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Research Article

Understanding higher education students' adoption of generative AI technologies: An empirical investigation using UTAUT2

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ABSTRACT

Generative artificial intelligence (GAI) technologies are gaining traction in higher education, offering potential benefits such as personalized learning support and enhanced productivity. However, successful integration requires understanding the factors influencing students' adoption of these emerging tools. This study investigates the determinants shaping higher education students' adoption of GAI through the lens of the unified theory of acceptance and use of technology 2 framework. Data was collected from Pyatigorsk State University students and analyzed using structural equation modeling. The findings reveal habit (HB) as the most influential predictor of GAI adoption among students, followed by performance expectancy. Hedonic motivation, social influence (SI), and price value positively influenced behavioral intention (BI) to use these technologies. Surprisingly, facilitating conditions (FCs) exhibited a negative effect on BI, suggesting potential gaps in support systems. The study identifies no significant gender differences in the underlying factors driving adoption. Based on the results, recommendations are provided to foster HB formation, communicate benefits, enhance hedonic appeal, leverage SI, address price concerns, and strengthen FCs. Potential limitations include the cross-sectional nature of the data, geographic constraints, reliance on self-reported measures, and the lack of consideration for individual differences as moderators. This research contributes to the growing body of knowledge on GAI adoption in educational contexts, offering insights to guide higher education institutions in responsibly integrating these innovative tools while addressing student needs and promoting improved learning outcomes.

Keywords: UTAUT2, generative AI, higher education, adoption of AI, hedonic motivation, habit

INTRODUCTION

Generative artificial intelligence (GAI) refers to a class of machine learning models and algorithms capable of generating new data, such as text, images, audio, or video, based on the patterns learned from training data (Alasadi & Baiz, 2023; Kohnke et al., 2023; Ofem & Chukwujama, 2024. These models use deep learning techniques, like variational autoencoders, generative adversarial networks, and large language models, to capture the underlying structure and patterns in the training data, allowing them to create novel and realistic outputs (Ramesh et al., 2022; Zastudil et al., 2023; Zhang & Aslan, 2021). Notable examples of GAI systems include image generators like DALL-E, Stable Diffusion, and Midjourney (Derevyanko & Zalevska, 2023), text generators like GPT-3/4 (Su & Yang, 2023), and audio generators like WaveNet (Jiao et al., 2021). The ability to generate human-like content has made GAI a disruptive technology with applications across various domains, including education, creative industries, and content generation (Anantrasirichai & Bull, 2022; Poola & Božić, 2023; Vallis et al., 2023; Zhang et al., 2023).

Students hold positive attitudes towards using GAI in higher education (Burkhard, 2022; Chan & Hu, 2023; Kwak et al., 2022; Lee et al., 2024; Chung & Jeong, 2024). They perceive benefits such as personalized learning support, enhanced productivity, and efficiency, leading to intentions to utilize GAI for various educational purposes (Vallis et al., 2023). However, concerns exist regarding accuracy, privacy, ethical issues, and the impact on personal development and societal values (Chan & Lee, 2023). While students recognize the potential advantages of GAI tools like ChatGPT for writing assistance, research capabilities, and brainstorming support (Bozkurt, 2023; Chan & Hu, 2023), they also express worries about academic integrity, loss of creativity, and the need for critical thinking in assessments (Bouteraa et al., 2024; Yusuf et al., 2024). Educators and policymakers can leverage these insights to tailor the integration of GAI technologies in higher education effectively, addressing student concerns and promoting responsible use for improved learning outcomes.

The aim of this study is to investigate the factors influencing higher education students' adoption and usage of GAI technologies. By exploring these factors, educators and policymakers can tailor effective strategies for integrating GAI in higher education, addressing student apprehensions and promoting responsible utilization to enhance learning outcomes.

Benefits of AI Implementation

The integration of GAI technologies in higher education offers numerous potential advantages. These tools can provide personalized tutoring and feedback tailored to individual students' needs, misconceptions, and levels of understanding, ultimately improving learning outcomes (Baskara et al., 2023; Damiano et al., 2024; Ishmuradova et al., 2025). For instance, AI-powered tutoring systems have demonstrated improved student performance and understanding by delivering customized explanations and learning support (Rizvi, 2023). Furthermore, GAI can automate tasks such as essay grading, enabling instructors to dedicate more time to other teaching aspects (Bozkurt, 2023; Chan & Hu, 2023). These AI-based grading systems have exhibited high accuracy, providing feedback comparable to human graders while significantly reducing the grading workload. Moreover, the integration of GAI models in education can lead to increased productivity, efficiency, and accessibility for both students and educators (Michel-Villarreal et al., 2023).

Moreover, the implementation of GAI models can lead to increased productivity, efficiency, and accessibility in educational settings (Michel-Villarreal et al., 2023). AI-powered virtual assistants and chatbots can provide instant support and guidance to students, addressing queries and facilitating their learning journey (Winkler & Söllner, 2018). Additionally, AI-enabled adaptive learning platforms can personalize course content and learning paths based on individual students' strengths, weaknesses, and learning styles, enhancing engagement and knowledge retention (Alsubhi et al., 2022; Yangui et al., 2022).

Challenges and Limitations of AI Implementation

While the potential benefits of AI in higher education are substantial, several challenges and limitations must be addressed to ensure fair and responsible implementation (Bouteraa et al., 2024; Yusuf et al., 2024). Ethical concerns surrounding data privacy and algorithmic bias are critical considerations (Ferrara, 2024; Golda et al., 2024). Institutions must develop robust data governance policies and ethical frameworks to protect student privacy and prevent unintended biases from influencing educational outcomes (Prinsloo et al., 2022).

Furthermore, technological barriers, such as the need for robust infrastructure, computational resources, and faculty/student training, can hinder effective AI implementation (Cubric, 2020; Okunade, 2024; Zemplényi et al., 2023). Higher education institutions must invest in reliable and scalable technological infrastructure, secure data storage and management systems, and the necessary computing power to run complex AI algorithms (Zawacki-Richter et al., 2019). Additionally, comprehensive training programs and ongoing professional development are crucial to equip faculty and students with the necessary skills to effectively utilize and manage AI technologies (Luan et al., 2020; Zhang & Aslan, 2021).

