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Are Peruvian Tertiary Students Using Artificial Intelligence in Their Academic Activities?

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Abstract: The widespread emergence of generative artificial intelligence (GAI) has prompted growing interest in understanding the factors that drive its adoption in academic contexts. This study explores the behavioral intention of Peruvian university students to use GAI tools in their educational activities by applying the technology acceptance model (TAM) through partial least squares structural equation modeling (PLS-SEM). A total of 350 valid responses were collected from students at the Universidad Nacional Agraria La Molina. The model demonstrated strong reliability and validity, with key constructs such as perceived usefulness and attitude toward use explaining 12% and 9% of the variance in intention, respectively. Notably, behavioral intention significantly predicted actual use, accounting for 58.8% of the variance. To address concerns of common method bias, statistical controls were implemented. The results underscore the importance of designing user-friendly and pedagogically relevant GAI tools because ease of use was found to strongly influence perceived usefulness and attitudes. This study contributes to the literature by validating a TAM-based model in the Latin American higher education context and identifying actionable variables that institutions can leverage to foster ethical and effective adoption of GAI. It also highlights students' current reliance on tools such as ChatGPT® and ChatPDF® for information retrieval and summarization. These findings support the development of informed policies and training initiatives to guide the responsible integration of AI in academic environments.

Keywords: generative artificial intelligence, technology acceptance, higher education, academic activities, technology acceptance model (TAM), information and communication technologies (ICT)

1. Introduction

Artificial intelligence (AI) is applied in a multitude of domains, including agriculture, medicine, industry, and services. Consequently, it has emerged as one of the most disruptive and promising technologies of the 21st century [1, 2]. The capacity to process extensive datasets and to make decisions with autonomy offers both significant opportunities and considerable challenges across a diverse range of sectors [3, 4]. In the contemporary digital era, AI has emerged as a disruptive technology exerting a significant impact, notably within the realm of education [5]. Across the globe, universities are actively investigating the potential of AI to augment learning experiences, pedagogical practices, and scholarly inquiry [6]. The disruptive impact of AI technology on education necessitates an analysis rooted in the re-evaluation of assessment activities, with the aim of enhancing teaching quality. Furthermore, it requires the alignment of student learning outcomes with the evolving needs of contemporary society to augment educational value [7].

The integration of AI in education presents multifaceted challenges. First, data privacy demands compliance with the General Data Protection Regulation (GDPR). Likewise, cultural disparities can lead to misinterpretations and the lack of universality in AI references. Furthermore, ethical implications such as algorithmic bias and opacity in decision-making are crucial [8]. Finally, it is vital to maintain human interaction and offer support mechanisms for educators to prevent excessive reliance on AI [9]. Overcoming these challenges is fundamental for educational innovation that ensures more equitable and effective learning environments.

Within the realm of education, it is paramount to comprehend the perceptions of future professionals regarding this technology and the potential influence of these perceptions on its subsequent adoption and efficacious utilization [10, 11]. Nevertheless, the realization of an efficacious implementation of AI within this educational landscape necessitates a thorough understanding of the factors that shape its acceptance among university students. These students constitute a pivotal element in the broader adoption of AI in educational settings. Their disposition toward utilizing AI tools, coupled with their perceptions of the inherent benefits and potential risks associated with this technology, is a critical determinant for the successful integration of AI within university environments.

In the educational context, the use of AI is rapidly evolving and represents significant implications for higher education institutions [12, 13]. Notable benefits associated with the utilization of AI include personalized learning experiences, the creation of adaptive assessments,

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predictive analytics capabilities, and the deployment of chatbots. These advancements collectively contribute to enhanced learning efficiency [14, 15]. Moreover, prominent international bodies, including UNESCO and the European Union, underscore the potential of AI to augment educational outcomes and stress the necessity of upholding ethical tenets such as transparency, accountability, and inclusivity [16].

