts a direct influence on their actual UB By providing sufficient resources, systematic training, and appropriate incentives, institutions can effectively reduce adoption barriers and foster the integration of AIGC tools into routine teaching practices. Therefore, the following hypotheses are proposed:

H7: IS has a positive and significant effect on PEOU.

H8: IS has a positive and significant effect on PU.

H9: IS has a positive and significant effect on UB.

Gender differences

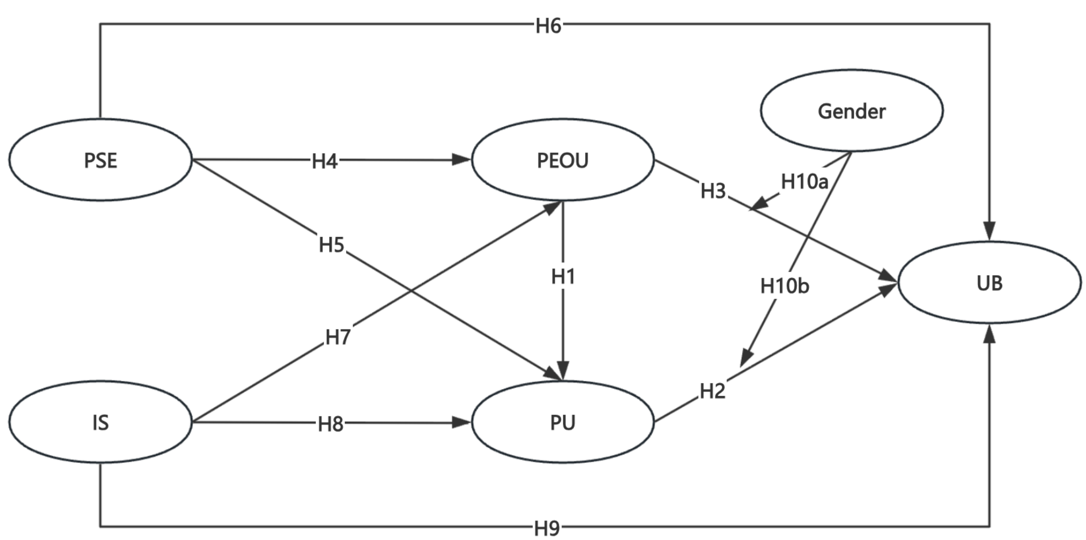
Gender differences have been shown to influence technological self-efficacy significantly (Huang, 2013). Men typically exhibit higher self-efficacy in fields such as mathematics, computer science, and social sciences, and this heightened self-efficacy may increase their willingness to adopt technology (Tang & Chen, 2024). A study examining gender differences in how PU and PEOU affect UB in educational contexts suggests that men are typically more influenced by PU, whereas women tend to be more motivated by PEOU (Ong & Lai, 2006). Scholars recommend that gender should be added as a moderating variable when modeling the adoption of educational technology (Al-Suqri, 2014). Because female educators in China are more likely to be anxious in technological environments (Fu et al., 2022), technical anxiety can be exacerbated by the complexity of the interface in particular (Liu & Liu, 2025). However, when users perceive the system to be easy to use, their level of technology anxiety decreases, and they are then more willing to use the technology (Gong & Liu, 2023). Thus, for female educators, PEOU will have a more significant contribution to their UB. In contrast, male are more inclined to rationally assess the actual value and efficiency-enhancing potential of their tools when it comes to technology adoption (Gong & Liu, 2023). At this point, PU has a greater impact on the UB of male educators. Therefore, the following hypotheses are proposed:

H10a: Gender has a moderating effect on the relationship between PEOU and UB.

H10b: Gender has a moderating effect on the relationship between PU and UB.

Figure 1 presents a comprehensive hypothetical model for this study, which is grounded in the conceptual hypotheses that underpin this research. This framework aims to elucidate the theoretical constructs and relationships integral to the study's objectives.

Figure 1 *Hypothetical Model*



Notes: PSE = Perceived self-efficacy, IS = Institutional support, PEOU = Perceived ease of use, PU = Perceived usefulness, UB = Usage behaviour.

