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Exploring graduate students' acceptance and use of generative AI: An application of the UTAUT2 model

Şeyma Yıldırım-Samuk [1,2*]
0000-0002-8103-0804

İsmail Fırat Altay [1]
0000-0003-0567-1818

[1] Department of English Language Teaching, Hacettepe University, Ankara, TURKEY
[2] Corporate Communication Office, Karadeniz Technical University, Trabzon, TURKEY
[*] Corresponding author: seyma.yildirim@hacettepe.edu.tr

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ABSTRACT

Generative artificial intelligence (GenAI) has recently gained significant attention within educational contexts, particularly among university students. Regardless of its significance, there are still a limited number of empirical studies on graduate students' intention to use this technology in higher education settings. Accordingly, this study investigated the acceptance of GenAI tools by master's and doctoral students for academic purposes. The research adapted the unified theory of acceptance and use of technology 2 model and surveyed 145 graduate students from various universities through convenience sampling. Data collected through online surveys were analyzed using the partial least squares approach to structural equation modelling. Key findings revealed that factors, including habit (HB), performance expectancy, and hedonic motivation, had a significant effect on students' behavioral intention (BI) to use GenAI tools. Additionally, the study indicated that the most important predictors for actual GenAI use were HB and BI. Notably, demographic variables, age, gender, and the level of study, showed no significant moderating influence on the relationships among the constructs. This study provides further insight into our understanding of how GenAI tools are accepted by graduate students for academic purposes and contribute to the literature on the factors affecting their intention to use these tools.

Keywords: generative artificial intelligence, UTAUT2, higher education, academic purposes

INTRODUCTION

Recent developments in generative artificial intelligence (GenAI) have significantly influenced educational environments. Mostly driven by machine learning, large language models, and neural networks, GenAI tools can generate realistic artificial media, including text, images, code, simulations, audio, and other forms of media (Peres et al., 2025). These tools learn the underlying structures in their training data and generate new structures with similar features (Sengar et al., 2024). At present, various GenAI tools are in use, with some of the most prominent examples being ChatGPT, Copilot, Gemini, and Deepseek.

Capable of understanding and generating human-like responses, these tools have significant potential to perform a wide range of educational tasks for both teachers and learners from K-12 to higher education settings (Ghimire et al., 2024; Hays et al., 2024). Teachers can generate lesson plans through specific instructions (Lou, 2023), develop teaching materials (Ooi, 2025), provide students with personalized feedback in a short time (Mijwil & Aljanabi, 2023), review assessments (Dao et al., 2023), and optimize administrative processes (Yan et al., 2023, Yusuf et al., 2024). For learners, these tools offer immense potential in supporting students in academic writing (Koltovskaia et al., 2024), studying grammar and vocabulary (Liu et al., 2024), and improving their speaking (Chen et al., 2025) and listening skills (Wang & Xue, 2024). GenAI tools also ensure them quick access to information (Giannakos et al., 2024), provide constant feedback (Alneyadi & Wardat, 2023), help them accomplish their assignments (Foroughi et al., 2024), support their critical thinking skills through high-quality tasks (Yan et al., 2024), and develop problem-solving skills (Surya Bahadur et al., 2024). Students have a chance to develop personalized learning pathways through interactions with these tools and their tailored guidance (Huh, 2023; Woo et al., 2025). Beyond these examples, GenAI tools have the potential for academic purposes, such as academic writing, research assistance (Ooi et al., 2025), giving feedback, creating ideas, and data analysis in higher education settings (Korinek, 2023). While these tools offer significant advantages in education and academia, they are not without concerns about academic integrity (Ghimire, 2024), practical misuse (Koltovskaia et al., 2024), and ethical issues (Yan et al., 2024). Considering all the achievements and concerns about the use of GenAI tools for learning and research, it is imperative that higher education institutions take significant steps in benefiting from this technology for education and adopt effective strategies to address academic misconduct (Henke, 2024).

With the increasing use of GenAI tools in education, extensive research has investigated students' intention to use the technology through various theoretical frameworks, such as the unified theory of acceptance and use of technology (UTAUT) model (Venkatesh et al., 2003). The model, which was created by synthesizing 8 pre-existing technology acceptance theories, includes four key constructs: performance expectancy (PE), social influence (SI), effort expectancy (EE), and facilitating conditions (FC). The findings indicate that these constructs ultimately impact individuals' technology acceptance. Recently, the model was modified and extended to the UTAUT2 with the addition of three more constructs: hedonic motivation (HM), price value (PV), and habit (HB) (Venkatesh et al., 2012). The model offers more comprehensive insights into the factors influencing technology acceptance within diverse settings, including information systems (I. P. H. Permana et al., 2024), mobile learning (Ameri et al., 2020), e-commerce (Dixit et al., 2025), and healthcare (Huang et al., 2024). Previous studies in educational settings have applied the UTAUT2 framework to explore the acceptance of various technologies, such as e-learning platforms (Zacharis & Nikolopoulou, 2022), virtual reality (Geriş & Kulaksız, 2025), mobile devices (Hoi, 2020), and ChatGPT (Namatovu & Kyambade, 2025).

