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Does Gender and Faculty Background Determine the Sustainability of GenAI Adoption in Higher Education? A Revised UTAUT Perspective

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ABSTRACT

The rapid integration of generative artificial intelligence (GenAI) in higher education has transformed learning practices, yet the sustainability of its adoption remains uneven across student groups. This study examines the determinants of sustained GenAI adoption in university settings, with particular attention to the roles of gender and faculty background. Drawing on an extended Unified Theory of Acceptance and Use of Technology (UTAUT) framework, the study employs a quantitative approach using survey data collected from 184 university students. Partial least squares structural equation modelling (PLS-SEM) is applied to evaluate the proposed relationships. The results indicate that performance expectancy, facilitating conditions, attitude toward use, and behavioural intention significantly influence sustained ChatGPT usage. In contrast, effort expectancy and social influence show limited direct effects. Multi-group analysis further reveals notable differences across gender and faculty background, with female students and those from exact science faculties demonstrating higher levels of sustained GenAI adoption. These findings extend the applicability of UTAUT to GenAI contexts and highlight the importance of demographic and disciplinary factors in designing inclusive and sustainable GenAI adoption strategies in higher education.

Keyword: Generative artificial intelligence, higher education, UTAUT

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1. INTRODUCTION

Digital technology has profoundly transformed higher education, particularly through the increasing integration of generative artificial intelligence (GenAI). Tools such as ChatGPT have reshaped how students access, analyse, and present knowledge (Dwivedi et al., 2023). Beyond accelerating academic task completion, GenAI influences students' learning approaches and cognitive engagement, thereby creating opportunities for deeper integration of intelligent technologies within higher education teaching and learning processes.

GenAI represents one of the fastest-growing technological innovations in contemporary education. GenAI systems generate new content—including text, images, audio, and programming code—by learning patterns from large-scale training data (Dwivedi et al., 2023). Among these systems, ChatGPT has gained widespread attention as a sophisticated language model that employs deep learning techniques to produce human-like natural language responses, making it a prominent example of GenAI implementation in educational contexts (Önden & Alnour, 2023).

Within higher education institutions, which function as formal environments for advanced learning and intellectual development, the emergence of GenAI presents both significant opportunities and critical challenges. Universities play a central role in fostering innovation, critical thinking, and digital competencies required for the twenty-first century. Consequently, the adoption of GenAI technologies has become an important indicator of ongoing educational transformation and institutional readiness to respond to digital disruption.

The application of GenAI in universities spans a wide range of academic activities, including essay writing, data analysis, and programming support. GenAI tools contribute to preparing students for digitally oriented workplaces, making their acceptance and responsible use increasingly essential. Equitable access to GenAI may help reduce digital disparities among students, while sustainable adoption requires attention to ethical concerns such as plagiarism, overreliance on automation, and responsible use. Sustained and ethical integration of GenAI therefore supports educational quality and enhances institutional and graduate competitiveness in the digital era. However, patterns of adoption and continued use may vary across demographic and academic groups.

Despite its growing presence, GenAI adoption and sustainability are not uniformly distributed among students. Amoozadeh et al. (2024) report that varying levels of trust in GenAI significantly influence students' adoption intentions and continued use. Such disparities indicate uneven engagement with GenAI technologies across student populations. Prior research also highlights that individual characteristics, including gender and academic background, play an important role in shaping perceptions, attitudes, and behavioural intentions toward technology adoption (Venkatesh et al., 2012). In university settings, students from different disciplinary backgrounds may exhibit distinct adoption patterns; for instance, engineering students often prioritise functionality and efficiency, whereas students in social or economic disciplines may emphasise ethical, practical, or societal considerations.

Against this backdrop, the present study aims to examine the influence of gender and faculty background on GenAI adoption in higher education. This investigation is significant because it contributes empirical insights into sustainable GenAI implementation and addresses gaps in prior research that have insufficiently examined gender and faculty as explanatory variables. Gender-related differences in perceived usefulness, ease of use, and risk may shape individuals' motivation and long-term engagement with GenAI tools. Similarly, faculty background influences technology exposure, academic needs, and contextual relevance, thereby affecting adoption behaviour across disciplines.