Method

Design of the Study

The research uses an empirical approach involving problem formulation, hypothesis development, data collection, and hypothesis testing. Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM), with SmartPLS 4.0 employed for the analysis (Ringle et al., 2024). PLS-SEM is particularly suitable for exploratory research and early stages of theory development, especially when the theoretical model is complex or when data do not meet multivariate normality assumptions. Although our sample size is adequate (e.g., more than 100 cases or 10 times the number of model indicators), we selected PLS-SEM due to its suitability for prediction-oriented modelling (Hair et al., 2017).

Respondent

The survey targeted 820 faculty and staff members from a HE institution in Guangzhou, Guangdong Province, China, including 320 females (39.02%) and 500 males (60.98%) participants. Convenience sampling was employed, with the criterion that eligible participants must have previously used any form of AIGC. Of 820 invited faculty, 300 responses were received (36.59%). After excluding 5 who had not used AIGC, the valid sample was N=295. This sample size meets the requirement of being at least ten times the number of parameters in the SEM (Kock & Hadaya, 2018).

Instrument

The questionnaire used in this study consists of two main sections. The first section gathers demographic information about the respondents, including gender, age, educational background and years of teaching experience. The second section comprises measurement scales for the study variables, encompassing 18 items (see Appendix A). The measurement items were adapted as follows: (i) PU (α =.97) and PEOU (α =.91) are measured using the scale developed by Davis (1989), each consisting of four items (ii) UB (α =.91) three items adapted from Polyportis (2024) (iv) IS (α =.795) is measured using the scale proposed by Xu et al. (2016), comprising three items (iv) PSE (α =.86) by Chen et al. (2001), consisting of four items. It is noteworthy that, since some of the assessment scales were originally in English and the survey participants are Chinese, the study employed the back-translation method to ensure the reliability and accuracy of the questionnaire content (Sun & Ma, 2022). The survey employed a five-point Likert scale for assessment, where responses ranged from “1 representing Strongly Disagree” to “5 representing Strongly Agree.”

Research Procedure and Data Analysis

Data were collected using an online electronic questionnaire, with a link generated through "www.wjx.cn". The research team posted the link to the questionnaire on the WeChat group of educators in the HE institution. To increase the response rate, the research team issued reminder notifications 1 times at intervals of 3 days. After the questionnaire was closed, the raw data were exported from the platform in Excel (.xlsx) format. The data cleaning process primarily involved two steps: (1) removing invalid responses, such as questionnaires with excessively short completion times or patterned answers, and (2) checking for missing values to ensure data completeness. The cleaned dataset was then exported in CSV format and imported into SmartPLS for partial least squares structural equation modeling (PLS-SEM). Prior to import, the dataset was verified to ensure that variable names were clearly defined in the first row and all items were numeric. This study was approved by the Institutional Review Board of Guangzhou Huashang College, and all participants provided informed consent and participated voluntarily.

Descriptive statistical analysis was conducted using Jamovi, revealing a sample distribution of 130 males and 165 females (The Jamovi Project, 2024). This gender imbalance may reflect the higher proportion of female faculty members in the population studied, which aligns with existing data on gender representation in the teaching profession (Ehrich et al., 2020). As shown in Table 1, some variables have kurtosis values close to 0 and relatively small standard errors, indicating that their distributions approximate a normal distribution. However, PEOU stands out with a higher standard deviation (SD=1.001) and a slightly lower kurtosis value (-.786) compared to other variables. This indicates a wider range of responses and a flatter distribution for PEOU, suggesting that participants had more varied perceptions of ease of use.

Table 1 *Descriptive statistics*

Variables	**M**	**Me**	**SD**	**Sk**	**K**
PSE	3.570	3.750	.942	-.508	-.270
IS	3.740	4.000	.855	-.589	.034
PEOU	3.510	3.500	1.001	-.277	-.786
PU	3.600	3.750	.842	-.450	.158
UB	3.680	4.000	.886	-.594	.117

N*otes*: M = Mean, Me = Median, SD = Standard Deviation, Sk = Skewness, K = Kurtosis, N = 295, PSE = Perceived self-efficacy, IS = Institutional support, PEOU = Perceived ease of use, PU = Perceived usefulness, UB = Usage behaviour.