Regardless of the substantial promises of GenAI tools in academia, graduate students' adoption of this technology for academic purposes remains largely unexplored. Understanding their adoption of GenAI tools in academic contexts plays a crucial role in integrating such tools into academic and research processes without violating academic integrity and ethical aspects. Unlike previous studies that have specifically focused on acceptance of ChatGPT in a broad subject area, covering both science and humanities (Grassini et al., 2024; Namatovu & Kyambade, 2025), this study explores the adoption of more diverse GenAI tools, such as ChatGPT, Copilot, and Scopus AI, by masters' and doctoral students studying in English-related fields of study (e.g., English language teaching, translation studies, and linguistics). To examine technology acceptance by this under-studied demographic group, this study utilizes the UTAUT2 model as a robust theoretical framework. With this diagnostic model empirically proven to interpret technology acceptance, this study will offer a comprehensive perspective on graduate students' acceptance and use of GenAI technology within their academic processes, thereby contributing to this nascent area of research. With this purpose in mind, this study was set out to address the following research questions:

1. What are the key factors that influence graduate students' acceptance and use of GenAI tools for academic purposes?
2. What are the structural relationships among UTAUT2 constructs in explaining students' acceptance and use of GenAI tools?

The research questions outlined above are intended to investigate the multifaceted determinants shaping master's and doctoral students' adoption of GenAI tools in their academic tasks. By examining their perceptions, motivations, and potential constraints, this research focuses on identifying the major drivers behind their engagement with this recently emerging and rapidly advancing technology. The findings are expected to inform key stakeholders in education, such as instructors, supervisors, curriculum developers, and institutional policymakers, allowing them to make decisions based on evidence and implement suitable strategies to enhance students' academic performance.

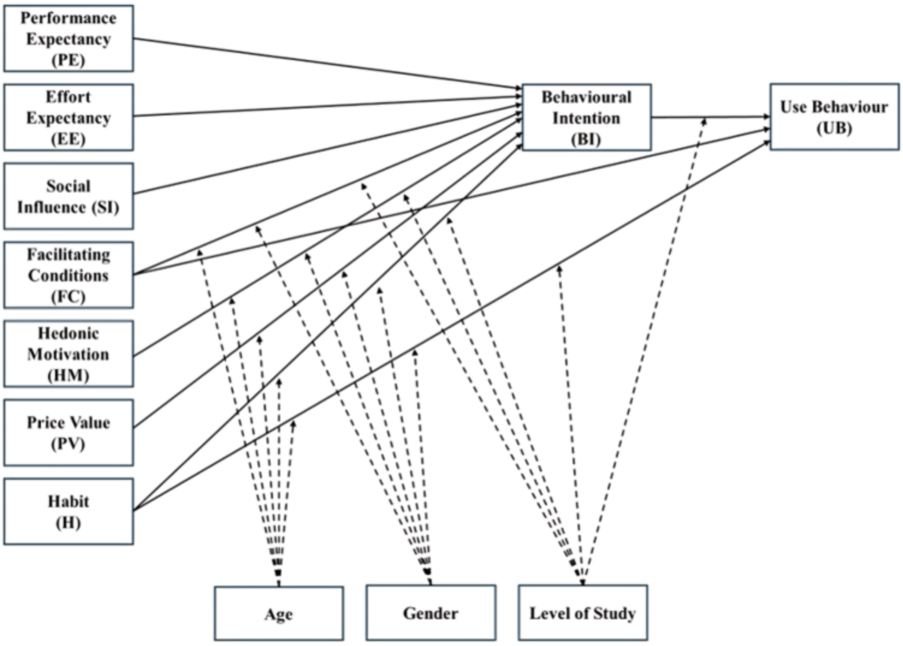

Figure 1. Research model adapted from Venkatesh et al. (2012)

LITERATURE REVIEW

Recently, the study of how technology is accepted and utilized has emerged as a major focus in academic studies. Among the leading theories discussed in this area of research, the "UTAUT2" stands out as particularly influential in predicting and explaining technology acceptance. Developed by Venkatesh et al. (2012), the model provides researchers with a validated and well-established framework to identify the factors influencing the acceptance and adoption of technology. Constructs, including "PE," "SI," "EE," "FC," "HM," "PV," and "HB," facilitate the identification of factors that affect both "behavioral intention (BI)" and, ultimately, "use behavior (UB)." Additionally, demographic differences, such as age, gender, and experience, are considered moderators influencing the relationship between the constructs, BI, and UB.

This study uses the UTAUT2 model as the foundational framework to examine GenAI adoption among master's and doctoral students studying in English-related programs. Examining the Turkish higher education context may provide insight into how distinct educational settings affect students' intentions to use GenAI. The conceptualization of the hypotheses in this study draws upon the UTAUT2 model. The theoretical model adapted from Venkatesh et al. (2012), and developed based on the proposed hypotheses is presented in **Figure 1**. The main factors influencing participants' acceptance and use of this recent technological advancement are briefly described below.

PE refers to individuals' belief that the use of a given technology can enhance the effectiveness of their work-related activities. According to Venkatesh et al. (2003), people are more inclined to adopt technologies when these tools assist them in accomplishing their objectives and tasks. For Strzelecki (2024a), "PE" influences learners' "BI" to utilize innovative technology within academic contexts. This view is supported by several research findings. For example, Teng et al. (2022) demonstrated that "PE" significantly influenced learners' adoption of an educational metaverse platform. Similarly, Camilleri (2024) explored the positive relationship between students' "PE" and their adoption of artificial intelligence (AI)-enabled large language models. In this study, "PE" reflects students' perception that the use of GenAI tools can improve the effectiveness of their academic work. Hence, it was hypothesized that:

H1. PE has a direct and significant effect on students' BI.