To analyse these relationships theoretically, this study employs the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. The UTAUT model incorporates core constructs such as performance expectancy, effort expectancy, social influence, and facilitating conditions, alongside moderating variables including age, gender, and experience (Venkatesh et al., 2012). In this research, the model is used to examine how gender and faculty background moderate the relationships between UTAUT constructs and GenAI usage in higher education, with a particular focus on sustainable adoption—an area that remains underexplored in existing literature.

Previous studies have applied the UTAUT framework within higher education contexts. For example, Tarhini et al. (2014) demonstrated that gender and age moderate students' intentions to use e-learning systems, while Shoufan (2023) found that perceived convenience and ethical considerations influence learning perceptions related to ChatGPT use. However, prior research has generally not examined the combined effects of gender and faculty background on the long-term sustainability of GenAI adoption using a UTAUT-based approach. Accordingly, this study offers a novel contribution by simultaneously analysing these factors, extending the application of UTAUT to generative AI technologies, and providing a nuanced understanding of GenAI adoption across diverse academic disciplines and demographic groups.

2. LITERATURE REVIEW, HYPOTHESES, AND METHODS

2.1 Literature Review

Recent research has increasingly focused on identifying the factors that influence the sustainability of GenAI adoption in higher education. Prior studies have contributed substantially by examining individual, technological, and contextual determinants that shape sustained engagement with GenAI tools. For instance, Elshaer et al. (2024) demonstrated that students' interaction patterns and utilisation of ChatGPT vary across gender and academic disciplines, highlighting the role of demographic and faculty-related characteristics in technology adoption. Similarly, Khlaif et al. (2024), in their investigation of lecturers' integration of GenAI tools, found that performance expectancy, effort expectancy, social influence, and hedonic motivation significantly affect both intention and actual use, thereby providing a theoretical basis for incorporating demographic factors such as gender into adoption models. In addition, Sergeeva et al. (2025) reported that habits, performance expectancy, social influence, and hedonic motivation influence behavioural intentions toward generative AI technologies. Although their findings did not reveal significant gender-based differences, the study underscores the importance of personal and academic characteristics in shaping GenAI adoption among university users. Collectively, these studies establish a strong conceptual foundation for the present research by identifying key determinants that support the sustained adoption of GenAI technologies, including ChatGPT, in higher education contexts.

2.2 Hypotheses

This study adopts an expanded UTAUT framework to examine the sustainability of GenAI adoption in higher education. As illustrated in Figure 1, the model includes performance expectancy, effort expectancy, social influence, and facilitating conditions as core predictors, with attitude toward using ChatGPT and behavioural intention to use ChatGPT modelled as mediating variables. Gender and faculty background are incorporated as control variables to capture demographic and disciplinary differences, while actual ChatGPT usage represents sustainable GenAI adoption. By extending the UTAUT framework to include gender and faculty background, this study enhances the model's explanatory power and contextual relevance within higher education settings.