Findings

Measurement Model

The measurement model analysis assessed Cronbach's Alpha (α) and composite reliability (CR) to confirm internal consistency. Discriminant validity included Average Variance Extracted (AVE), Fornell-Larcker criterion, Outer Loadings, and Cross-Loadings (Hair et al., 2021). In Table 2, Cronbach's Alpha, AVE, CR values, and Fornell–Larcker criterion for each latent variable were provided. The Cronbach's Alpha (Column 3) and CR (Column 4) demonstrated strong internal consistency and reliability, as they were all above the recommended threshold of 0.7 (Hair et al., 2021). The AVE for all latent variables were also greater than 0.5, which indicated good reliability for each construct (Hair et al., 2021). The square roots of the AVE for each latent variable are greater than the corresponding correlation coefficients in the same column, indicating that discriminant validity was satisfied according to the Fornell–Larcker criterion.

Table 2 *Cronbach's Alpha, AVE, CR, Fornell–Larcker criterion*

Variables	Item	Cronbach's alpha	CR	AVE	UB	PEOU	PU	PSE	IS
UB	3	.857	.858	.777	**.882**				
PEOU	4	.880	.881	.735	.544	**.857**			
PU	4	.899	.900	.768	.571	.460	**.876**		
PSE	4	.888	.888	.749	.561	.420	.481	**.865**	
IS	3	.815	.824	.729	.558	.536	.469	.504	**.854**

Notes: The values on the diagonal, highlighted in bold, represent the square roots of AVE. PSE = Perceived self-efficacy, IS = Institutional support, PEOU = Perceived ease of use, PU = Perceived usefulness, UB = Usage behaviour.

Next, the outer loadings of all measurement items were greater than .70 (*see* Table 3), indicating that the scale had good convergent validity (Hair et al., 2021). The loadings of each measurement item on its respective latent variable were higher than the loadings on other latent variables, indicating that the scale had good discriminant validity. VIF values below 5 were generally considered acceptable, with values below 3 were considered preferable for strong evidence of low multicollinearity (Hair et al., 2021). For all items in Table 3, the highest VIF value is 3.027 for items PEOU1 and PU1, but these values were still below the critical threshold of 5, which indicated no significant multicollinearity issues. As shown in Table 4, the HTMT values were all less than .85, further indicating that the scale possessed good discriminant validity (Hair et al., 2021).

Table 3 *Outer loadings, Cross-loadings, and VIF*

Item	UB	PEOU	PU	PSE	IS	VIF
UB1	**.896**	.467	.519	.501	.534	2.380
UB2	**.856**	.497	.459	.439	.437	1.902
UB3	**.892**	.476	.529	.541	.502	2.299
PEOU1	.489	**.905**	.352	.352	.516	3.026
PEOU2	.459	**.843**	.373	.391	.402	2.191
PEOU3	.438	**.852**	.361	.388	.462	2.273
PEOU4	.477	**.829**	.485	.314	.455	1.970
PU1	.508	.428	**.902**	.434	.411	3.027
PU2	.525	.387	**.885**	.425	.409	2.779
PU3	.466	.371	**.888**	.397	.394	2.883
PU4	.497	.423	**.830**	.426	.427	1.955

PSE1	.450	.341	.414	**.878**	.408	2.685
PSE2	.489	.342	.439	**.875**	.435	2.586
PSE3	.508	.353	.398	**.884**	.429	2.690
PSE4	.491	.412	.410	**.822**	.466	1.851
IS1	.553	.514	.438	.429	**.871**	1.785
IS2	.425	.422	.425	.401	**.861**	1.876
IS3	.438	.430	.327	.465	**.829**	1.744

Notes: PSE = Perceived self-efficacy, IS = Institutional support, PEOU = Perceived ease of use, PU = Perceived usefulness, UB = Usage behaviour.

Table 4 *Heterotrait–monotrait (HTMT) criterion*

Variables	UB	PEOU	PU	PSE
PEOU	.627			
PU	.649	.514		
PSE	.642	.475	.537	
IS	.661	.628	.543	.593

Notes: PSE = Perceived self-efficacy, IS = Institutional support, PEOU = Perceived ease of use, PU = Perceived usefulness, UB = Usage behaviour.