EE is defined as the degree to which individuals perceive a technology as easy to use in completing their tasks (Venkatesh et al., 2003). Recent studies have emphasized the importance of adopting educational technologies. For instance, the research by Strzelecki (2024b) has shown that "EE" has a positive effect on higher education learners' "BI" to use AI technology. Additionally, Sobaih et al. (2024) found that ease of use increased learners' willingness to use chatbots. Similarly, Surya Bahadur et al. (2024) found that students were more willing to use ChatGPT thanks to its effortless usage. Taken together, in the present research, "EE" refers to students' perceptions of the ease associated with using GenAI tools. In light of these findings, the hypothesis below was proposed:

H2. EE has a direct and significant effect on students' BI.

SI signifies the importance an individual places on the technology UBs of people who are significant to them (friends, teachers, professors, and so forth). Many research studies have shown that positive SI from social surroundings has been found to significantly influence technology use in education. For example, studies conducted by Menon and Shilpa (2023) and Namatovu and Kyambade (2025) found that perceived support from influential people in the social circle influenced the adoption of educational technologies. In Russian educational setting, Sergeeva et al. (2025) found that SI positively influenced BI to use GenAI among undergraduate students. "SI" in this study denotes the extent to which students are encouraged by peers, educators, or other influential individuals within their social surroundings to use GenAI in their educational activities. Thus, it was hypothesized that:

H3. SI has a direct and significant effect on students' BI.

FC are defined as the degree of availability and accessibility of resources needed to use a particular technology (Venkatesh et al., 2012). In higher education contexts, "FC" emphasize the importance of access to resources, such as technical infrastructure, support, and training, which can influence the use of these educational technologies. Findings of various studies have shown that "FC" are found to be a crucial determinant for learners' technology acceptance and usage. For instance, Dwivedi et al. (2021) and Xu et al. (2024) identified the positive influence of available resources and support on learners' intention to use AI technology in higher education technology adoption contexts. In addition, Sergeeva et al. (2025) found that FC had a significant positive effect on BI to use GenAI among undergraduate students. In this research, "FC" mean students' beliefs about their access to sufficient resources and support to accept and adopt GenAI tools. Accordingly, the following hypotheses were stated:

H4. FC have a direct and significant effect on students' BI.

H5. FC have a direct and significant effect on students' UB.

HM means the level of enjoyment a user experiences while utilizing a particular technology. Perceived enjoyment from using technology influences its acceptance and use (Venkatesh et al., 2012). Accordingly, studies have shown that enjoyment serves as a strong motivator for technology use, and "HM" serves as a key determinant of the acceptance and use of various educational technologies, including e-learning platforms (Twum et al., 2022), mobile learning (García de Blanes Sebastián et al., 2025), and AI tools (Cambra-Fierro et al., 2025; Sergeeva et al., 2025). Similarly, a study conducted with graduate student groups also showed that HM positively influenced students' acceptance of technology (Salifu et al., 2025). Within the scope of the present study, "HM" reflects students' perceived enjoyment and pleasure arising from interactions with GenAI tools. Hence, this study hypothesized that:

H6. HM has a direct and significant effect on students' BI.

PV is defined as the perceived cost associated with the benefits of using a technological system (Venkatesh et al., 2012). Prior studies have identified "PV" as a key factor influencing technology adoption by users who are more inclined to prefer particular tools which offer high value and are cost-effective. Studies conducted by García de Blanes Sebastián et al. (2025), Romero-Rodríguez et al. (2024), and Sergeeva et al. (2025) found that the price cost of technological tools had a positive effect on participants' adoption of mobile learning tools and AI-based chatbots, respectively. "PV" in this research means participants' cognitive evaluation of GenAI- related benefits for academic purposes and the monetary cost associated with such tools. Drawing on these findings, the following hypothesis was proposed:

H7. PV has a direct and significant effect on BI.

HB relates to the extent to which individuals engage in behaviors automatically through repeated practice. Recent research has demonstrated its significant influence on technology adoption and usage across different contexts. Its importance has been highlighted in the case of virtual reality technology (Yang et al., 2022), mobile learning (Yu et al., 2021), and AI (Gansser & Reich, 2021) in educational settings. Additionally, Zheng et al. (2024) demonstrated that "HB" is a significant predictor of Chinese EFL learners' "BI" to use GenAI tools for English learning. In the present study, "HB" refers to the extent to which master's and doctoral students use GenAI tools automatically as part of their academic activities. Hence, the following hypotheses were established:

H8. HB has a direct and significant effect on students' BI.

H9. HB has a direct and significant effect on students' UB.

BI is a fundamental concept that underlies the actual adoption of technology, bridging technology acceptance and use (Venkatesh et al., 2012). This refers to users' willingness to adopt a certain technology for a particular purpose (Venkatesh et al., 2003, 2012). Recent research presents evidence that "BI" is a crucial predictor of the actual use of technology (Nikolopoulou et al., 2020; Romero-Rodríguez et al., 2024; Sergeeva et al., 2025). In this research, "BI" refers to the willingness of graduate students to adopt GenAI tools for scholarly activities. Hence, this study hypothesized that:

H10. BI has a direct and significant impact on the UB.

UB pertains to the behavior of an individual's actual technology usage (Venkatesh et al., 2012). Within the scope of the present study, it refers to students' actual utilization of GenAI tools in their academic activities. In their initial research, Venkatesh et al. (2012) gave no details on how to measure technology use. For this reason, as in their scale, the frequency of GenAI usage was assessed using a seven-item scale that ranges from never to several times a day.