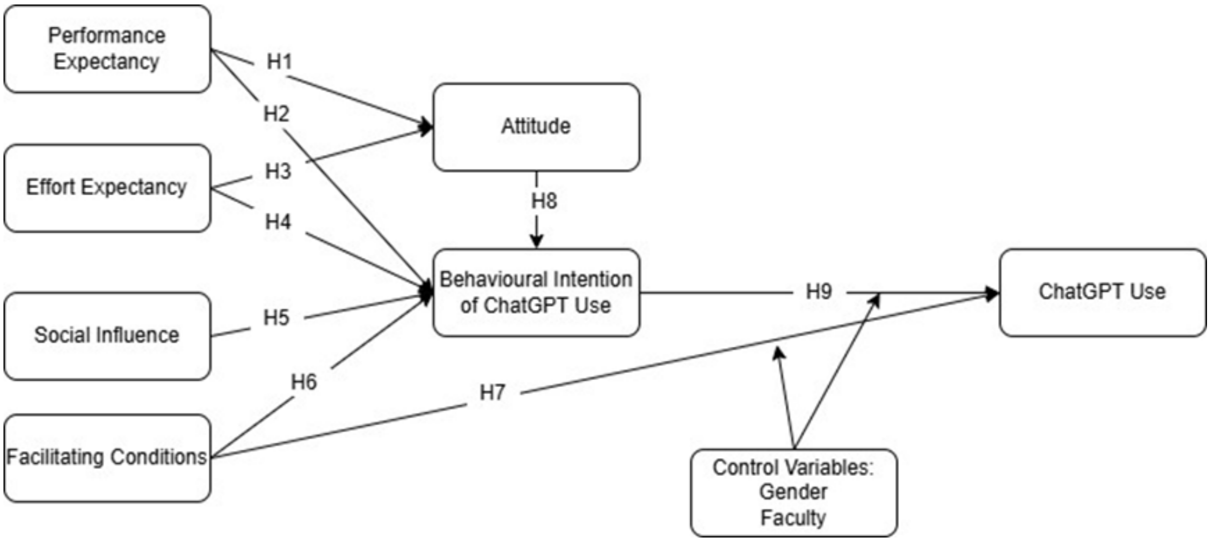

Figure 1. Proposed research model

Performance expectancy refers to individuals' beliefs that using a system will enhance their academic or task performance. Prior studies have consistently demonstrated the predictive power of performance expectancy in technology adoption contexts. Venkatesh et al. (2003) established performance expectancy as a key determinant of technology use, while Wan et al. (2020) showed its positive effect on students' sustained engagement with Massive Open Online Courses (MOOCs). Post-pandemic studies further confirm its relevance, with Hussain Akbar et al. (2023) and Narayan & Naidu (2024) reporting strong effects of performance expectancy on e-learning adoption. Evidence from non-educational contexts, such as Sengkalit et al. (2025), also highlights its role in driving technology uptake. These findings support the assumption that performance expectancy shapes both attitudes and behavioural intentions toward ChatGPT use.

H1: Performance Expectancy influences Attitude toward Using ChatGPT.
H2: Performance Expectancy influences Behavioral Intention to Use ChatGPT.

Effort expectancy reflects the perceived ease associated with using a system and is conceptually related to perceived ease of use in the Technology Acceptance Model (TAM) and system complexity in the Model of PC Utilisation (MPCU). Empirical studies consistently show that lower perceived effort increases technology acceptance. Ma et al. (2025) found that perceived ease of use significantly affects ChatGPT adoption behaviour, while Balaskas et al. (2025) reported a strong influence of effort expectancy on students' behavioural intentions in higher education. Similar findings were reported by Yakubu et al. (2025) for AI-based learning systems and by Narayan & Naidu (2024) in post-pandemic learning contexts. Accordingly, effort expectancy is expected to influence both attitudes toward ChatGPT and intentions to use it.

H3: Effort Expectancy influences Attitude toward Using ChatGPT.
H4: Effort Expectancy influences Behavioral Intention to Use ChatGPT.

Social influence refers to the extent to which individuals perceive that important others believe they should use a particular system. Within UTAUT, social influence is closely linked to subjective norms and has been shown to affect behavioural intention across various domains (Venkatesh et al., 2003). Empirical evidence supports its relevance in technology adoption, including telemedicine usage (Febrianti, 2024) and Generation Z's online purchasing behaviour (Persada et al., 2019). However, prior research also indicates that the effect of social influence may vary across contexts, as demonstrated by Ali et al. (2024) in the tourism sector. Given the collaborative and peer-driven nature of higher education, social influence is expected to shape students' intentions to use ChatGPT.

H5: Social Influence influences Behavioral Intention to Use ChatGPT.

Facilitating conditions describe individuals' perceptions of the availability of technical infrastructure, resources, and support required to use a system effectively. This construct represents external conditions that enable or constrain technology use (Fath & Rahardjo, 2023). Prior studies show that supportive environments significantly influence technology adoption in higher education. Qazi et al. (2021) and Batucan et al. (2022) demonstrated that conducive learning environments enhance students' behavioural intentions toward e-learning systems, while Zheng et al. (2025) emphasised the importance of technological infrastructure and technical support. Therefore, facilitating conditions are expected to influence both behavioural intention and actual ChatGPT usage.

H6: Facilitating Conditions influence Behavioral Intention to Use ChatGPT.
H7: Facilitating Conditions influence Use of ChatGPT.

Attitude toward technology use reflects an individual's overall affective evaluation of using a system, including feelings of enjoyment, interest, and satisfaction. Attitude has been shown to play a crucial role in shaping behavioural intention across multiple technology contexts. Yang & Qian (2025) found that positive attitudes significantly influenced students' intention to continue using online learning systems, while Juliani et al. (2021) reported similar effects in mobile banking adoption. Based on this evidence, attitude toward using ChatGPT is expected to positively influence behavioural intention.