Next, a Harman's single-factor test was performed to assess the presence of common method bias. Four factors with eigenvalues greater than 1 were extracted from the data, with the variance explained by the first factor being only 19.90%. This was well below the commonly accepted threshold of 40%, as suggested by Podsakoff (2003). This result indicated that there was no significant common method bias.

Results

Structural Model

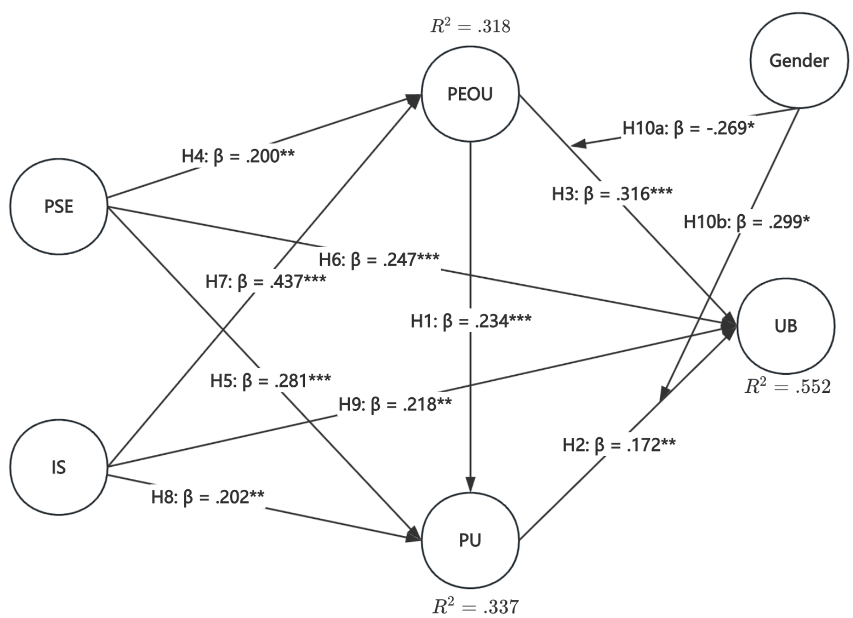
Table 5 showed the hypothesis testing results from 5,000 bootstrap samples. PEOU had a significant positive effect on PU and UB, supported H1 and H3. PU also had a significant positive effect on UB, which supported H2. PSE further showed a significant positive effect on PEOU, PU, and UB, supported H4, H5, and H6. IS also had a significant positive effect on PEOU, PU, and UB, which supported H7, H8, and H9. The results in Figure 2 showed that the model explained 55.20% of the variance in UB. It also explained 31.80% and 33.70% of the variances in PEOU and PU, respectively. The effect sizes (f^2) further supported the significance of the relationships, with notable effects of PEOU on UB (f^2 = .175), PU on UB (f^2 = .227), and IS on PEOU (f^2 = .207), among others (Hair et al., 2021). These results indicated that these relationships had moderate effect sizes, which underscored their importance in the model. Predictive relevance (Q^2) values of .321 for UB, .254 for PU, and .228 for PEOU suggested that the model demonstrated sufficient predictive accuracy for these outcomes (Hair et al., 2021).

Table 5 *Structural model analysis*

RQ	Hypothesis	β (t-value)	Result
RQ1	H1：PEOU -> PU	.234*** （3.587）	Supported
	H2：PU -> UB	.172** （2.867）	Supported
	H3：PEOU -> UB	.316** （3.471）	Supported
RQ2	H4：PSE -> PEOU	.200** （3.219）	Supported
	H5：PSE-> PU	.281*** （4.424）	Supported
	H6：PSE -> UB	.247*** （3.953）	Supported
	H7：IS -> PEOU	.437*** （7.433）	Supported
	H8：IS -> PU	.202** （3.069）	Supported
	H9：IS -> UB	.218** （2.867）	Supported

Note: Values in parentheses represent t-values. ***p < .001; **p < .01; *p < .05. PSE = Perceived self-efficacy, IS = Institutional support, PEOU = Perceived ease of use, PU = Perceived usefulness, UB = Usage behaviour.

Figure 2 *Structural Model Results*



Notes: *** p < .001; ** p < .01; * p < .05. PSE = Perceived self-efficacy, IS = Institutional support, PEOU = Perceived ease of use, PU = Perceived usefulness, UB = Usage behaviour.