This study also included age, gender, and the level of study as moderators which could affect the associations between the constructs. In the original model developed by Venkatesh et al. (2012), these variables moderate the effects of core constructs on "BI" and "UB." Different from the original model, this study substituted the moderator "experience" with the level of study due to the difficulty in measuring students' experience in using GenAI tools because of their recent availability in a short time (Grassini et al., 2024; Romero-Rodríguez, 2023; Xu et al., 2024). Educational level has been considered an indicator related to individuals' cognitive capacity, analytical thinking skills, and critical reasoning (Lövdén et al., 2020; Putra & Gilda, 2023). In particular, GenAI systems require users to possess skills in effective query formulation, output evaluation, and contextual interpretation, rather than relying solely on experience based on usage duration. In the literature, educational level has already been tested as a moderator for UTAUT2 model and has shown a significant effect in some studies (I. S. Permana et al., 2021; Munyoka & Maharaj, 2017). Therefore, it has been assessed that educational level could serve as an indirect indicator of experience reflecting such advanced interactions. Consequently, the following hypotheses were proposed:

H11. The level of study moderates the effect of BI on UB.

H12. Age, gender, and level of study moderate the effect of FC, HM, and HB on BI.

H13. Age, gender, and level of study moderate the effect of HB on UB.

H14. Age and gender moderate the effect of PV on BI.

In the research model presented in **Figure 1**, this study tested 14 hypotheses adapted from the UTAUT2 framework developed by Venkatesh et al. (2012). PE, EE, SI, PV, FC, HM, and HB are considered independent variables of BI. Furthermore, the variables of BI, FC, and HB serve as predictors of UB. In addition, the variables, consisting of age, gender, and the level of study, are included in the model as moderator variables in accordance with the theoretical assumptions of UTAUT2. These moderators are assumed to alter the strength of the associations linking the predictor variables to BI and UB. This model provides a theoretical basis for the hypotheses tested in the study, allowing for a comprehensive assessment of the interactions between the variables.

METHODOLOGY

Research Design

A quantitative research approach was employed using data gathered through an online self-administered questionnaire and analyzed statistically to examine graduate students' acceptance of technology. Partial least squares structural equation modelling (PLS-SEM) was applied to examine the correlation between the

Table 1. Participants' demographic information

Variable	Value	Frequency (n)	Proportion (%)
Gender	Female	108	74.5
	Male	37	25.5
Age	21-25	45	31.0
	26-30	55	37.9
	31-35	27	18.6
	36-40	14	9.7
	41-45	4	2.8
Level of study	Master's student	72	49.7
	Doctoral student	73	50.3
Field of study	English language teaching	85	58.7
	English language and literature	22	15.1
	Translation studies	20	13.8
	Linguistics	17	11.7
	Comparative literature	1	0.7

variables which were expanded from the UTAUT2 model. Following the clarification of the theoretical concepts based on the literature, the necessary analyses were conducted to assess the validity and reliability of the collected responses. Following confirmation of the validity of the research findings, the proposed hypotheses were examined using path coefficient analysis and model fit indices.

Survey Instrument

The current study collected data through a questionnaire divided into two sections. The first section gathered information on participants' demographic profile, including gender, age, current state of education, and field of study as graduate students. The second section, consisting of 29 items adapted from Venkatesh et al. (2012), was created to explore determinants influencing graduate students' intention to use GenAI tools. To better suit the objective of this study, the original items in their study were changed from "using mobile internet" to "using GenAI tools" and "in my daily life" to "in my academic works." Participants responded to each item on a 5-point Likert scale, ranging from "strongly disagree" to "strongly agree." Since Venkatesh et al. (2012) gave no details on the method for evaluating UB, it was evaluated in the same manner as in their original study using a scale with seven options, ranging from "never" to "several times a day" for different types of GenAI tools, including Bing, ChatGPT, Copilot, DeepSeek, Gemini, Grammarly (PRO), Quillbot, Paperpal AI, Perplexity AI, and Scopus AI, which are among the most preferred tools. To facilitate access to more participants and ensure efficient data collection, the questionnaire was administered through an online survey developed using Google Forms.

Sampling and Data Collection

Data collection was conducted in June 2025 through a convenience sampling strategy, with participation on a voluntary basis. Participants consisted of graduate students studying in an English-related master's or doctoral program, including English language teaching, English language and literature, linguistics, translation studies, and comparative literature in Turkey. The criteria of Hair et al. (2019), at least 5 to 10 times the number of variables, were followed to evaluate the minimum sample size due to the difficulty of estimating the exact number of the population in Turkey. Considering the 29 items included in the questionnaire, a sample size ranging from 145 to 290 participants was considered adequate for the study. Participants were selected using snowball sampling strategy, where the first group of participants helped identify and invite additional participants. Additionally, social media platforms, such as LinkedIn, were utilized to reach a wider audience and encourage more individuals to participate. Participants were informed about the confidentiality of the study, and voluntary participation through an informed consent form provided prior to the survey. A total of 150 respondents completed the survey; however, 5 of them excluded from the study as they did not satisfy the specified field-of-study criteria, resulting in 145 valid questionnaires. In line with ethical guidelines, the study received ethical approval from the Research Ethics Committee of Hacettepe University.