THEORETICAL FRAMEWORK OF THE UNIFIED THEORY OF ACCEPTANCE AND USE OF TECHNOLOGY 2

The concept of the unified theory of acceptance and use of technology (UTAUT) represents a theoretical framework extensively utilized in the realm of information systems to elucidate the process by which individuals embrace and utilize technology. Initially crafted by Venkatesh et al. (2003), the original UTAUT model builds upon and consolidates various established technology acceptance models (TAMs), such as the TAM (Davis, 1989), theory of reasoned action (Fishbein & Ajzen, 2011), and theory of planned behavior (Ajzen, 1991). In the UTAUT model, four core constructs–performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FCs)–are essential in influencing individuals' intentions to adopt a technology, subsequently impacting their actual usage behavior. Through extensive validation and application in diverse technological settings, the model displays its efficacy in predicting technology acceptance.

Nonetheless, with the evolution of technology and the emergence of novel adoption patterns, a necessity arose among researchers to enhance and refine the original UTAUT model. This necessity culminated in the inception of the UTAUT2 framework by Venkatesh et al. (2012). UTAUT2 integrates supplementary constructs and contextual variables to furnish a more comprehensive comprehension of technology acceptance. The newly introduced constructs in UTAUT2 encompass hedonic motivation (HM), price value (PV), and habit (HB), which encapsulate intrinsic motivation, perceived monetary value, and repetitive behavior linked to technology utilization, respectively. Moreover, UTAUT2 considers the moderating influence of factors like gender, age, and cultural background, which can impact the associations between the core constructs and technology acceptance (Venkatesh et al., 2012). The application and validation of the UTAUT2 framework across various technological domains, encompassing information systems, e-commerce (Zhou et al., 2021), social media (Zhou et al., 2021), and mobile technology (Martinez & McAndrews, 2023), teacher education (Adelana et al., 2023), contribute significantly to a deeper insight into individuals' engagements with technology.

The UTAUT2 model consists of two main parts, dependent and independent variables. one of them is the main constructs related to using technology: behavioral intention (BI) and adoption or actual use of technology. The second one is related to the affecting factors: PE, EE, SI, FCs, HM, PV, and HB.

Adoption and Actual Use

Actual use or adoption is the ultimate dependent variable in the UTAUT2 model. Adoption refers to the decision to accept and start using a particular technology (Venkatesh et al., 2012) . Actually use, on the other hand, refers to the extent to which an individual actively employs the technology for its intended purpose (Tamilmani et al., 2021). It represents the realized or observed behavior, as opposed to BI, which is the individual's planned or intended behavior. Together, these concepts capture the process of technology acceptance, from initial adoption to ongoing usage.

Behavioral Intention

BI is defined as "the degree to which a person has formulated conscious plans to perform or not perform some specified future behavior" (Warshaw & Davis, 1985). BI refers to an individual's intention or plans to perform a specific behavior (Ajzen, 1991). In the context of technology acceptance, BI represents the user's intention to adopt or use a particular technology (Davis, 1989). It represents an individual's willingness or intention to engage in a particular behavior, such as using specific technology. It is a central construct in the UTAUT2 model. According to the UTAUT2 framework, BI is a direct determinant of actual technology use (Venkatesh et al., 2012).

H1: BI affects the ADP.

Performance Expectancy

PE is one of the core constructs of the UTAUT2 model (Venkatesh et al., 2012). It refers to the degree to which an individual believes that using a particular technology will help them attain gains in job performance (Camilleri, 2024). In the context of consumer technology adoption, PE is defined as "the degree to which using a technology will provide benefits to consumers in performing certain activities"(Venkatesh et al., 2012).

According to the UTAUT2 framework, PE is a direct determinant of BI to use a technology, which in turn influences actual technology use (Venkatesh et al., 2012). Several empirical studies have provided evidence for the positive influence of PE on BI and technology use across various contexts. For example, in the study conducted by Camilleri (2024), PE is one of the main factors affecting the use of ChatGPT. According to the results of another study (Sari et al., 2024) examining the use of technology among nursing students, students' performance expectations are positively related to their intention to adopt information and communication technologies and social media. According to Kwak et al. (2022), to increase nursing students' intent to use AI-based healthcare technologies, interventions that promote PE is required to foster BI via a positive attitude.

H2: PE affects the ADP.

H3: PE affects BI.

Effort Expectancy

EE, another critical construct in UTAUT2, relates to individuals' perceptions of the ease of use and simplicity associated with technology (Venkatesh et al., 2012). The degree of ease associated with the use of technology (Rahi et al., 2019). EE relates to individuals' perceptions of the ease of use and simplicity associated with technology (Abbad, 2021). It is analogous to the perceived ease of use construct in the TAM (Venkatesh et al., 2003).

In the context of GAI, EE would involve people views on technology's user-friendliness and the level of effort required to utilize it effectively. The ease of use and user-friendliness of GAI tools have also been identified as crucial factors affecting people acceptance (Gupta et al., 2024).

Scherer and Teo (2019) revealed that the perceived ease of use of AI-powered tutoring systems significantly influenced students' intentions to use tools for learning purposes. Additionally, the perceived complexity and difficulty in using GAI tools for creative tasks acted as a barrier to their adoption (Russo, 2024).

Research indicates mixed opinions among students regarding the EE of GAI tools. While some students appreciate the intuitive nature of AI interfaces and find them easy to navigate (Chan & Hu, 2023), others have expressed concerns about the complexity of certain AI applications (Burkhard, 2022).

H4: EE affects BI.

Social Influence

As per the UTAUT2 framework, SI plays a crucial role in shaping the BI towards technology usage. Defined as the perception of significant others' endorsement of a specific technology, SI encompasses the impact of one's social circle, such as family and friends, on the decision to embrace a technology (Venkatesh et al., 2012). This concept reflects the extent to which an individual feels pressured by others to adopt a technology (Strzelecki & ElArabawy, 2024). The SI component within the UTAUT2 framework draws upon established theories and empirical findings, indicating that individuals are more inclined to accept and utilize technology when they perceive support and encouragement from influential figures within their social sphere.

The findings of the research highlight the positive correlation between SI and the intention to utilize GAI (Bouteraa et al., 2024). Strzelecki and ElArabawy (2024) illustrated the significant impact of SI on BI, particularly evident in the ChatGPT usage patterns among Egyptian and Polish university students.

H5: SI affects BI.

Price Value

The notion of PV is connected to the cognitive assessments carried out by individuals concerning the monetary expenses and advantages tied to the implementation and application of a particular technology (Venkatesh et al., 2012). This concept aims to encapsulate the impact of financial aspects on an individual's choice to embrace and use a new technological system or innovation (Tamilmani et al., 2018).

The PV construct is distinct from the UTAUT 2 (UTAUT2) framework, an expansion of the original UTAUT model formulated to comprehend technology acceptance and usage in a consumer environment (Venkatesh et al., 2012). Within the realm of higher education, PV would encompass the evaluations made by students concerning the financial repercussions of adopting and utilizing GAI tools and technologies (Ivanov et al., 2024).