Important Performance Map Analysis

Important Performance Map Analysis (IPMA) was conducted on the data to further measure the practical impact and performance of the path model (Ringle & Sarstedt, 2016). The conclusions were based on assessing each latent variable's impact and performance on UB. The results in

Table 6 indicated that PSE had the highest impact (β = .376), followed closely by IS (.370), while PEOU (.274) and PU (.262) have relatively smaller impacts. This meant that PSE and IS had the greatest impact on UB, while PEOU and PU also had effects, but comparatively smaller. In terms of performance, IS scored the highest (68.681), followed by PEOU (65.049), PSE (64.349), and PU (62.536). The IPMA graph visually illustrates these findings, where IS stood out as the best-performing variable.

Table 6 *Important Performance Map Analysis*

Construct	Importance for UB	Performance for UB
PEOU	.274	65.049
PU	.262	62.536
PSE	.376	64.349
IS	.370	68.681

Notes: PSE = Perceived self-efficacy, IS = Institutional support, PEOU = Perceived ease of use, PU = Perceived usefulness, UB = Usage behaviour. In IPMA, *importance* reflects total effects (direct + indirect) on UB, so these coefficients are not identical to the direct path coefficients reported in Table 5; *performance* is the rescaled latent variable mean on a 0–100 scale.

Moderating effect analysis

The results of the moderation effect analysis were shown in Table 7. In the path of the impact of gender and PEOU on UB, the path coefficient for females **(**β = .376) was significantly higher than that for males (β = .119). This indicated that women were more likely to be influenced by the PEOU of a product or service, which, in turn, affected UB. This path was supported by the Parametric test and Henseler's MGA p-values (both less than .05), thus hypothesis H10a was supported. In the path of the impact of gender and PU on UB, the path coefficient for males (β = .445) was significantly higher than that for females (β = .177). This indicates that men were more likely to be influenced by the PU of a product or service, which, in turn, affected UB. This path was supported by the Parametric test and Henseler's MGA p-values (both less than .05), thus hypothesis H10b was supported.

Table 7 *Results of Moderating Variable Hypothesis Testing*

Hypothesis	Male		Female					
	Path	Confidence	Path	Confidence	Path differences	p-Value Parametric test	p-Value Henseler's MGA	Result
H10a：Gender x PEOU -> UB	.119	[-.057, .290]	.376***	[.231, .521]	-.269	.026*	.027*	Supported
H10b：Gender x PU -> UB	.445***	[.241, .648]	.177	[.039, .309]	.299	.025*	.032*	Supported

Notes: *** p < .001; ** p < .01; * p < .05. PEOU = Perceived ease of use, PU = Perceived usefulness, UB = Usage behaviour.

Multi-group Analysis

The moderation effect analysis distinguished between male and female samples to further investigate the variation of the model across different genders. In PLS-SEM, multi-group analysis was used to examine gender as a moderating variable. However, before performing the multi-group analysis, the Measurement Invariance of Composite Models (MICOM) procedure was conducted to assess the measurement invariance of the composite model (Dybro Liengaard, 2024). MICOM consisted of three steps: evaluating configural invariance, assessing compositional invariance, and finally, evaluating measurement invariance of means and variances (Cheah et al., 2020). The results of the MICOM analysis between the two groups were summarized in Table 8.

The results indicated that partial measurement invariance was established across all constructs, as both configural and compositional invariance were supported for all variables. The equal mean and variance assessments for most constructs fell within the specified confidence intervals, thereby supporting full measurement invariance. However, the results for PU required additional clarification, as this construct showed mixed results: it was supported under compositional invariance and partial measurement invariance but was not supported under equal variance assessment (Step 3b). Specifically, the original difference for PU **(**β = -.217**)** lay outside the confidence interval range **(**-.255, .251), indicating that variance invariance was not established. This suggested that the variability in PU perceptions between male and female groups was significant and may have reflected meaningful differences in how the two genders perceived the usefulness of the technology under study.