Table 1 provides detailed information about the demographic profiles of the participants. The findings showed that the study group mostly consisted of female participants (74.5%). Most participants were within the 26-30 age range, while few respondents were 41 years old or older. They were balanced by their level of study (72 master's, 73 doctoral), studying mostly English language teaching (58.7%).

Data Analysis

This study employed structural equation modelling (SEM) using partial least squares (PLS) in the R environment (R Core Team, 2018). Several key factors contributed to the use of PLS-SEM. First, this approach was deemed suitable for the current dataset because it does not strictly require the assumption of normality. Furthermore, the ability of PLS-SEM to produce robust and reliable results, even with relatively small sample sizes (N < 200), made it especially appropriate for the present sample of 145 participants (Hair et al., 2022). In addition, the use of bootstrapping procedures improves the stability and reliability of parameter estimates. Accordingly, the combined use of PLS-SEM and bootstrapping was considered appropriate for obtaining reliable results despite the moderate sample size. The analysis encompassed three stages: the measurement model, model fit, and structural model. The examination of the measurement model involved analysis of the reliability and validity of data, including calculations of average variance extracted (AVE) (Farrell, 2010), composite reliability (CR) (Churchill, 1979), confirmatory factor analysis (CFA), and discriminant validity. After confirming adequate model fit, the structural model was analyzed by examining the path coefficients.

RESULTS

Measurement Model Assessment

Before testing the structural model, the reliability and validity of the constructs were evaluated by examining the internal consistency, convergent validity, and discriminant validity (Hair et al., 2022). Reflective constructs were evaluated based on the standardized factor loadings (λ) of their corresponding items, which indicate the extent to which each measurement item corresponds to its associated latent variable, with values exceeding 0.50, suggesting that the construct explains over half of the variance and is generally considered acceptable. **Table 2** indicates that all items exceeded the 0.50 threshold and are significant, except for FC4 (λ = 0.293) in the FC construct, which was excluded from further analysis and was not considered.

Table 2. Construct reliability and validity measures

Construct	Item	Loadings (λ)	α	CR	AVE
PE			0.86	0.86	0.61
	PE1	.790			
	PE2	.802			
	PE3	.776			
	PE4	.764			
EE			0.91	0.91	0.72
	EE1	.888			
	EE2	.792			
	EE3	.913			
	EE4	.811			
SI			0.95	0.95	0.87
	SI1	.935			
	SI2	.949			
	SI3	.919			
FC			0.74	0.79	0.52
	FC1	.633			
	FC2	.907			
	FC3	.772			
HM			0.96	0.97	0.91
	HM1	.964			
	HM2	.989			
	HM3	.904			
PV			0.83	0.84	0.64
	PV1	.657			
	PV2	.865			
	PV3	.838			

Table 2 (Continued).

Construct	Item	Loadings (λ)	α	CR	AVE
HB			0.86	0.85	0.60
	HB1	.832			
	HB2	.679			
	HB3	.685			
	HB4	.836			
BI			0.87	0.90	0.74
	BI1	.877			
	BI2	.789			
	BI3	.923			

Table 3. Discriminant validity of measurement model

Constructs	1	2	3	4	5	6	7	8	9
1. PE	-								
2. EE	.559	-							
3. SI	.439	.160	-						
4. FC	.672	.780	.428	-					
5. HM	.648	.526	.254	.548	-				
6. PV	.349	.215	.107	.289	.236	-			
7. HB	.648	.301	.340	.514	.573	.387	-		
8. BI	.789	.454	.324	.584	.691	.420	.835	-	
9. UB	.340	.199	.086	.188	.436	.106	.335	.360	-

Table 4. Goodness-of-fit indices

Fit index	Values obtained	Criteria
Chi-square/df (χ^2/df)	1.53 (492.533/322)	< 3
CFI	0.939	> .90
TLI	0.928	> .90
RMSEA [%90 CI]	0.068 [.058, .078]	< .08
SRMR	0.066	< .08

Note. df: Degrees of freedom

Cronbach's alpha (α) and CR were used to assess internal consistency (Hair & Alamer, 2022). Results with values ranging from 0.70 to 0.95 are considered indicator of a high level of internal consistency reliability (Hair et al., 2022). **Table 2** indicates the findings regarding the reliability of the constructs in the current study, with results higher than 0.7, suggesting good internal consistency. Convergent validity was evaluated using the AVE by indicating the extent to which item variance is explained by the latent constructs by their underlying constructs. Values above 0.50 are considered acceptable (Fornell & Larcker, 1981). **Table 2** indicates that all constructs met this criterion, supporting adequate convergent validity.

Discriminant validity, a key component of the PLS-SEM measurement model, was assessed using the Heterotrait-Monotrait (HTMT) ratio (Henseler et al., 2015). HTMT values below the threshold of 0.90 are recommended to ensure discriminant validity. **Table 3** demonstrates that all HTMT values across the construct pairs were lower than the established cutoff criterion, confirming satisfactory discriminant validity. Analysis of the measurement model provided strong evidence that the scale had good reliability and validity, demonstrating that the variables were consistently measured and accurately represented the intended theoretical concepts. Consequently, this model offers a solid and trustworthy foundation for conducting further structural analyses.

Goodness-of-Fit Indices

Following the measurement assessment, the overall model fit was examined using CFA. **Table 4** shows that the eight-dimensional measurement model demonstrated satisfactory alignment with the observed data. The Chi-square value for degrees of freedom (χ^2/df = 1.53) was well below the acceptable limit of 3, while the comparative fit index (CFI = 0.939) and Tucker-Lewis index (TLI = 0.928) exceeded the 0.90 threshold, indicating a good model fit. Moreover, the root mean square error of approximation (RMSEA= 0.068, 90% confidence interval [CI] = 0.058-0.078) and the standardized root mean square residual (SRMR= 0.066) values were below the 0.08 criterion.