Despite the limited direct empirical investigations on PV concerning GAI technologies in higher education contexts, the broader literature on technology acceptance indicates that cost could act as a significant hindrance to the adoption of novel technologies (Strzelecki & ElArabawy, 2024; Wang & Zhang, 2023). Consequently, the perceived affordability and value proposition of GAI tools might impact on the willingness of students to adopt and incorporate these technologies into their academic endeavors. Further exploration is necessary to clarify how PV interacts with and correlates to other factors within the UTAUT2 framework in influencing the acceptance and utilization of AI technologies in educational settings.

H6: PV affects BI.

Hedonic Motivation

HM pertains to the intrinsic drivers, enjoyment, and satisfaction acquired from utilizing a specific technology, surpassing its mere utilitarian purposes (Venkatesh et al., 2012). It encompasses the intrinsic incentives and emotional encounters linked to technology utilization. The HM component of the UTAUT2 framework, which clarifies users' acceptance and utilization of information technologies, serves as a crucial determinant. It is highly improbable that this aspect focuses on the intrinsic joy and delight that individuals derive from using a specific technology, and it has been proven to be a major driving factor for technology adoption in various scenarios (Ivanov et al., 2024; Martinez & McAndrews, 2023). In line with the UTAUT2 model, HM directly impacts the intention to use technology, subsequently influencing actual technology usage behavior (Venkatesh et al., 2012).

Within the realm of online gaming, HM has emerged as a strong predictor of usage patterns. Gamers are incentivized by the pleasure, thrill, and social interaction opportunities that games provide (Baabdullah, 2018; Ramírez-Correa et al., 2019). Take, for instance, Liu and Li (2011) pointed out that HM had a considerable influence on the sustained usage of mobile games among young individuals. The utilization of social media platforms is often driven by hedonic motives, including entertainment, social engagement, and self-representation (Mucundorfeanu & Lupaș, 2018). Stollfuß (2020) examined Instagram usage and unveiled that HM had a favorable effect on users' continuous participation with the platform. Moreover, HM has been associated with the adoption and utilization of mobile applications (Akdim et al., 2022; Al-Azawei & Alowayr, 2020).

H7: HM affects BI.

H8: HM affects the ADP.

Habit

The concept of HB, as defined in the UTAUT2 framework, refers to the degree to which individuals perform actions automatically due to previous learning (Venkatesh et al., 2012). It delineates the automatic or ingrained behaviors exhibited by individuals when utilizing a specific technology, which are established through repetitive and consistent usage over time (Tamilmani et al., 2018).

In the UTAUT2 model, HB is theorized as a direct influencer of effective technology utilization, in conjunction with BI (Venkatesh et al., 2012). This suggested link is rooted in diverse theoretical viewpoints, including those that underscore the significance of prior behavior and repeated use in shaping future conduct (Tamilmani et al., 2019).

Several empirical investigations spanning various fields have offered empirical evidence supporting the importance of HB in shaping technology acceptance and usage. In the realm of utilization of information systems, HB has emerged as a reliable predictor of sustained usage. Within the sphere of mobile technology, the strength of HB has been associated with continuous use of LMS (Raman & Don, 2013). The habitual engagement with social media platforms has also been examined, with HB identified as a significant predictor of ongoing involvement, even as initial motivations for platform usage diminish over time (Mucundorfeanu & Lupaș, 2018). Furthermore, HB has been implicated in the emergence of problematic technology usage patterns and technology dependency, wherein individuals develop strong HBs related to technology usage that disrupt their daily routines (Billieux et al., 2008; Paiman & Fauzi, 2023). These outcomes underscore the critical role of HB as a key factor influencing technology acceptance and usage, with implications for the design, implementation, and advancement of diverse technological systems and innovations.

H9: HB affects BI.

H10: HB affects the ADP.

Facilitating Condition

The concept of FCs plays a crucial role in the UTAUT2 framework, which extends the original UTAUT model proposed by Venkatesh et al. (2003). FCs are described as the level to which an individual believes that there is organizational and technical infrastructure in place to support the utilization of a system (Venkatesh et al., 2012). In the realm of consumer technology adoption, this concept pertains to the perceived access to resources and assistance that aid in the utilization of a specific technology (Ramírez-Correa et al., 2019).

In the framework of UTAUT2, FCs are suggested to directly influence actual technology usage and BI (Ramírez-Correa et al., 2019; Sharif et al., 2019). This assertion is in alignment with established theories and empirical findings, indicating that individuals are more inclined to embrace and utilize a technology when they believe in the presence of a conducive environment with the essential resources, knowledge, and support.

The integration of FCs into the UTAUT2 model recognizes the potential moderating impact of environmental and contextual elements on the acceptance and usage of technology. Specifically, the model proposes that the existence of favorable FCs can bolster the transformation of BI into practical technology usage (Venkatesh et al., 2012). Conversely, the inadequacy of resources and support may hinder the realization of intended behavior, even in cases where individuals possess a strong desire to adopt and use specific technology.

H11: FC affects BI.

H12: FC affects the ADP.

Figure 1 shows the hypothetical model.

METHODOLOGY

To investigate the factors influencing the adoption of GAI (ADP) technologies among university students, this study employed a quantitative research approach using survey data and partial least squares structural equation modeling (PLS-SEM). The research model was grounded in the UTAUT2, a widely adopted theoretical framework for understanding technology acceptance and usage behavior.

Data Collection Tools

To construct the data collection instrument, an initial literature review was conducted to identify constructs (e.g., adoption, behavioral intension, HB, and HM) within the UTAUT2 model (Abbad, 2021; Raman & Don, 2013; Ramírez-Correa et al., 2019; Tamilmani et al., 2018). Scales utilizing the UTAUT2 model for measuring technology usage were examined in the literature, and items pertaining to each construct were developed. The scale items underwent a validity check by a group of experts in the technology field. The complete version of the scale used as the measurement tool is provided in **Appendix A**. Data analysis employed the PLS-SEM approach, both to assess the reliability of the scale and to perform path analysis.