H8: Attitude toward Use influences Behavioral Intention to Use ChatGPT.

Behavioural intention represents an individual's readiness to perform a specific behaviour and is widely recognised as a strong predictor of actual system use. Previous studies confirm this relationship in educational and organisational contexts. Anthony et al. (2021) demonstrated that behavioural intention significantly influences blended learning use among academic staff, while Zacharis & Nikolopoulou (2022) reported similar findings for post-pandemic e-learning adoption. Moura et al. (2020) further validated behavioural intention as a key determinant of ICT use in professional environments. Accordingly, behavioural intention is expected to directly influence actual ChatGPT usage.

H9: Behavioral Intention to Use ChatGPT influences Use of ChatGPT.

2.3 Methods

This study employs a quantitative research approach to examine factors influencing the sustainability of GenAI adoption in higher education. Quantitative methods provide a systematic framework for collecting, analysing, and interpreting numerical data in an objective manner. As noted by Ardiansyah et al. (2023), this approach enables researchers to measure research variables precisely and analyse relationships among them using statistical techniques. Accordingly, this study collects numerical data through structured research instruments, primarily questionnaires, which are subsequently analysed using appropriate statistical tools to explain the phenomena under investigation.

The population of this study consists of students who are actively enrolled in higher education institutions. Sample selection was conducted using purposive sampling, whereby respondents were chosen based on predefined criteria relevant to the research objectives and their willingness to participate in the study (Etikan et al., 2015). This sampling technique was deemed appropriate to ensure that participants possessed adequate experience and exposure to the use of GenAI tools, particularly ChatGPT, within academic contexts.

To determine the minimum required sample size, this study applied power analysis using G*Power software (Faul et al., 2007). The analysis was conducted assuming six predictor variables, a medium effect size of 0.15, a significance level of 5%, and a statistical power of 95%. Based on these parameters, a minimum of 74 responses was required. To enhance the robustness and reliability of the statistical analysis, data were ultimately collected from 184 respondents, exceeding the minimum sample size requirement.

3. RESULTS AND DISCUSSION

This section presents the results of the study based on data collected from university students and discusses the findings in relation to the research objectives. Data collection was conducted over a three-month period at Universitas Papua, West Papua, Indonesia, from February to April 2025. Respondents were characterised according to demographic variables, including gender and faculty background, as summarised in Table 1. Data were collected using an online questionnaire distributed via Google Forms, with responses measured on a five-point Likert scale ranging from strongly disagree to strongly agree. The questionnaire comprised demographic information, clear instructions for respondents, and measurement items for each research variable, adapted from established instruments. The survey link was disseminated through social media platforms, including Instagram and WhatsApp, to facilitate participant recruitment.

Table 1. Demographic profile of respondents

No.	Category	Item	Total	Percentage
1	Gender	Male	74	40.2%
		Female	110	59.8%
2	Faculty	Social	45	24.5%
		Exact	139	75.5%

3.1 Measurement Model Evaluation

This study evaluated the measurement model by examining reliability as well as convergent and discriminant validity to ensure the adequacy of the research instruments. Convergent validity was assessed using indicator outer loadings and average variance extracted (AVE). According to established criteria, outer loading values should exceed 0.70, indicating that each observed indicator adequately represents its underlying latent construct (Inan et al., 2023). The results show that the majority of indicators in this study meet this threshold, thereby confirming satisfactory convergent validity.

In addition to outer loadings, AVE values were examined to further assess convergent validity. An AVE value above 0.50 indicates that a latent construct explains more than 50% of the variance of its indicators rather than measurement error. All constructs achieved AVE values exceeding the recommended cutoff, providing additional support for the convergent validity of the measurement model.

The internal consistency reliability of the constructs was assessed using Cronbach's Alpha (CA) and Composite Reliability (CR). Composite reliability values above 0.70 indicate satisfactory construct reliability, while Cronbach's alpha values between 0.60 and 0.70 are considered acceptable in exploratory and behavioural research contexts. As shown in Table 2, all constructs meet these reliability criteria, indicating that the measurement instruments are reliable and appropriate for assessing the sustainability of GenAI adoption in higher education.