Table 8 *Multi-group analysis*

Variables	Configurational Invariance (Step 1)	Compositional Invariance (Step 2)		Partial Measurement Invariance	Equal Mean Assessment (Step 3a)		Equal Variance Assessment (Step 3b)		Full Measurement Invariance
		Original Correlation	5.00 %		Original Differences	Confidence Interval	Original Differences	Confidence Interval	
UB	Supported	1.000	.999	Supported	.113	[-0.232,0.231]	.066	[-.343, .321]	Supported
PEOU	Supported	.999	.998	Supported	.057	[-0.237,0.243]	-.015	[-.348, .327]	Supported
PU	Supported	.999	.999	Supported	.288	[-0.215,0.218]	-.217	[-.255, .251]	Partial / Only variance supported
PSE	Supported	1.000	.999	Supported	.025	[-0.232,0.244]	-.109	[-.317, .288]	Supported
IS	Supported	1.000	.997	Supported	.244	[-0.245,0.236]	-.190	[-.347, .320]	Supported

Notes: PSE = Perceived self-efficacy, IS = Institutional support, PEOU = Perceived ease of use, PU = Perceived usefulness, UB = Usage behaviour.

Discussion

Main findings

Based on the TAM, this study analysed the behaviour of Chinese higher educators' use of AIGC and its influencing factors in terms of educators' psychological factors and external environmental factors, revealing the moderating role of gender in technology adoption. The structural equation modelling analysis demonstrated that the proposed model explained 55.20% of the variance in UB, as well as 31.80% and 33.70% of the variance in PEOU and PU, respectively. These findings show that the model has strong explanatory power regarding AIGC adoption among HE faculty. Overall, the main TAM pathways were validated: PEOU significantly affected both PU and UB, and PU significantly influenced UB. This finding validates the robustness of the TAM in explaining AIGC adoption (Balaskas et al., 2025). More importantly, these results suggest that, in the AIGC context, ease of use remains a decisive factor in driving actual usage among educators (Lu et al., 2024b; Oved & Alt, 2025). While Chinese faculty members may possess varying levels of digital literacy (Zongyao H, 2024), regarding the utilization of AIGC, tools that are perceived as intuitive and less burdensome tend to have more pronounced utility, thereby ultimately enhancing usage behaviour. Consequently, the ongoing refinement of user-friendly design in AIGC platforms is imperative to promote broader adoption within higher education.

Next, we also observed that PSE showed significant positive effects in predicting educators' PEOU, PU, and UB for AIGC. The direct effect of PSE on UB was particularly significant, suggesting that higher educators' confidence in their technical competence is an important prerequisite for their willingness to use AIGC. The IPMA results further reinforce this point, as PSE was identified as one of the most important influencing factors and should be emphasized in adoption, especially when levels of digital literacy (Zongyao H, 2024) can also significantly influence educators' adoption of AIGC. Concurrently, such a suggestion is also consistent with the broader literature on digital literacy gaps among Chinese educators which reports that significant hierarchical differences in digital literacy levels emerge among different teacher groups, including notable urban-rural disparities and variations across educational stages (Dai, 2025). Dehghani and Mashhadi (2024), such confidence-building comes not only from past technical experience, but is also closely related to whether the HE institution provides competency-based training

Equally, IS also showed a significant positive effect on PEOU, PU, and UB, thus underscoring the critical role of the organizational environment in the adoption of AIGC (Wang et al., 2025). Specifically, educators are more inclined to perceive AIGC as "good" and "useful," and consequently, they are more likely to proactively incorporate it into their teaching practices, provided that the higher education institution has offered adequate support in terms of technical equipment, policy incentives, and professional development training. From the IPMA perspective, IS demonstrated both high importance and high performance, indicating that organizational support is already a strong enabler of AIGC adoption in Chinese universities. However, its effectiveness depends on continuous investment in infrastructure and long-term institutional strategies to embed AIGC into pedagogical reform. This underscores that the adoption of AIGC is driven not only by faculty members' psychological readiness but also by the structural conditions created through institutional policies, organizational design, and resource allocation.