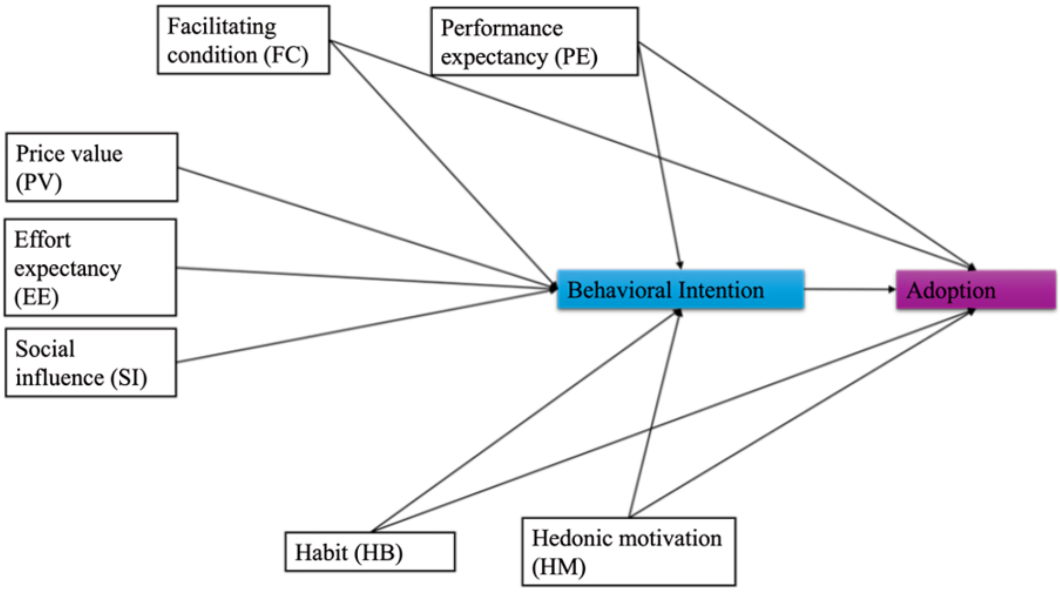

Figure 1. Hypothetical model (the authors' own work)

Sample

The study sample consists of undergraduate students enrolled at Pyatigorsk State University. Among the 379 participants, 74.7% are female, and 25.3% are male. When examining age groups, individuals aged between 18 and 20 years constitute 73.2% of the sample. Those aged between 21 and 23 years represent 26.8%, while participants aged 24 years and above account for 2.7%.

Data Analysis

The data analysis for this study was conducted using the PLS-SEM approach with the SeminR package (Ray & Danks, 2020) in R statistical software. PLS-SEM is a widely used technique for analyzing complex models involving multiple constructs and relationships, making it suitable for investigating the factors influencing the ADP technologies in higher education. The PLS-SEM approach involves two main stages: the assessment of the measurement model and the evaluation of the structural model. The measurement model examines the relationships between the observed indicators (survey items) and the underlying latent constructs, ensuring the reliability and validity of the measurement scales. The structural model, on the other hand, evaluates the hypothesized relationships between the latent constructs based on the theoretical framework.

In the first stage, the measurement model was assessed by examining factor loadings, internal consistency reliability (Cronbach's alpha and composite reliability), and convergent validity (average variance extracted [AVE]). Items with factor loadings below the recommended threshold of 0.7 were eliminated to ensure the reliability and validity of the measurement scales. Discriminant validity was evaluated using the Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT).

The second stage involved the assessment of the structural model, which tested the hypothesized relationships between the UTAUT2 constructs and the dependent variables (BI and ADP). The path coefficients, representing the strength and direction of the relationships, were estimated using the bootstrapping technique. The significance of the path coefficients was evaluated using t-statistics and confidence intervals (CIs). To assess the predictive power of the model, the coefficient of determination (R-squared [R^2]) and the effect sizes (f-squared [f^2]) were calculated for the endogenous constructs. The R^2 value indicates the proportion of variance explained by the exogenous constructs, while the f^2 value reflects the impact of each exogenous construct on the endogenous constructs.

Additionally, multi-group analysis was performed to examine potential differences in the relationships between the UTAUT2 constructs and the dependent variables across gender groups. This analysis helped identify any variations in the factors influencing GAI adoption among female and male students.

Table 1. Factors loading, Cronbach's alpha, rhoC, AVE, and rhoA for each dimension

Dimension	Items	Factors loading	Cronbach's alpha	rhoC	AVE	rhoA
Performance expectancy	PE2	0.850	0.889	0.923	0.750	0.895
	PE3	0.901				
	PE4	0.836				
	PE5	0.876				
Effort expectancy	EE3	0.895	0.886	0.929	0.814	0.895
	EE4	0.925				
	EE5	0.887				
Social influence	SI1	0.746	0.830	0.887	0.662	0.842
	SI2	0.809				
	SI3	0.882				
	SI4	0.813				
Price value	PV1	0.884	0.909	0.936	0.787	0.908
	PV2	0.911				
	PV3	0.924				
	PV4	0.826				
Hedonic motivation	HM1	0.818	0.909	0.936	0.787	0.914
	HM2	0.910				
	HM3	0.934				
	HM4	0.882				
Habit	HB1	0.767	0.921	0.941	0.762	0.933
	HB2	0.904				
	HB3	0.873				
	HB4	0.909				
	HB5	0.904				
Facilitating condition	FC1	0.900	0.913	0.935	0.741	0.925
	FC2	0.847				
	FC3	0.901				
	FC4	0.798				
	FC5	0.854				
Behavioral intention	BI1	0.924	0.901	0.93	0.771	0.925
	BI2	0.936				
	BI3	0.808				
	BI4	0.836				
Adoption of GAI	ADP1	0.920	0.953	0.966	0.877	0.953
	ADP2	0.947				
	ADP3	0.933				
	ADP4	0.947				

FINDINGS

Reflective Measurement

In reflective measurement models, each indicator represents the effect of the underlying construct, causality flows from the construct to its indicators, the relationship between each indicator and the construct (factor loading) is the indicator's absolute contribution to the construct, and the indicators are assumed to be highly correlated (Ghasemy et al., 2020; Hair et al., 2021).

Table 1 presents factor loadings and reliability coefficients for exploring higher education students' ADP. Items (PE1, EE1, and EE2) with a loading factor having less than 0.7 have been eliminated. The measurement model demonstrates good reliability and validity. PE, EE, PV, HM, HB, BI, SI, and ADP constructs exhibit high factor loadings and acceptable internal consistency, as indicated by Cronbach's alpha and composite reliability values (rhoC and rhoA). All constructs have AVE values above the recommended threshold of 0.5, indicating they explain a substantial amount of variance in their indicators (Hair et al., 2019). The highest AVE is observed for the ADP construct, followed by HM and PV. FC has an AVE close to the acceptable threshold.

Table 1 suggests that the items effectively represent their respective constructs, and the measurement model is reliable and valid for interpreting structural relationships in the PLS-SEM analysis.