Table 2. Confirmatory analysis of constructs

Construct	Statement Item	Code	LF	CA, CR, AVE
Performance Expectation (PE)	ChatGPT increases my productivity in learning.	PE1	0.827	CA: 0.852, CR: 0.857, AVE: 0.693
	ChatGPT increases my effectiveness in learning.	PE2	0.873	
	ChatGPT makes my work or learning process easier	PE3	0.772	
	ChatGPT is useful for me to learn.	PE4	0.854	
Effort Expected (EE)	ChatGPT is easy to understand when used.	EE1	0.883	CA: 0.874, CR: 0.824, AVE: 0.727
	Easy to interact with ChatGPT while in use.	EE2	0.817	
	ChatGPT is easy to learn to use.	EE3	0.878	
	ChatGPT is easy to use.	EE4	0.830	
Social Influence (SI)	My friends are influential in my decision to use ChatGPT.	SI1	0.765	CA: 0.782, CR: 0.824, AVE: 0.694
	My family is influential in my decision to use ChatGPT.	SI2	0.833	
	My social environment is influential in my decision to use ChatGPT.	SI3	0.896	
Facilitating Conditions (FC)	I have resources such as a smartphone, which are sufficient to use ChatGPT.	FC1	0.816	CA: 0.701, CR: 0.706, AVE: 0.626
	I have the skills needed to use ChatGPT.	FC2	0.809	
	ChatGPT can work with other apps	FC3	0.746	
Attitude (AT)	I am very satisfied and happy in using ChatGPT.	AT1	0.891	CA: 0.853, CR: 0.854, AVE: 0.773
	I feel comfortable when using ChatGPT.	AT2	0.892	
	I had a positive experience using ChatGPT to learn.	AT3	0.855	
Behavioral Intention to Use ChatGPT (BI)	I would like to use ChatGPT in the near future.	BI1	0.947	CA: 0.883 CR: 0.883 AVE: 0.896
	I would like to use ChatGPT in the future.	BI2	0.946	
ChatGPT Usage (CU)	I am willing to use ChatGPT long-term.	CU1	0.908	CA: 0.838, CR: 0.856, AVE: 0.755
	I don't mind putting in the time and money to use ChatGPT.	CU2	0.828	
	I always use ChatGPT in learning activities.	CU3	0.869	

Discriminant validity was subsequently assessed to ensure that each construct is empirically distinct from the others. Discriminant validity is essential because insufficient discriminant validity suggests that two or more constructs may measure the same or highly overlapping concepts (Sarstedt et al., 2021). In this study, discriminant validity was evaluated using the HTMT criterion, which is considered a robust and widely accepted approach in PLS-SEM analysis. HTMT values below 0.85 or, in more lenient cases, below 0.90 indicate adequate discriminant validity (Sarstedt et al., 2021).

The HTMT results presented in Table 3 demonstrate that all inter-construct values fall below the recommended thresholds. These findings confirm that the measurement model satisfies discriminant validity requirements and that the constructs used in this study are conceptually and empirically distinct.

Table 3. HTMT discriminant validity results

	AT	BI	CU	EE	FC	PE	SI
AT	—	—	—	—	—	—	—
BI	0.813	—	—	—	—	—	—
CU	0.819	0.816	—	—	—	—	—
EE	0.813	0.674	0.604	—	—	—	—
FC	0.894	0.782	0.695	0.871	—	—	—
PE	0.837	0.765	0.736	0.778	0.771	—	—
SI	0.598	0.494	0.770	0.585	0.758	0.575	—

3.2 Structural Model Evaluation

This study evaluates the structural model to examine the relationships among latent constructs and to test the proposed hypotheses. Following the assessment of the measurement model, the structural model was analysed using key statistical indicators, including the coefficient of determination (R^2) and the Variance Inflation Factor (VIF), to assess predictive accuracy and potential multicollinearity among constructs.

Given that all variables were measured using a single survey instrument, Common Method Bias (CMB) was examined to ensure the robustness of the findings. Harman's single-factor test indicated that the largest factor accounted for 47.21% of the total variance, which is below the recommended threshold of 50%. This result suggests that common method bias is unlikely to pose a serious threat to the validity of the study. In addition, multicollinearity was assessed using VIF to ensure that the constructs were not excessively correlated. VIF values exceeding 5 or falling below 0.20 indicate potential multicollinearity concerns. As presented in Table 4, the VIF values range from 1.533 (SI → BI) to 2.848 (AT → BI), all of which fall below the conservative threshold of 3.3, indicating the absence of multicollinearity issues.