Finally, as hypothesised, gender played a significant moderating role in both the PU→UB and PEOU→UB. While male educators are more concerned with the usefulness of AIGC in teaching and learning, female educators are more interested in whether the tools themselves are easy to use. This result echoes a difference in gender (Zhao & Zhao, 2021) and addressing the gendered digital divide in AIGC adoption reveals that female faculty may necessitate more targeted training and supportive interventions to overcome technology-related anxiety. Conversely, male faculty tend to respond more positively to evidence emphasizing efficiency and productivity improvements. Hence, designing differentiated AIGC training programs that consider different adoption pathways could therefore enhance inclusivity and accelerate integration. To avoid reinforcing stereotypes, training should be choice-based and non-stigmatizing, offering pathways that emphasise usability (PEOU) and demonstrable productivity gains (PU), so all educators can adopt AIGC with confidence.

Theoretical contributions and practical implications

This study makes several contributions to the existing theoretical framework. First, by extending the TAM to the context of AIGC adoption, it demonstrates that PEOU and PU remain robust predictors of UB (Balaskas et al., 2025; Davis, 1989), while the inclusion of PSE and IS provides a richer explanatory framework. Secondly, the findings underscore a multilevel mechanism whereby individual psychological factors, as evidenced by PSE, organizational conditions through IS, and socio-cultural elements such as gender, collectively influence AIGC adoption. This advances prior work on technology adoption in HE by demonstrating that technology usage is not merely an individual decision but also a function of institutional structures and cultural contexts (Hameed et al., 2012; Scott et al., 2023). Concurrently, several practical implications can be inferred. Firstly, the pronounced influence of PSE on UB indicates that higher education institutions should focus on systematic digital and AI literacy training to enhance faculty members' confidence in using AIGC tools. This aligns with evidence showing that higher PSE significantly boosts educators' engagement and technology adoption (Ge, 2022; Yang, 2021). Next, as institutional support emerged as both highly important and a high-performing factor, it underscores the necessity for universities to uphold investments in infrastructure, policies, and professional development in order to sustain the integration of AIGC (Liu et al., 2025; Scott et al., 2023; Wang & Wang, 2024). Finally, the moderating role of gender highlights the need for differentiated strategies that mutually emphasize productivity gains, reduce technology-related anxiety, and increase ease of use. Together, these findings provide actionable insights for universities aiming to enhance the sustainable integration of AIGC into teaching practices.

Conclusion

This study examines how individual beliefs in efficacy, organizational support, and acceptance of technology interact at multiple levels to influence the adoption of new GenAI technologies by higher education educators. The findings not only validate and extend the applicability of the TAM within the context of HE and emerging AI technologies but also emphasize the significance of perceived self-efficacy and institutional support in China as key external variables. We also observed significant differences, with a particular focus on gender-related differences that shape the pathway to AIGC acceptance. The research transcends the traditional individual perspective of the technology acceptance model, elucidates the three-tiered driving mechanism of "psychological empowerment-organizational support-technology perception," and offers a theoretical foundation for the integration of AIGC in this domain of China's HE.

Limitations of the Research

The limitations of this study are primarily anchored in the geographical and methodological scope. Firstly, the data collection was exclusively conducted within higher education institutions in Guangdong Province, China. This reliance on convenience sampling introduces potential biases, particularly concerning the representativeness and diversity of the sample. Consequently, the findings may not be generalizable to other regions or educational contexts, thereby constraining the broader applicability of the results. Therefore, future studies could consider expanding the sample to cover different regions and types of HE institutions to enhance the generalizability of the findings. Second, this study used cross-sectional data and was unable to track the dynamics of educators' behaviour in using AIGC. Future research could consider a mixed-methods approach to explore the dynamic relationship between self-efficacy, institutional support, and technology adoption over time. However, this study only examines educators in higher education institutions. Nonetheless, the use and spread of AIGC across all educational levels are also recommended. Future research should, therefore, broaden the scope to include other educational stages like basic and vocational education, to investigate how technology adoption mechanisms vary across different levels contexts. In addition, considering the rapid iteration of AIGC, future research should also focus on the variability of the functionality of different types of AIGC platforms and assess the differential impact of technological evolution on educators' perceived ease of use and usefulness, to further optimize the theory and practice of technology adoption.

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Appendix A

Perceived Self-Efficacy (PSE)

PSE1: I believe using AIGC such as Kimi-chat, ERNIE Bot, and Doubao can significantly improve my work efficiency.

PSE2: I believe using AIGC such as Kimi-chat, ERNIE Bot, and Doubao can enhance my overall work performance.