Table 2. Fornell-Larcker cross loading

	PE	EE	SI	PV	HM	FC	HB	BI	ADP
PE	**0.866**								
EE	0.794	**0.902**							
SI	0.426	0.404	**0.814**						
PV	0.471	0.543	0.527	**0.887**					
HM	0.486	0.482	0.568	0.698	**0.887**				
FC	0.598	0.584	0.519	0.386	0.377	**0.861**			
HB	0.792	0.773	0.416	0.490	0.491	0.608	**0.873**		
BI	0.488	0.498	0.558	0.675	0.756	0.337	0.545	**0.878**	
ADP	0.762	0.767	0.444	0.472	0.459	0.561	0.862	0.539	**0.937**

Table 3. HTMT

	PE	EE	SI	PV	HM	FC	HB	BI
PE								
EE	0.896							
SI	0.488	0.459						
PV	0.523	0.604	0.601					
HM	0.539	0.533	0.644	0.769				
FC	0.654	0.634	0.607	0.415	0.409			
HB	0.872	0.85	0.47	0.534	0.54	0.658		
BI	0.528	0.539	0.629	0.734	0.827	0.362	0.584	
ADP	0.825	0.835	0.491	0.508	0.493	0.591	0.911	0.569

Discriminant validity measures the extent to which a construct is empirically distinct from other constructs in the structural model. To determine discriminant validity, we checked Fornell-Larcker cross loading and HTMT.

Table 2 assesses discriminant validity in the PLS-SEM model by comparing the square root of the AVE with correlations between constructs. The square root of AVE is expected to be smaller than the square root of AVE in the diagonal dimension (Hair et al., 2019). PE exhibits strong correlations with EE and HB. EE also shows a strong correlation with PE. SI has moderate correlations with PE, EE, and PV. PV displays moderate to strong correlations with EE, SI, and HM.

HM shows moderate correlations with PE, EE, PV, and BI. FC is strongly correlated with HB and moderately with PE and PV. HB exhibits strong correlations with PE and EE and a moderate correlation with BI. BI has moderate correlations with HM, HB, and ADP. ADP displays strong correlations with PE and HB and a moderate correlation with BI. Overall, **Table 2** indicates acceptable discriminant validity, with constructs showing distinct characteristics despite their relationships.

Table 3 assesses discriminant validity by comparing the HTMT of correlations between constructs. Values above 0.90 indicate a potential lack of discriminant validity, while values below this threshold suggest distinct constructs (Henseler et al., 2017). PE, EE, HB, and ADP exhibit strong correlations with each other, as indicated by values above 0.85. This suggests that these constructs are highly related but still distinct. SI, PV, HM, and BI show moderate correlations with other constructs, with values ranging from 0.4 to 0.7. This indicates relationships between these constructs while maintaining their distinctiveness.

FC has moderate to strong correlations with several constructs, including HB and PE, suggesting relatedness but distinct constructs. Overall, the HTMT ratios suggest that the constructs in the model have acceptable discriminant validity, as most values are below the critical threshold of 0.90. This provides evidence that each construct uniquely captures a distinct aspect of the theoretical framework.

Formative Measurement

The quality of the formative measurement models is evaluated by looking at collinearity issues within the formative indicators. **Table 4** presents variance inflation factor (VIF) for antecedent constructs in a PLS-SEM model, indicating potential multicollinearity issues.

Multicollinearity occurs when independent variables are highly correlated. For BI as the dependent variable, most constructs have VIF values below 5, suggesting multicollinearity is not a concern. PE, EE, and HB have slightly higher VIF values, indicating a potential issue, but they remain below the critical threshold.

Table 4. VIF

Dimensions	BI	ADP
PE	3.583	2.919
EE	3.483	
SI	1.818	
PV	2.272	
HM	2.296	2.469
FC	1.956	1.706
HB	3.357	3.171
BI		2.595

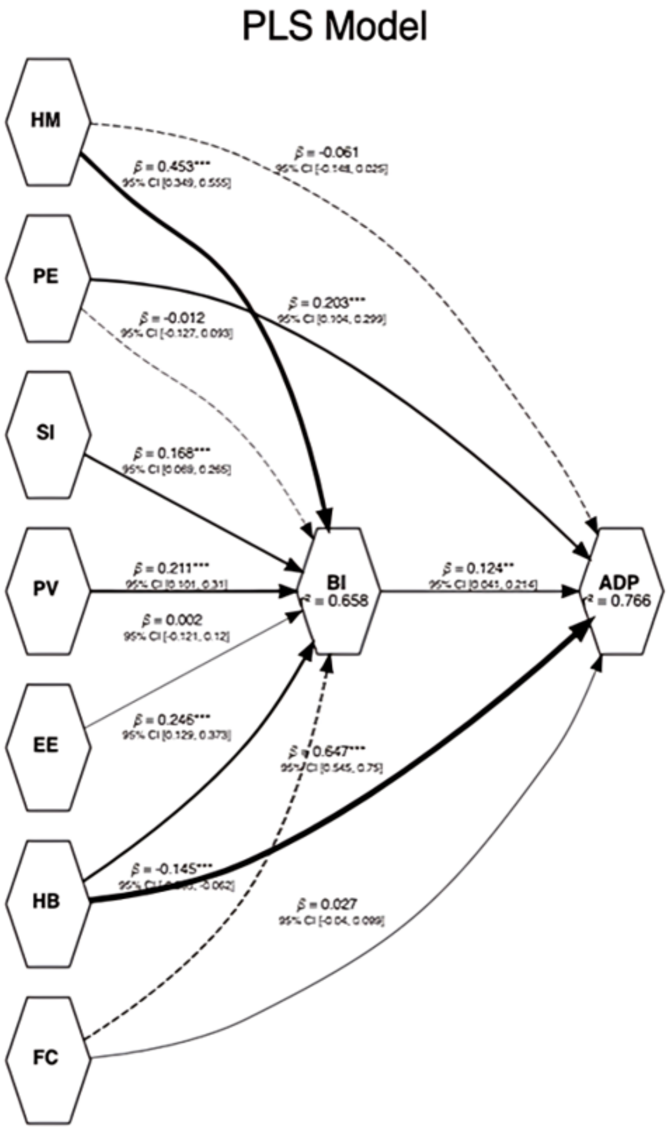

Figure 2. Final model (the authors' own work)

For ADP as the dependent variable, all constructs exhibit VIF values below 10, indicating no significant multicollinearity issues (Hair et al., 2021). PE and HB have the highest VIF values but are still within acceptable limits. Overall, multicollinearity does not seem to be a major concern in this model.