The technology acceptance model (TAM), despite its maturity, remains a foundational framework for evaluating user acceptance of technology. Its constructs—perceived usefulness (PU) , perceived ease of use (PEU), attitude toward use (ATU), and behavioral intention to use (BIU)—have been validated in diverse educational contexts [17]. This study builds on the TAM and addresses contemporary challenges posed by generative artificial intelligence (GAI), especially within Latin American universities, a region still underrepresented in empirical AI research [12].

Recent literature has emphasized the benefits and risks of GAI in education, including improved academic writing, enhanced personalization, and ethical concerns regarding bias and transparency [1]. Additionally, studies suggest that although students are eager to experiment with AI tools, their effective use depends on usability, support mechanisms, and their awareness of both benefits and limitations [18, 19].

According to the TAM, the adoption of AI among both faculty and university students is contingent upon a range of determinants. Specifically, concerning faculty members, the TAM offers a comprehensive elucidation of the direct and indirect pathways through which AI influences teaching methodologies, assessment practices, and the generation of educational materials [20]. Salient factors influencing acceptance encompass the perception of utility in augmenting teaching efficacy and students' academic outcomes, alongside positive dispositions and the professional aspirations of faculty members [21].

Concerning students, PU and PEU exert a positive influence on their attitudes, intentions to use, and the actual utilization of AI [22]. Additionally, other determinants, including performance expectancy and facilitating conditions, may exert an influence on students' attitudes and behavioral intentions concerning their engagement with AI in educational contexts [23, 24].

Conversely, students' attitudes toward AI are shaped by their awareness of its implications, their inclination to pursue further learning in AI, and their current knowledge limitations stemming from insufficient training [18]. Accordingly, the efficacy of AI education hinges on the provision of authentic use case scenarios and a clear articulation of the technology's inherent limitations. This is paramount to guaranteeing that students can employ AI with both assurance and accountability in their future professional endeavors [19].

This study seeks to answer the following research question: What are the determinants of students' BIU AI tools in academic activities at the Universidad Nacional Agraria La Molina as framed by the TAM? By doing so, the study aims to contribute empirical evidence on the acceptance and use of GAI, offering theoretical and practical implications for Latin American higher education institutions.

2. Literature Review and Research Hypotheses

2.1. Technology acceptance and AI in education

The integration of AI in higher education has accelerated with the advancement of GAI tools, prompting a reassessment of how students perceive, engage with, and adopt emerging technologies [6]. The widespread adoption of tools such as ChatGPT®, Gemini®, and ChatPDF® has introduced new paradigms in knowledge acquisition and academic productivity. Understanding students' intention to adopt such technologies requires robust theoretical frameworks grounded in behavioral research. Among them, the TAM continues to be a valuable model for explaining user acceptance and behavioral intention toward new technologies, despite being developed decades ago [17]. Nevertheless, this scenario poses a considerable challenge for higher education: the imperative to strategically plan, meticulously organize, thoughtfully design, and effectively implement technological competencies for the preparation of professionals in alignment with the evolving demands of this rapidly changing global landscape in the years ahead [25, 26].

2.2. The inclusion of AI in education

The advent of novel technologies has instigated such a profound transformation that the modalities of communication, interaction, reading, writing, and information acquisition have necessitated considerable adaptation on the part of users [27], and its adoption has become widespread within the educational sphere [28], which could introduce new methods of learning and teaching [11]. Nevertheless, it also engenders critical issues, including ethical considerations, thereby necessitating concerted efforts to establish a robust framework that effectively integrates AI within the realm of higher education [15]. Similarly, higher education institutions bear the responsibility of ensuring the availability of qualified advisors to offer appropriate support as required for the effective utilization of AI [29]. Conversely, although university students are increasingly utilizing AI to a certain degree, it cannot supplant human instructors because students value guidance characterized by empathy and sensitivity. This inherent human element represents a recognized limitation in the comprehensive application of the technology [30]. Nonetheless, a significant number of educators lack a comprehensive understanding of its full scope and, more critically, its fundamental nature [27]. Despite this, AI is gaining significant traction within education, and over the preceding three decades, its integration into the educational sector has occurred via diverse modalities [19].