Table 5. Hypotheses results

Hypotheses	Path	Beta (β)	t-values	p-values	Result
H1	PE -> BI	0.341	2.570	.000**	Supported
H2	EE -> BI	0.043	0.302	.763	Not supported
H3	SI -> BI	-0.040	-0.492	.623	Not supported
H4	FC -> BI	-0.044	-0.261	.771	Not supported
H5	HM -> BI	0.156	1.562	.050*	Supported
H6	PV -> BI	0.052	0.538	.591	Not supported
H7	HB -> BI	0.528	4.865	< .000***	Supported
H8	BI -> UB	0.272	1.386	.049*	Supported
H9	FC -> UB	-0.076	-0.412	.532	Not supported
H10	HB -> UB	0.153	0.746	.042*	Supported
H11, **H12**, **H13**, **H14**	Moderating effect of age, gender, and the level of study				Not supported

Note. *p < 0.05; **p < 0.01; & ***p < 0.001

When all fit indices were considered collectively, the eight-factor theoretical structure proposed in this study was strongly supported by the data. The fit statistics indicated that the model demonstrated an adequate level of fit across both the global fit indices and item-level parameters. These findings suggested that the eight-factor structure adequately captured the intended conceptual dimensions and that the model effectively represented the theoretically expected structure in this study.

Structural Model Assessment

The structural model was evaluated by estimating path coefficients between constructs using PLS-SEM in the R environment (Hair et al., 2022). Bootstrap analysis was performed with 5,000 samples at a 95% CI. Bootstrapping is a nonparametric procedure, which empirically estimates parameter distributions, providing more accurate standard errors and p-values, even when data are not normally distributed, thereby confirming that the observed relationships are not due to chance, following Ringle et al. (2022).

Table 5 shows the findings of the structural model assessment, indicating the relationships between variables. The analysis revealed that five hypotheses were confirmed, whereas the others were not. For BI, three of the seven predictors were significant: HB had the strongest effect ($\beta = 0.528$, $p < .001$), followed by PE ($\beta = 0.341$, $p < .01$) and HM ($\beta = 0.156$, $p < .05$), supporting **H1**, **H5**, and **H7**. In contrast, the findings provided evidence that contradicted **H2**, **H3**, **H4**, and **H6** because there was no significant effect of EE, SI, PV, and FC on BI. Regarding UB, two hypotheses were supported. BI ($\beta = 0.272$, $p < .05$) and HB ($\beta = 0.153$, $p < .05$) had significant positive effects, while FC were insignificant in determining students' UB of GenAI tools ($\beta = -0.076$, $p > .05$). This study also tested the moderating effects of age, gender, and the level of study. The results revealed that none of the three moderating variables had a significant ($p > 0.05$) effect on the relationship between constructs. Therefore, **H11**, **H12**, **H13**, and **H14** were rejected.

DISCUSSION

The present research expands the literature on how GenAI tools are accepted by graduate students. The limited investigation into the use of GenAI tools within the educational activities of master's as well as doctoral students highlights the importance of our results in deepening the understanding of how these tools are adopted within the realm of higher education. Utilizing the core constructs of the UTAUT2 model, the study satisfied all established criteria related to reliability and validity standards for the variables. This study confirms the central role of PE, HM, and HB in shaping students' BI toward GenAI use, aligning with Strzelecki's (2024a) study on students' acceptance of ChatGPT. More precisely, HB had the strongest effect on BI, suggesting that participants' intention to use GenAI tools is strongly driven by routine use, considering them as an integral part of their learning HBs. This finding aligns with earlier studies that found a positive correlation between HB and technology acceptance across different settings, including e-learning adoption (Osei et al., 2022), mobile learning applications (García de Blanes Sebastián et al., 2025), and Google Classroom (Alotumi, 2022). Regarding GenAI tools, this result is also consistent with Strzelecki's (2024b) findings that HB emerged as the most predominant predictor of BI in his study. Consistent with this, Sergeeva et al. (2025) reported positive effect of HB on undergraduate students' use of GenAI in Russian context. However, our findings differ from those of Rahim et al. (2022), Foroughi et al. (2024), Habibi et al. (2023), and Salifu et al. (2025), who did not find any direct effect of HB on BI to adopt AI tools. Similarly, this research confirms the significant effect of HB on UB, in line with findings reported by Romero-Rodríguez et al. (2023), Hu et al. (2025), Sergeeva et al. (2025), and Strzelecki (2024a), who found that participants' actual use of AI tools was influenced by routine or automatic behavior patterns. This suggests that graduate students routinely utilize these tools throughout their academic work and improve their skills in using them for scholarly activities.

The results also revealed that PE was identified as another major determinant influencing BI. Accordingly, graduate students appear to perceive GenAI tools as enabling more efficient completion of academic tasks. This finding is supported by earlier studies on the use of different technologies, including learning management systems (Raza et al., 2022), video conferencing tools (Edumadze et al., 2022), and mobile learning applications (García de Blanes Sebastián et al., 2025) regarding correlations between students' intention to use emerging technologies and their performance benefits. Specifically, within the realm of GenAI tools, such as ChatGPT and Gemini, our findings are consistent with those identifying PE as an important predictor of students' intention to use ChatGPT (Duong et al., 2024; Grassini et al., 2024). Likewise, PE was found to be a significant predictor of intention to use among graduate students in Ghana (Salifu et al., 2025). They revealed that the perceived benefits users experience when adopting GenAI technologies play a critical role in their decision-making processes. However, our results deviate from those of some studies (Haq et al., 2025; Hu et al., 2025; Sergeeva et al., 2025) that reported an insignificant effect of PE on students' adoption of the emerging technology.