PSE3: I believe using AIGC such as Kimi-chat, ERNIE Bot, and Doubao can help me achieve my work goals and expected outcomes.

PSE4: I believe using AIGC such as Kimi-chat, ERNIE Bot, and Doubao can help solve practical problems within the team.

Institutional Support (IS)

SS1: My institutional (or department) encourages the use of AIGC such as Kimi-chat, ERNIE Bot, and Doubao in teaching work from a policy perspective.

SS2: My institutional (or department) provides financial support for activities or competitions related to AIGC such as Kimi-chat, ERNIE Bot, and Doubao.

SS3: My institutional (or department) provides training or technical support for the use of AIGC such as Kimi-chat, ERNIE Bot, and Doubao.

Perceived Usefulness (PU)

PU1: I believe using AIGC such as Kimi-chat, ERNIE Bot, and Doubao can help me complete tasks more quickly.

PU2: I believe using AIGC such as Kimi-chat, ERNIE Bot, and Doubao can improve my work performance.

PU3: I believe using AIGC such as Kimi-chat, ERNIE Bot, and Doubao can significantly enhance my work effectiveness.

PU4: I believe AIGC such as Kimi-chat, ERNIE Bot, and Doubao are highly valuable for my work.

Perceived Ease of Use (PEOU)

PEOU1: I find it very easy to operate AIGC such as Kimi-chat, ERNIE Bot, and Doubao.

PEOU2: I can easily use AIGC such as Kimi-chat, ERNIE Bot, and Doubao to complete tasks.

PEOU3: I have a clear understanding of the functionalities of AIGC such as Kimi-chat, ERNIE Bot, and Doubao.

PEOU4: I feel that I can skillfully use AIGC such as Kimi-chat, ERNIE Bot, and Doubao for work.

Usage Behaviour (UB)

UB1: I frequently use AIGC such as Kimi-chat, ERNIE Bot, and Doubao in my work.

UB2: I use AIGC such as Kimi-chat, ERNIE Bot, and Doubao almost every day to complete work tasks.

UB3: I plan to continue using AIGC such as Kimi-chat, ERNIE Bot, and Doubao in the future to support my work.

感知自我效能

1.我认为使用Kimi-chat、文心一言、豆包等AIGC应用能够显著提高我的工作效率。

2.我认为使用Kimi-chat、文心一言、豆包等AIGC应用能够提升我的整体工作表现。

3.我认为使用Kimi-chat、文心一言、豆包等AIGC应用能够帮助我实现工作目标和预期结果。

4.我认为使用Kimi-chat、文心一言、豆包等AIGC应用能够帮助解决团队中的实际问题。

机构支持

1.我所在的机构（或部门）从政策层面鼓励在教学工作中使用Kimi-chat、文心一言、豆包等AIGC应用。

2.我所在的机构（或部门）在资金上支持与Kimi-chat、文心一言、豆包等AIGC应用相关的活动或竞赛。

3.我所在的机构（或部门）提供了关于Kimi-chat、文心一言、豆包等AIGC应用的培训或技术支持。

感知有用性

1.我认为使用Kimi-chat、文心一言、豆包等AIGC应用可以帮助我更快速地完成工作。

2.我认为使用Kimi-chat、文心一言、豆包等AIGC应用能够提升我的工作表现。

3.我认为使用Kimi-chat、文心一言、豆包等AIGC应用能够显著增强我的工作成效。

4.我认为Kimi-chat、文心一言、豆包等AIGC应用对我的工作具有非常重要的价值。

感知易用性

1.我觉得操作Kimi-chat、文心一言、豆包等AIGC应用非常简单。

2.我能轻松地使用Kimi-chat、文心一言、豆包等AIGC应用完成任务。

3.我对Kimi-chat、文心一言、豆包等AIGC应用的功能有清晰的理解。

4.我觉得我可以熟练地使用Kimi-chat、文心一言、豆包等AIGC应用完成工作。

使用行为

1.在工作中，我经常使用Kimi-chat、文心一言、豆包等AIGC应用。

2.我几乎每天都会使用Kimi-chat、文心一言、豆包等AIGC应用完成工作任务。

3.我计划在未来继续使用Kimi-chat、文心一言、豆包等AIGC应用支持我的工作。