Table 4. Inner VIF results

	AT	BI	CU	EE	FC	PE	SI
AT	—	2.848	—	—	—	—	—
BI	—	—	1.619	—	—	—	—
CU	—	—	—	—	—	—	—
EE	1.831	2.563	—	—	—	—	—
FC	—	2.498	1.619	—	—	—	—
PE	1.831	2.362	—	—	—	—	—
SI	—	1.533	—	—	—	—	—

In addition to assessing multicollinearity, the explanatory power of the structural model was evaluated using the coefficient of determination (R^2). The R^2 values indicate the extent to which the independent variables explain the variance in the dependent variables. Following established guidelines, R^2 values of 0.75, 0.50, and 0.25 are interpreted as substantial, moderate, and weak, respectively.

Table 5. R-square results

Variables	R-Square	Description
AT	0.601	Moderate
BI	0.569	Moderate
CU	0.519	Moderate

The results presented in Table 5 show that the R^2 values for all endogenous constructs range from 0.519 to 0.601, indicating a moderate level of explanatory power. Among the constructs, attitude toward use (AT) exhibits the highest R^2 value (0.601), while ChatGPT usage (CU) shows the lowest (0.519), although both remain within the moderate range. These findings suggest that the independent variables included in the model provide a meaningful explanation of the variance in the dependent variables, while also indicating that additional factors beyond those examined in this study may further contribute to explaining GenAI adoption behaviour.

3.3 Hypothesis Testing

This study conducted hypothesis testing to evaluate the proposed relationships within the structural model. Consistent with established statistical criteria, a hypothesis was considered supported when the t-statistic exceeded 1.96 and the p-value was below 0.05. The results of the structural model assessment are presented in Table 6. Of the nine hypotheses tested, seven were supported, as indicated by significant p-values and t-statistics exceeding the threshold, while two hypotheses were not supported due to non-significant results.

Table 6. Hypothesis-testing results

Hypothesis	Variables	T-Statistic	P Values	Description
H1	PE → AT	6.984	0.000	Accepted
H2	PE → BI	3.057	0.002	Accepted
H3	EE → AT	6.478	0.000	Accepted
H4	EE → BI	0.325	0.745	Rejected
H5	SI → BI	0.032	0.975	Rejected
H6	FC → BI	2.095	0.036	Accepted
H7	FC → CU	2.120	0.034	Accepted
H8	AT → BI	4.098	0.000	Accepted
H9	BI → CU	8.123	0.000	Accepted

The findings in Table 6 show that performance expectancy significantly influences both attitude toward using ChatGPT (H1) and behavioural intention to use ChatGPT (H2). Effort expectancy also demonstrates a significant effect on attitude (H3), although its direct effect on behavioural intention (H4) is not supported. Social influence does not exhibit a significant effect on behavioural intention (H5). In contrast, facilitating conditions significantly affect both behavioural intention (H6) and actual ChatGPT usage (H7). Furthermore, attitude toward using ChatGPT significantly influences behavioural intention (H8), and behavioural intention strongly predicts actual ChatGPT usage (H9). Collectively, these results confirm the central role of expectancy, facilitating conditions, and attitudinal factors in explaining GenAI adoption sustainability.

To further explore demographic and disciplinary differences, gender and faculty background were incorporated as control variables in the hypothesis testing. As summarised in Table 7, the inclusion of these control variables reveals notable variations in hypothesis support across subgroups. In the male subgroup, four hypotheses were supported and five were not, whereas in the female subgroup, six hypotheses were supported and three were rejected. Similarly, when faculty background was considered, four hypotheses were supported within the social faculty group, while six were supported within the exact faculty group.