HM emerged as a key predictor of BI to adopt GenAI tools among master's and doctoral students. Consistent with earlier research, a significant positive relationship has also been reported regarding students' acceptance of technology across diverse domains. For instance, some scholars have highlighted HM as a key factor driving the adoption of mobile learning systems (Kumar & Bervell, 2019), mobile phone technology (Nikolopoulou et al., 2020), and an AI-powered chatbot (Strzelecki, 2024b). Similarly, this finding supports prior research (Sergeeva et al., 2025), indicating that HM significantly influence undergraduate students' BI to use GenAI. Likewise, this result further corroborated by Salifu et al. (2025), who found HM to be a significant predictor of graduate students' intention to use GenAI in Ghanaian context. However, while HM is often treated in the literature only as a mere predictor of motivation, both studies show that this variable plays a more decisive role. This suggests that, despite different socio-cultural contexts, pleasure and experience-oriented interaction is becoming increasingly central to the use of AI technologies. Nevertheless, these similar findings obtained in different contexts, such as Turkey and Ghana, should be evaluated not only in terms of individual motivation but also in relation to contextual factors, such as SI, digital infrastructure, and the educational environment. These results provide further support for the proposition that GenAI tools are seen as an entertaining platform for academic tasks among graduate students. In addition to their practical utility, students focused on the pleasure of using these tools. In contrast, our results are not the same as those of Grassini et al. (2024) and Surya Bahadur et al. (2024), who discovered that HM did not have a significant impact on the BI to use ChatGPT.

This study did not reveal a significant effect of EE and SI on BI to use GenAI tools among master's and doctoral students, suggesting that the ease of using these tools and encouragement from the social circle do not promote technology adoption. Given that the use of GenAI is generally considered a phenomenon that spreads through social interaction, this result is noteworthy. However, this can be explained by certain specific dynamics related to the nature of GenAI use in an academic context. In particular, it can be argued that students may refrain from openly sharing their use of such tools within their social circles due to some concerns about academic integrity (Ghimire, 2024), practical misuse (Koltovskaia et al., 2024), and ethical issues (Yan et al., 2024). In the context of academic integrity, the use of GenAI tools can create uncertainties regarding issues such as plagiarism, originality, and the assessment of individual performance; this situation can lead students to feel academically at risk when using these tools. Furthermore, concerns about potential misuse also shape students' attitudes toward these tools. The use of GenAI tools for completing assignments, preparing for exams, or directly generating outputs for academic tasks raises concerns that it may superficialize the learning process and reduce students' cognitive engagement. Ethical concerns similarly emerge as a significant limiting factor in the social aspect of GenAI. Issues such as the continuity, durability, and accountability of GenAI-generated content have far-reaching consequences. These multifaceted factors may explain why the SI variable has had a limited effect, leading GenAI use to remain largely an individual and implicit practice. Nevertheless, the finding that EE and SI do not have a significant effect on BI aligns with some studies on e-learning platforms (Zacharis & Nikolopoulou, 2022), and GenAI adoption among graduate students (Salifu et al., 2025), who found that user-friendly design and intuitive features did not promote technology acceptance.

Similarly, the findings indicated that PV and FC did not affect students' BI. The non-significant effect of FC indicates that access to the required resources was not a determining factor in students' BI. This may have been due to their access to the necessary systems or support. In a similar vein, FC had an insignificant effect on UB, suggesting that the availability of technical and organizational resources may not directly determine the actual adoption of AI-assisted tools among users. This aligns with some studies on technology adoption within higher education. For example, research has shown that FC were found to have no significant effect on the acceptance of Google Classroom (Alotumi, 2022), mobile learning environments (García de Blanes Sebastián et al., 2025), and ChatGPT (Romero-Rodríguez et al., 2023). Likewise, the non-significant effect of PV suggests that master's and doctoral students do not prioritize financial considerations when adopting GenAI tools. Another possible explanation may be that these tools are offered free of charge or at minimal cost. This result supports evidence from previous research on mobile learning environments (Nikolopoulou et al., 2020), e-learning (Osei et al., 2022), and AI tools (Hu et al., 2024). On the other hand, this finding differs from Sergeeva et al. (2025), highlighting the importance of both cost-benefit considerations and the availability of technical and organizational support. They underscored offering more cost-effective solutions and developing accessible infrastructure and effective support systems to support the adoption of GenAI technologies. Consistent with this, Salifu et al. (2025) reported that, in the context of graduate students in Ghana, FC were a significant factor in GenAI technology adoption. They also emphasized the importance of enhancing functional benefits to promote more effective use.

In this model, BI exhibited an explained variance of 83%, indicating a strong level of explanatory power. Additionally, BI was found to be a direct and significant factor influencing UB. The model also accounts for 29% of the variance in UB, which is considered a moderate level of explanatory power. It is seen that this conceptual model provides a particularly robust explanation, particularly for understanding the formation of intentions.