Significance of Path Coefficient

Figure 2 shows the final model. **Table 5** shows the path coefficients. PE has a negative and insignificant effect on BI, with a coefficient of –0.012. However, PE positively influences ADP with a coefficient of 0.203, indicating that an increase in PE leads to a higher likelihood of ADP. EE has a negligible positive effect on BI, with a coefficient of 0.002 but not significant. SI exhibits a positive influence on BI, with a coefficient of 0.168.

Table 5. Path coefficients

Path	Original estimation	Bootstrap mean	Bootstrap standard deviation	t-statistics	2.5% CI	97.5% CI
PE → BI	–0.012	–0.013	0.058	–0.214	–0.127	0.093
PE → ADP	0.203	0.203	0.050	4.07*	0.104	0.299
EE → BI	0.002	0.002	0.060	0.036	–0.121	0.120
SI → BI	0.168	0.168	0.051	3.256*	0.069	0.265
PV → BI	0.211	0.207	0.054	3.879*	0.101	0.310
HM → BI	0.453	0.454	0.054	8.349*	0.349	0.555
HM → ADP	–0.061	–0.061	0.043	–1.407	–0.148	0.025
FC → BI	–0.145	–0.146	0.045	–3.245*	–0.235	–0.062
FC → ADP	0.027	0.028	0.035	0.786	–0.040	0.099
HB → BI	0.246	0.25	0.061	4.022*	0.129	0.373
HB → ADP	0.647	0.649	0.054	12.047*	0.545	0.750
BI → ADP	0.124	0.123	0.043	2.866*	0.041	0.214

Table 6. Path coefficients for total effect

Path	Original estimation	Bootstrap mean	Bootstrap standard deviation	t-statistics	2.5% CI	97.5% CI
PE → ADP	0.201	0.201	0.050	4.021*	0.102	0.298
EE → ADP	0.000	0.001	0.008	0.035	–0.014	0.017
SI → ADP	0.021	0.021	0.010	2.021*	0.004	0.047
PV → ADP	0.026	0.026	0.012	2.213*	0.006	0.051
HM → ADP	–0.005	–0.006	0.036	–0.130	–0.073	0.064
FC → ADP	0.009	0.010	0.033	0.276	–0.053	0.074
HB → ADP	0.677	0.679	0.049	13.715*	0.583	0.772

PV has a positive effect on BI, with a coefficient of 0.211, indicating that PV positively influences individuals' BIs. HM strongly and positively influences BI, with a coefficient of 0.453, suggesting that HM plays a significant role in shaping individuals' BIs. However, HM has a negative but insignificant effect on ADP, with a coefficient of –0.061. FC negatively influence BI, with a coefficient of –0.145, indicating that FC may hinder the formation of BIs. FC has a weak positive effect on ADP, with a coefficient of 0.027 that is insignificant.

HB positively influences both BI and ADP, with coefficients of 0.246 and 0.647, respectively. This suggests that HB plays a crucial role in shaping individuals' BIs and their ADP. Lastly, BI positively influences ADP, with a coefficient of 0.124, indicating that individuals' BIs positively impact their ADP.

Table 6 shows the total effects, which include both direct and indirect effects mediated through other variables in the model. PE, the total effect on ADP (0.201) is very close to the direct effect 0.203, suggesting minimal mediation through BI. EE has a negligible total effect on ADP (0.000) as its direct effects on BI and ADP were also negligible. SI has a small but significant total effect (0.021) on ADP, mediated entirely through its effect on BI (0.168) since it had no direct effect on ADP.

PV similarly has a small total effect (0.026) on ADP mediated through its effect on BI (0.211). HM had a large positive direct effect on BI (0.453) but a small negative direct effect on ADP (–0.061), resulting in a negligible total effect (–0.005) on ADP. FC had a negative direct effect on BI (–0.145) but no significant total effect on ADP (0.009) after accounting for mediation. HB had the largest total effect (0.677) on ADP, driven by its very large direct effect (0.647) as well as an indirect effect mediated through BI (0.246).

So, in summary, HB was the strongest total predictor of adoption, followed by PE. SI, PV and BI itself also had modest total effects on adoption mediated through BI.

The f^2 and R^2 results provide insights into predictive power and explains variance of the PLS-SEM model. f^2 values indicate the predictive power of the independent variables for each dependent variable, while R^2 values represent the proportion of variance explained in the dependent variables by the independent variables (**Table 7**). For BI as the dependent variable:

- Most independent variables have f^2 values close to zero, suggesting weak predictive power.
- HM has an f^2 value of 0.254, indicating substantial predictive power in explaining BI.
- The R^2 value for BI is 0.658, indicating that the independent variables collectively explain 65.8% of the variance in BI.
- The adjusted R^2 value is 0.652, considering number of predictors in the model, indicating a good fit.

Table 7. f^2, R^2, and adjusted R^2 values

Dimensions	BI	ADP
PE	0.000	0.060
EE	0.000	0.000
SI	0.045	0.000
PV	0.057	0.000
HM	0.254	0.006
FC	0.033	0.002
HB	0.052	0.563
BI	0.000	0.025
ADP	0.000	0.000
R^2	0.658	0.766
Adjusted R^2	0.652	0.763

Table 8. Comparing path coefficient based on gender

Path	Female	Male	p-value
PE → BI	−0.048	0.088	0.810
EE → BI	0.005	0.041	0.493
SI → BI	0.183	0.127	0.357
PV → BI	0.177	0.301	0.811
HM → BI	0.472	0.395	0.286
FC → BI	−0.145	−0.122	0.600
HB → BI	0.288	0.082	0.148
BI → ADP	0.105	0.170	0.758
HB → ADP	0.652	0.653	0.516
PE → ADP	0.241	0.095	0.145
FC → ADP	0.014	0.072	0.774
HM → ADP	−0.080	−0.027	0.676

For ADP as the dependent variable:

- Most independent variables have f^2 values close to zero, suggesting weak predictive power.
- HB stands out with an f^2 value of 0.563, indicating strong predictive power in explaining ADP.
- The R^2 value for ADP is 0.766, suggesting that the independent variables collectively explain 76.6% of the variance in ADP, indicating a good fit.
- The adjusted R^2 value is 0.763, considering the number of predictors, indicating a high proportion of explained variance.

Overall, **Table 7** suggests that the model has good predictive power and explained variance for both BI and ADP. The high R^2 values indicate that the model captures a substantial portion of the variance in the dependent variables. However, the low f^2 values for most independent variables suggest that their individual predictive power is limited, with the exception of HM for BI and HB for ADP.