2.3. Justification for using the TAM

Although more recent frameworks such as UTAUT2, Task-Technology Fit (TTF), and the Theory of Planned Behavior (TPB) have emerged, the TAM remains a parsimonious and empirically robust model. Its constructs—PU, PEU, ATU, and BIU—are well established and have been extensively validated in educational settings, including AI-related studies [31, 32]. Given the objective of evaluating students' subjective beliefs and intentions toward AI systems in a developing country context, the TAM offers conceptual clarity and methodological suitability for identifying key adoption determinants [33].

Furthermore, the selection of the TAM is due to its proven robustness in modeling direct and mediated relationships in environments where technology is still in the early stages of adoption. This contrasts with the UTAUT2 model, which necessitates prior behavioral history of sustained usage. Consequently, the use of the TAM is justified by its applicability, structural simplicity, high explanatory power, and widespread acceptance in recent studies concerning AI in higher education (e.g., [18] and [19]).

Although more recent frameworks such as UTAUT [34], UTAUT2 [35], and TAM3 [36] exist, this study opted for the original TAM due to its parsimony and suitability for contexts where technology adoption is still in its early stages (Table 1) [15, 18, 37]. Unlike UTAUT2—which includes constructs such as habit and price value, more applicable to continuous-use environments—the TAM focuses on PU and PEU, which are critical determinants during initial stages of

Table 1
Comparative framework

Model	Explanatory variables	Moderating variables	Applicability
TAM	Perceived usefulness, perceived ease of use	N/A	Initial adoption stages, low technological expertise
TAM2/TAM3	PU, PEU + motivational and cognitive antecedents	Experience, voluntariness	Advanced educational contexts
UTAUT	Performance expectancy, effort expectancy, social influence, facilitating conditions	Gender, age, experience, voluntariness	Organizational environments
UTAUT2	UTAUT + hedonic motivation, price value, habit	Gender, age, experience	Sustained technology use, commercial contexts

acceptance of emerging technologies such as AI in education [15, 18]. Furthermore, the TAM supports parsimonious mediation modeling with lower statistical complexity, making it appropriate for populations with limited prior exposure to AI. This methodological decision is aligned with the comparative model analysis reported by Mourtajji and Arts-Chiss [37], who reaffirmed TAM's relevance for studies centered on users' initial cognitive and attitudinal evaluations.

2.4. Perceived ease of use

In the context of educational technologies, PEU plays a foundational role in shaping how students engage with digital tools. It refers to an individual's assessment of the simplicity and efficiency associated with using a particular technology, specifically the degree to which its use is perceived as free of effort or difficulty [17]. This perception includes dimensions such as interface clarity, intuitive navigation, learning curve simplicity, and user flexibility, all of which have been shown to influence adoption processes in educational settings [38].

Prior research demonstrates that when students perceive a system as easy to use, they are more likely to regard it as useful and to develop a favorable attitude toward its adoption [39–41]. This cognitive appraisal becomes particularly relevant for emerging technologies such as GAI, where students often explore the tools independently. Consequently, PEU is expected to influence both PU and ATU in the adoption of AI-based educational applications. Based on these arguments , hypotheses 1 and 2 are formulated.

H1: Perceived ease of use positively influences perceived usefulness of AI.

H2: Perceived ease of use positively influences attitude toward use of AI.

2.5. Perceived usefulness

PU reflects the extent to which students believe that using AI tools will enhance their academic productivity and learning outcomes. It represents an individual's subjective assessment of the value inherent in a technology, particularly as it pertains to their academic needs and personal aspirations [42]. This perception is influenced by factors such as prior experiences, educational background, personal beliefs, and self-efficacy [15, 43].

In the context of AI adoption in higher education, students who perceive that such tools help them perform tasks more efficiently and effectively are more likely to develop favorable attitudes toward their use and to use them regularly [41]. Furthermore, the integration of digital technologies fosters not only knowledge acquisition and academic development but also creativity, digital literacy, and cognitive engagement [44]. Understanding how students internalize the utility of AI is therefore central to predicting their behavioral responses and supporting successful integration within academic environments. Stemming from this premise, the following hypotheses are proposed.

H3: Perceived usefulness positively influences attitude toward use of AI.