Three moderating variables, age, gender, and the level of study, showed no significant influence on the relationships among the constructs in the model. In accordance with the present results, previous studies have demonstrated that students' technology acceptance did not differ across diverse student groups (Romero-Rodríguez et al., 2023; Strzelecki, 2024a; Xu et al., 2024). This result may come from the fact that students were from similar educational background, resulting in more consistent technology acceptance patterns for GenAI tools in their academic tasks.

GenAI tools may have different functional features. However, all the tools discussed in this study, including Grammarly Pro, currently incorporate GenAI capabilities. For this reason, the tools in question have been evaluated under a common GenAI category within the scope of this study. Although GenAI tools are addressed under a single category in this study, it is assessed that different types of tools may differ in terms of adoption. Specifically, within the framework of the UTAUT2, the adoption of interaction-based AI systems, such as ChatGPT, Gemini, and Copilot, might be better explained by experience-oriented factors, such as HM and HB. This can be interpreted by the fact that experiential tools are more readily integrated into everyday use and, through their interactive nature, tend to enhance users' sense of enjoyment. In contrast, the use of more functional and task-oriented tools, including Grammarly Pro and Paperpal AI, is likely to be associated with more instrumental variables, such as PE and FC. Given their capacity to produce responses aligned with users' immediate needs, such tools are likely to contribute more directly to PE. Moreover, the integration of tools, such as Grammarly, into commonly used platforms (e.g., word processors and web browsers) may further enhance FC, thereby supporting more effective and efficient use.

A distinctive aspect of this study is its comprehensive emphasis on different types of GenAI tools, not only on a recently emerged and adopted tool, ChatGPT. Additionally, the present findings provide additional insight into a relatively under-researched population of graduate students studying exclusively in English-related programs. Consequently, the present findings enrich the existing research on GenAI technology adoption by the understudied sample group of master's and doctoral students in scholarly activities.

CONCLUSION

This research set out to investigate graduate students' adoption and utilization of GenAI tools in academic contexts using the UTAUT2 framework. The research confirmed that HB, PE, and HM were identified as significant predictors of BI to use these tools among master's and doctoral students. In contrast, the other four variables, EE, SI, PV, and FC, showed no significant influence on students' intention to adopt such tools. When examining the factors influencing UB, the final dependent variable in the model, two of the three hypotheses were supported. As expected, BI and HB had significant and positive effects on UB. In contrast, FC showed no significant influence on actual usage behavior. These results suggest that for this specific and technologically inclined group of users, technology acceptance extends beyond traditional models, being primarily shaped by automated behavioral patterns, perceptions of practical usefulness, and enjoyment rather than perceived value, social endorsement, and ease of use.

These findings carry several pedagogical implications for academic practitioners, universities, and developers of educational technologies. Given that PE and HB have been identified as the primary determinants of GenAI acceptance, providing students with mere exposure or access to such tools (i.e., FC) appears insufficient. Rather, incorporating these tools into the curriculum and research practices is essential to help students derive tangible academic benefits, such as expediting thesis writing and simplifying literature review processes, and in turn, foster early-stage habitual use. The significant role of HM further indicates that engaging and meaningful activities can encourage sustained use. In particular, PE for ELT students can be strengthened by making the tangible outcomes of effective teaching practices visible. Students who achieve quick and effective results may become more productive in academic writing and research, while also making faster, more systematic, and more informed decisions with support from GenAI tools in processes, such as creating lesson plans, diversifying activities, and producing sample dialogues and instructional materials. In addition, the role of HB is particularly significant in the field of translation, as the regular use of GenAI tools in academic text translation and post-editing processes can yield substantial benefits. Students' critical evaluation, editing, and restructuring of AI-generated texts can enhance both their academic writing skills and the quality of their translations. Furthermore, HM highlights the potential for more effective use of these tools for academic purposes. In fields such as linguistics, language and literature, and comparative literature, GenAI tools can facilitate more interactive and exploratory learning experiences in text analysis, discourse analysis, literature review, and academic interpretation. These tools can support students in engaging more actively with academic content and in developing their analytical thinking skills. The use of GenAI tools in these areas will allow students to experience the tangible academic benefits of these technologies. Regular and structured implementation of such applications will encourage the use to become habitual over time, while the interactive and exploratory features offered by the tools can contribute to greater student enjoyment of the process. In this context, it is recommended that GenAI tools be integrated into academic production processes in a systematic and guided manner, tailored to the specific needs of each discipline.

Meanwhile, the non-significant effects of EE, SI, PV, and FC imply that students already find these tools accessible and easy to use. Therefore, pedagogical efforts should focus less on usability and more on fostering purposeful, informed, and responsible engagement with GenAI tools. By offering structured training on the use of these tools, institutions can foster more effective and informed student engagement. Even though PV did not emerge as a significant predictor in the present study, expanding institutional access to academic tool subscriptions may still promote more effective and purposeful use of such technologies among students.

Notwithstanding its contributions, this research had certain limitations. This study included only graduate students studying English-related programs. Accordingly, future studies could extend the sample to other programs to generalize our results. Besides, reliance on participants' self-reports may have affected the objectivity of the findings. Further investigations could encompass educators' responses in addition to students' responses to offer a more thorough insight into the acceptance of technology in educational activities. A further limitation of this study concerns moderating variables. To be specific, digital literacy and prompt engineering skills are variables that could more directly reflect the use of GenAI. The fact that these variables were not measured in the current study is considered a limitation. It is recommended that these variables be included as moderators in future research.

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