Gender Effects

Table 8 presents the results of a multi-group analysis comparing the path coefficients between female and male groups in the context of using GAI in higher education. The p-values indicate whether the differences between the path coefficients for the two groups are statistically significant. Regarding the influence on BI, the results show that HM and HB have the strongest positive effects for both female and male students, though the effect of HB is stronger for females. SI and PV also positively influence BI, with PV having a stronger impact on males. Interestingly, PE and FC have negative effects on BI, though the effect is stronger for females in the case of FC. When it comes to ADP, HB emerges as the most influential factor for both genders, with almost identical effects. PE positively influences ADP for females, while FC have a positive effect for males. Surprisingly, HM has a negative impact on ADP for both groups, though the effect is slightly stronger for females. The p-values indicate that the differences between the path coefficients for females and males are not statistically significant for most relationships. Overall, the results suggest that while there are some variations in the strength of the relationships, the underlying factors influencing the BI and ADP in higher education are similar for female and male students. **Table 9** shows the supporting of the hypotheses.

Table 9. Supporting of the hypotheses

Hypotheses	Results
H1: BI affects the ADP.	Supported
H2: PE affects the ADP.	Supported
H3: PE affects BI.	Not supported
H4: EE affects BI.	Not supported
H5: SI affects BI.	Supported
H6: PV affects BI.	Supported
H7: HM affects BI.	Supported
H8: HM affects the ADP.	Not supported
H9: HB affects BI.	Supported
H10: HB affects the ADP.	Supported
H11: FC affects BI.	Supported
H12: FC affects the ADP.	Not supported

DISCUSSION

The present study sheds light on the key factors influencing higher education students' adoption and use of GAI technologies. The findings from the structural equation modeling analysis provide empirical support for the applicability of the UTAUT2 framework in understanding technology acceptance within the context of GAI in higher education settings.

HB emerged as the most influential predictor of students' ADP tools, exhibiting the largest total effect. This result aligns with previous research highlighting the significance of HB in shaping technology usage patterns (Billieux et al., 2008; Nikolopoulou et al., 2021; Paiman & Fauzi, 2023; Sharif et al., 2019; Tamilmani et al., 2018). As students develop habitual behaviors through repeated interactions with GAI applications, the likelihood of sustained adoption increases. This finding underscores the importance of fostering positive experiences and routines early on to facilitate the formation of favorable HBs toward these technologies.

PE, which reflects the perceived benefits and gains associated with using technology (Venkatesh et al., 2012), also exhibited a substantial positive influence on students' ADP. This finding resonates with prior studies emphasizing the role of PE in driving technology acceptance (Abbad, 2021; Camilleri, 2024; Kwak et al., 2022; Sari et al., 2024). However, Ramírez-Correa et al. (2019) stated that PE does not affect BI and actual use of technology. Students who recognize the potential advantages of GAI in improving their academic performance and productivity are more likely to embrace these tools. However, the lack of a significant relationship between PE and BI suggests that perceived benefits alone may not be sufficient to shape intentions, highlighting the need for a holistic approach that considers other determinants.

HM, representing the intrinsic enjoyment and pleasure derived from using a technology (Venkatesh et al., 2012), emerged as a strong predictor of BI. This aligns with previous research on the importance of hedonic factors in technology adoption across various contexts (Akdim et al., 2022; Liu & Li, 2011; Ramírez-Correa et al., 2019). Students who find GAI tools engaging, entertaining, and enjoyable to use are more likely to develop positive intentions toward their adoption. However, HM did not significantly influence actual adoption, suggesting that while enjoyment may foster initial intentions, other factors ultimately determine the realization of adoption behavior.

SI, which captures the impact of influential individuals or groups on technology acceptance (Venkatesh et al., 2012), positively influenced students' BIs. This finding resonates with prior studies emphasizing the role of SI in shaping technology adoption decisions (Bouteraa et al., 2024; Strzelecki & ElArabawy, 2024). Students who perceive support and encouragement from peers, instructors, or other influential figures within their social circles are more likely to develop favorable intentions toward using GAI tools.

PV, reflecting the perceived trade-off between the monetary cost and the benefits of using a technology (Venkatesh et al., 2012), positively influenced BI. This result aligns with the broader literature on technology acceptance, which suggests that cost considerations can impact individuals' willingness to adopt new technologies (Strzelecki & ElArabawy, 2024; Wang & Zhang, 2023). Students who perceive GAI tools as affordable and offering good value for their investment are more likely to develop positive intentions toward their adoption.

Interestingly, FCs, which encompass the perceived availability of resources and support for using technology (Venkatesh et al., 2012), exhibited a negative influence on BI. This finding contradicts the proposed positive relationship in the UTAUT2 framework (Ramírez-Correa et al., 2019; Sharif et al., 2019). A possible explanation could be that students perceive the existing infrastructure and support systems as inadequate or lacking, hindering their intention formation. This highlights the need for higher education institutions to address potential gaps in FCs to foster more positive attitudes toward GAI adoption.

The multi-group analysis revealed no statistically significant differences between female and male students in the relationships between the UTAUT2 constructs and BI or adoption. This suggests that the underlying factors influencing the acceptance and use of GAI in higher education are generally consistent across genders. However, some variations in the strength of relationships were observed, such as the stronger impact of HB on adoption for females compared to males. These nuances warrant further investigation to tailor interventions and support mechanisms more effectively for different student groups.

The findings of this study contribute to the growing body of literature on the acceptance and ADP technologies in educational contexts. By leveraging the UTAUT2 framework, the study provides a comprehensive understanding of the key determinants influencing students' intentions and actual use of these emerging tools. The insights gained can inform strategies for higher education institutions, educators, and policymakers to facilitate the responsible integration of GAI in a manner that addresses student concerns, promotes ethical usage, and enhances learning outcomes.

Future research could explore the potential moderating effects of individual differences, such as age, academic discipline, or prior experience with AI technologies, on the relationships between the UTAUT2 constructs and adoption behavior. Additionally, longitudinal studies could shed light on the dynamic nature of technology acceptance over time, capturing changes in attitudes and usage patterns as students gain more exposure to GAI tools.

Overall, this study highlights the importance of considering a multitude of factors, including HB, PE, HM, SI, and PV, in shaping students' adoption and usage of GAI technologies in higher education. By addressing these determinants holistically, educational institutions can better position themselves to leverage the potential benefits of these innovative tools while mitigating potential challenges and concerns.