H4: Perceived usefulness positively influences behavioral intention to use AI.

2.6. Attitude toward use

Attitude toward the use of technology refers to an individual's inclination or predisposition to adopt a given technological tool, which can influence both the teaching–learning process and students' academic and professional performance [45, 46]. In the context of the TAM, attitude plays a central mediating role, translating students' cognitive evaluations—such as PU and PEU—into behavioral intentions.

When applied to GAI tools in education, students' attitudes reflect their willingness to integrate these technologies into their academic routines [6]. A positive attitude can lead to more efficient and personalized learning experiences, increasing the likelihood of sustained adoption and meaningful engagement [18, 30]. As such, understanding the formation and influence of attitudes is critical to anticipating student behavior toward AI applications in higher education, particularly in contexts where digital transformation is still emerging [3]. Stemming from this premise, the following hypothesis is proposed.

H5: Attitude toward use positively influences behavioral intention to use AI.

2.7. Behavioral intention and actual use

Behavioral intention refers to an individual's readiness to perform a specific behavior, which corresponds to the use of GAI tools for academic purposes in this context. It has been widely established as one of the strongest predictors of actual system use (ASU) across TAM-based studies [47, 48]. Behavioral intention serves as a reliable proxy for the likelihood of real-world adoption, particularly when examining emerging technologies such as ChatGPT® and ChatPDF®, which are increasingly available to students.

Actual usage is typically regarded as the observable manifestation of an individual's intention to engage with a technology [49]. In the case of educational technologies, numerous studies have confirmed the positive and significant impact of behavioral intention on system utilization, especially among university students navigating new digital environments [48]. Based on the preceding, hypothesis 6 is formulated.

H6: Behavioral intention to use AI positively influences actual system use.

3. Methodology

3.1. Participants

The sample for this study was selected using a random sampling method from a population of 5000 students enrolled in the 2024-I semester at the National Agrarian University La Molina. Strata were defined by faculty departments to ensure proportional representation. The minimum required sample size was calculated using G*Power with the following parameters: effect size $f^2 = 0.15$, power = 0.95, and $\alpha = 0.05$, yielding a minimum of 138 observations. To enhance representativeness, 358 responses were collected. After data cleaning based on completeness and attention checks, the final dataset included 350 valid responses. The mean age was 21.34 years (SD = 3.47), with gender distribution of 50.57% male and 49.43% female. Academic advancement was measured by credit accumulation, with an average of 67.71 credits (SD = 60.18), reported in Table 2.

The breakdown of the student participants by their respective academic majors was as follows: agricultural engineering (3.7%), agronomy (10.6%), environmental engineering (7.1%), biology (13.1%), economics (8.3%), statistical and informatics engineering (6.6%), forestry engineering (3.7%), business management engineering (30.6%), food industries engineering (4.9%), meteorological engineering and climate risk management (3.7%), fisheries engineering (5.4%), and animal science (2.3%).

3.2. Instrument design

The questionnaire was designed based on established constructs in the TAM, validated in previous educational research [17]. Items for each latent variable were adapted from studies such as Mailizar et al. [41] and Sharma et al. [15] using a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). All constructs were operationalized with at least three observed indicators, in line with recommendations by Hair et al. [50].

3.3. Data analysis

The data analysis employed partial least squares structural equation modeling (PLS-SEM) using SmartPLS 4, selected due to the model's predictive orientation and the formative-reflective structure of constructs [51]. Measurement model evaluation included assessments of internal consistency reliability (Cronbach's α and composite reliability), convergent validity (average variance extracted (AVE)), and discriminant validity (Fornell–Larcker criterion and HTMT ratio). The structural model was evaluated using R^2, Q^2, path coefficients with bootstrapping (n = 5,000), and Cohen's f^2 effect sizes. All methodological steps followed the guidelines proposed by Hair et al. [50] and Cheah et al. [52].

3.4. Pilot test

The proposed research model was examined using PLS-SEM, a variance-based approach for structural equation modeling [33, 53]. The application of PLS-SEM has witnessed exponential growth and is now prevalent across diverse scientific disciplines, with a notable presence in the social sciences [51].