Table 7. Hypothesis-testing results with control variables

Hypothesis	Variables	All Respondents	Gender		Faculty	
			Male	Female	Social	Exact
H1	PE → AT	Accepted	Accepted	Accepted	Accepted	Accepted
H2	PE → BI	Accepted	Rejected	Accepted	Rejected	Accepted
H3	EE → AT	Accepted	Accepted	Accepted	Accepted	Accepted
H4	EE → BI	Rejected	Rejected	Rejected	Rejected	Rejected
H5	SI → BI	Rejected	Rejected	Rejected	Rejected	Rejected
H6	FC → BI	Accepted	Rejected	Rejected	Rejected	Accepted
H7	FC → CU	Accepted	Rejected	Accepted	Rejected	Rejected
H8	AT→ BI	Accepted	Accepted	Accepted	Accepted	Accepted
H9	BI → CU	Accepted	Accepted	Accepted	Accepted	Accepted

Overall, these subgroup analyses indicate that the sustainability of GenAI adoption in higher education is not uniform across student populations. Differences in gender and faculty background appear to moderate several relationships within the model, suggesting that demographic and disciplinary contexts play an important role in shaping students' adoption and continued use of GenAI technologies.

3.4 Discussion

This study provides empirical evidence on the sustainability of GenAI adoption in higher education by examining key determinants within an extended UTAUT framework. The findings indicate that performance expectancy, facilitating conditions, attitude toward use, and behavioural intention are the primary drivers of sustained ChatGPT usage. These results reinforce the central role of perceived usefulness and institutional support in explaining continued engagement with GenAI technologies, while effort expectancy and social influence exhibit limited direct effects on behavioural intention.

The non-significant influence of effort expectancy and social influence suggests that, in academic contexts, students' GenAI usage decisions are less shaped by ease-of-use considerations or peer pressure and more driven by perceived performance benefits and available support infrastructure. This pattern partially contrasts with the findings of Fath & Rahardjo (2023) and indicates that GenAI adoption in higher education may follow a more utilitarian and self-directed logic.

Notably, subgroup analysis reveals that gender and faculty background moderate several relationships within the model. Female students demonstrate stronger adoption sustainability, particularly when performance benefits and facilitating conditions are salient. Similarly, students from exact science faculties exhibit higher adoption levels than those from social science faculties, likely due to greater technological exposure and task-oriented learning environments. These findings highlight the importance of demographic and disciplinary context in shaping GenAI adoption behaviour.

Overall, the moderate explanatory power of the model suggests that while UTAUT constructs effectively capture core adoption drivers, additional factors—such as trust, ethical concerns, or self-regulation—may further enhance understanding of sustainable GenAI adoption in higher education.

3.5 Theoretical Implications

This study contributes to the technology adoption literature by extending the application of UTAUT to the context of GenAI adoption in higher education. The findings reaffirm the theoretical importance of performance expectancy and facilitating conditions as key determinants of sustained technology use. However, the non-significant effects of effort expectancy and social influence on behavioural intention suggest that the traditional UTAUT framework may require contextual adaptation when applied to GenAI technologies in academic environments.

Moreover, by incorporating gender and faculty background as control variables, this study highlights the role of demographic and disciplinary contexts in shaping GenAI adoption. The results indicate that female students and students from exact faculties exhibit stronger adoption tendencies, driven by perceived usefulness and institutional support. These insights underscore the importance of integrating demographic considerations into future extensions of UTAUT and other technology adoption models, particularly in rapidly evolving digital learning environments.

4. CONCLUSION

This study investigates technology adoption in higher education by examining the sustained use of GenAI and the role of demographic factors, particularly gender and faculty background. The findings indicate that female students demonstrate a higher propensity to adopt and continue using GenAI than male students, while students from exact science faculties show greater acceptance of GenAI adoption compared to those from social science faculties. These results highlight the importance of demographic and disciplinary contexts in shaping patterns of GenAI adoption within university environments.

From a theoretical perspective, this study reinforces the validity and applicability of UTAUT in explaining the adoption of emerging technologies in higher education. By incorporating gender and faculty background as contextual variables, the study extends the UTAUT framework and enhances its explanatory power in the context of GenAI. This extension provides a more nuanced understanding of how demographic and disciplinary differences influence technology adoption behaviour.

From a practical standpoint, the findings offer actionable insights for higher education institutions. Recognising that female students and those from exact science faculties exhibit greater openness toward GenAI adoption, universities can design more inclusive and targeted technology implementation strategies. Such strategies may help ensure equitable access to GenAI tools, promote sustainable adoption, and maximise the educational benefits of GenAI across diverse student populations.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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