CONCLUSION

This study provides valuable insights into the factors driving higher education students' adoption and use of GAI technologies. By leveraging the UTAUT2 framework, the research offers a comprehensive understanding of the key determinants influencing students' intentions and actual adoption behavior. The findings underscore the pivotal role of HB in shaping sustained usage of GAI tools. As students develop habitual patterns through repeated interactions, the likelihood of continued adoption increases substantially. This highlights the importance of fostering positive initial experiences and routines to facilitate the formation of favorable HBs toward these emerging technologies. Furthermore, the study emphasizes the significance of PE, HM, SI, and PV in influencing students' ADP. Students who recognize the potential benefits, derive enjoyment, perceive social support, and consider the tools affordable are more likely to embrace these technologies in their academic pursuits. Interestingly, FCs exhibited a negative influence on BI, suggesting a potential gap in the perceived availability of resources and support systems. This finding underscores the need for higher education institutions to address infrastructure and support mechanisms to foster more positive attitudes toward GAI adoption.

Recommendations

Based on the study's findings, several recommendations can be made to facilitate the successful integration of GAI technologies in higher education:

1. Promote early adoption and hands-on experiences to foster HB formation among students. Workshops, tutorials, and guided projects can help students develop familiarity and routine use of these tools.

2. Communicate the potential benefits and applications of GAI in academic contexts, such as personalized learning support, enhanced productivity, and research capabilities. Highlighting real-world examples and use cases can increase students' PE.
3. Incorporate elements of gamification and interactive experiences to enhance the hedonic appeal of GAI tools, making the learning process more engaging and enjoyable for students.
4. Leverage SI by involving influential figures, such as respected faculty members or student leaders, in promoting responsible use of GAI. Peer-to-peer advocacy and mentorship programs can also contribute to positive SI.
5. Ensure the affordability and accessibility of GAI tools by considering subscription models, institutional licenses, or open-source alternatives. Clearly communicating the value proposition can address PV concerns.
6. Strengthen FCs by investing in robust technological infrastructure, providing comprehensive training programs, and establishing dedicated support systems for students and faculty.
7. Develop ethical guidelines and academic integrity policies to address concerns surrounding the appropriate use of GAI in educational settings, promoting responsible adoption and mitigating potential misuse.

Limitations and Future Research

While this study provides valuable contributions, several limitations should be acknowledged:

1. The cross-sectional nature of the data limits the ability to capture the dynamic evolution of technological acceptance over time. Longitudinal studies could offer insights into how attitudes and usage patterns change as students gain more experience with GAI tools.
2. The study focused on higher education students in a specific geographic region. Expanding the scope to include students from diverse cultural backgrounds and educational systems could enhance the generalizability of the findings.
3. The research primarily relied on self-reported data, which may be subject to biases and limitations inherent to survey methodologies. Future studies could incorporate observational or experimental approaches to complement the self-reported data.
4. The study did not consider potential moderating effects of individual differences, such as age, academic discipline, or prior experience with AI technologies. Investigating these factors could provide a more nuanced understanding of technology acceptance in educational contexts.

Future research could address these limitations and further explore the interplay between individual characteristics, institutional factors, and technology acceptance in the realm of GAI adoption in higher education. Additionally, qualitative studies could provide deeper insights into the underlying motivations, concerns, and perceptions of students toward these emerging technologies. As GAI continues to evolve and gain traction in educational settings, ongoing research efforts are crucial to informing effective strategies for responsible integration, addressing ethical concerns, and ultimately enhancing learning outcomes for students while embracing the transformative potential of these innovative tools.

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APPENDIX A

Table A1. The scale

Dimensions		Items
Performance expectancy	PE_1	Using GAI technology enables me to accomplish tasks more quickly.
	PE_2	GAI-powered learning activities could enhance the efficiency of the higher education system.
	PE_3	GAI has the potential to revolutionize how we access knowledge.
	PE_4	GAI can ensure error-free responses, enhancing my performance and understanding of the subject matter.
	PE_5	Smart educational content, tailored to individual needs, can be created using GAI technology.
Effort expectancy	EE_1	GAI technology is accessible and user-friendly.
	EE_2	Learning GAI technology requires manageable effort.
	EE_3	With a basic understanding of GAI technology, I am confident I can quickly learn and adapt to AI-based applications.
	EE_4	Interacting with GAI technology often requires little effort on my part.
	EE_5	With GAI technology, I can envision a future where individualized content is seamlessly prepared for each student.
Facilitating conditions	FC_1	My institute has all the required resources to utilize GAI technology for smart content creation.
	FC_2	I have access to knowledgeable staff, advanced technology, and any tools I need to learn and apply GAI effectively.
	FC_3	I feel that the infrastructure and facilities fully enable my engagement with GAI in the learning environment.
	FC_4	All the classrooms in my institute are equipped with the latest devices and technology to support GAI-enhanced teaching.
	FC_5	My institute actively encourages the use of modern technology, including GAI.
Social influence	SI_1	My classmates believe that using GAI for our coursework is beneficial.
	SI_2	Instructors in my department encourage the use of GAI for educational purposes.
	SI_3	Most students in my program use GAI to assist with their learning.
	SI_4	There is a general consensus among my peers that integrating GAI into our studies is important for academic success.
Price value	PV_1	The benefits of using GAI in my studies are worth the cost.
	PV_2	The value I receive from GAI-assisted learning justifies the investment of time and resources.
	PV_3	GAI technology enhances my learning experience, making it worth any associated costs or opportunity costs.
	PV_4	The cost of accessing GAI tools is reasonable for the advantages they provide in my education.
Hedonic motivation	HM_1	I enjoy using GAI tools because they make my learning experience more fun and engaging.
	HM_2	I find it exciting to interact with GAI technology as it adds an element of novelty to my education.
	HM_3	I feel excited about the possibilities of using GAI in my coursework.
	HM_4	Using GAI for my studies is fun.
Habit	HB_1	Using GAI tools has become a regular part of my study routine.
	HB_2	I automatically turn to GAI technology when I need assistance with my academic tasks.
	HB_3	I find myself using GAI-assisted learning platforms out of habit, even when I don't consciously plan to.
	HB_4	GAI is an integral part of my learning process.
	HB_5	I often find myself using GAI tools out of habit when studying.
Behavioral intention	BI_1	I intend to continue expanding my knowledge of GAI technology.
	BI_2	In the future, I will prioritize learning about emerging GAI applications.
	BI_3	I plan to develop my GAI skills further, recognizing their potential impact on my career prospects and future opportunities.
	BI_4	I intend to actively incorporate GAI tools into my learning process wherever possible.
Adoption of GAI	ADP_1	The application of GAI in higher education has the potential to bring about positive societal change.
	ADP_2	With GAI integration, education becomes more dynamic and engaging.
	ADP_3	GAI technology can make higher education more cost-effective.
	ADP_4	By offering interactive and tailored learning experiences, GAI keeps students invested in their education.