Table 2
Demographic characteristics of the study participants and Likert scale

Demographic characteristics	Description	N	Percentage
Gender	Male	177	50.57%
	Female	173	49.43%
Age (years)	Average	21.34	
	SD	3.47	

To address potential concerns regarding the pilot sample, it is important to clarify that the pilot study was conducted using a non-probabilistic, purposive sampling strategy, with the specific aim of semantic and lexical validation of the instrument items. It was not intended to produce population-level inferences or preliminary estimations of the structural model.

Although the average age of the pilot participants was higher than that of the final sample (above 27 years), they were enrolled in the same academic programs as the main study participants and belonged to the same institutional context (Universidad Nacional Agraria La Molina). This ensured that their academic experiences and exposure to digital tools and AI technologies were comparable and relevant to the study's focus. Their input allowed for refining item clarity and ensuring contextual appropriateness before large-scale data collection.

Table 3 elucidates that the preliminary results confirm the internal consistency of the constructs (Cronbach's $\alpha > 0.80$). To assess common method bias (CMB), Harman's single-factor test was conducted: the first factor explained 34.2% of the total variance, below the 50% threshold. Although a stringent threshold for the variance inflation factor (VIF) in PLS-SEM is typically suggested at 3.3, the pilot test yielded three VIF values over 3.3 (ASU1, ASU2, and PEU2). It is important to highlight that this value remains below the more commonly accepted threshold of 5, which generally indicates the absence of severe multicollinearity issues among the predictor constructs [50].

3.5. Mathematical formulation of the structural model

Let the latent variables be defined as follows:

1) PEU: perceived ease of use
2) PU: perceived usefulness
3) ATU: attitude toward use
4) BIU: behavioral intention to use

Table 3
Pilot test validation

Construct/indicator	Cronbach's α	VIF
Actual system use (ASU)	0.916	
ASU1		3.484
ASU2		3.484
Behavioral intention to use (BI)	0.883	
BIU1		2.666
BIU2		2.666
Attitude toward use (A)	0.844	
ATU1		2.14
ATU2		2.14
Perceived usefulness (U)	0.844	
PU1		2.633
PU2		2.337
PU3		2.495
PU4		1.867
Perceived ease of use (E)	0.853	
PEU1		1.964
PEU2		3.334
PEU3		2.336

5) ASU: actual system use.

The structural relationships among these constructs are expressed through the following equations:

$$PU = \beta_1 \times PEU + \zeta_1, \tag{1}$$

$$ATU = \beta_2 \times PEU + \beta_3 \times PU + \zeta_2, \tag{2}$$

$$BIU = \beta_4 \times PU + \beta_5 \times ATU + \zeta_3, \tag{3}$$

$$ASU = \beta_6 \times BIU + \zeta_4, \tag{4}$$

where β_i represents the standardized path coefficients and ζ_i denotes the error terms associated with each endogenous latent variable. These equations reflect the causal structure of the TAM as implemented in the present study.

3.6. Measurements

The development of the research instrument commenced with a thorough review of the relevant literature and the incorporation of insights from previous investigations. This initial phase aimed to identify appropriate measures for each theoretical construct. Following this, procedures were undertaken to ascertain the reliability and validity of the instrument.

Table 4 illustrates that the assessed constructs exhibit strong internal consistency and reliability. Specifically, all constructs yielded Cronbach's α coefficients and composite reliability scores exceeding 0.7, thereby confirming the reliability of the items employed to measure each construct. Moreover, the majority of the constructs demonstrated AVE values greater than 0.5, suggesting that a substantial proportion of the variance in the indicators is accounted for by their respective constructs. Consequently, the model validation demonstrates robust internal consistency and reliability across all evaluated constructs, affirming the model's adequacy for measuring the proposed theoretical constructs.

Finally, the standardized factor loadings consistently ranged from 0.686 to 0.958, with 92% (12 of the 13 indicators) exceeding the 0.7 threshold and 100% of the AVE values surpassing 0.5, which is deemed satisfactory. This indicates that over 50% of the variance in the observed variables is accounted for by their respective latent constructs [50].

4. Results

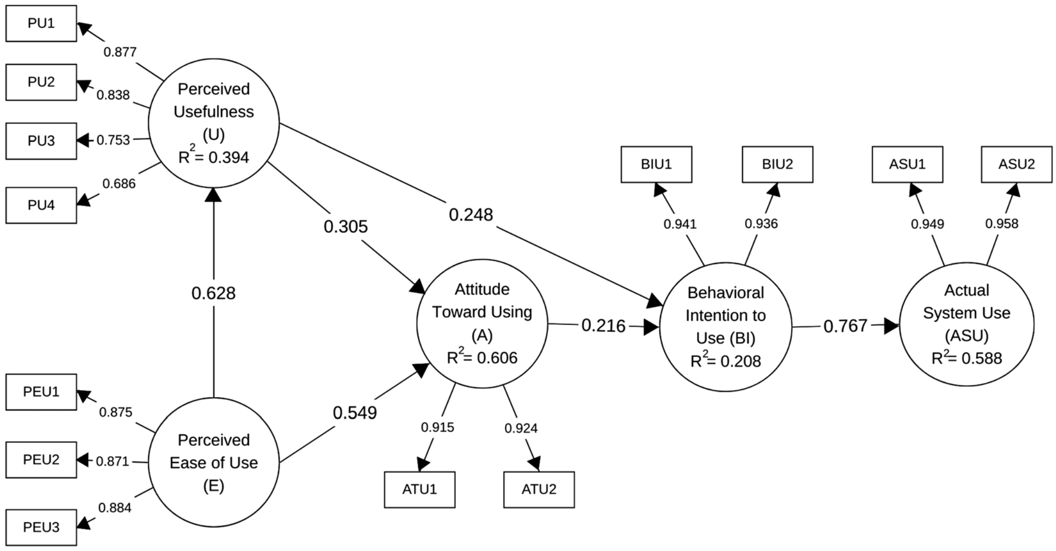
4.1. Structural model

Figure 1 presents the structural model resulting from the application of PLS-SEM, illustrating the relationships between the core

Table 4
Model evaluation

Construct/indicator	Loading	Cronbach's α	rho_A	Average variance extracted	Composite reliability
Actual system use (ASU)		0.900	0.906	0.909	0.952
I frequently use AI in my academic activities. (ASU1)	0.949				
I'm using AI more and more to conduct my academic activities. (ASU2)	0.958				
Behavioral intention to use (BI)		0.865	0.867	0.881	0.916
You would use AI for academic papers, assignments, or reports. (BIU1)	0.941				
I would recommend using AI to perform academic assignments or work. (BIU2)	0.936				
Attitude toward use (A)		0.817	0.819	0.846	0.937
I am confident in my ability to effectively use artificial intelligence in my studies. (ATU1)	0.915				
I believe I can learn to use artificial intelligence with relative ease. (ATU2)	0.924				
Perceived usefulness (U)		0.798	0.813	0.627	0.909
Using artificial intelligence would improve my academic performance. (PU1)	0.877				
The use of artificial intelligence would make it easier for me to accomplish my academic tasks. (PU2)	0.838				
The use of artificial intelligence would increase my efficiency in studying. (PU3)	0.753				
I would be motivated to use artificial intelligence if I see other students doing well. (PU4)	0.686				
Perceived ease of use (E)		0.850	0.85	0.769	0.87
I think it would be easy to learn how to use AI tools. (PEU1)	0.875				
The user interfaces of AI applications would be intuitive and easy to understand. (PEU2)	0.871				
I wouldn't have a hard time navigating and using the features of artificial intelligence. (PEU3)	0.884				

Figure 1
Findings of the structural model analysis



constructs of the TAM. Each path coefficient reflects the strength and significance of the direct effects between PEU, PU, ATU, BIU, and ASU. The model demonstrates solid explanatory power, with R^2 values indicating substantial variance explained in the endogenous variables.

To assess the discriminant validity of the proposed model, both the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT) were employed (Table 5). Following the Fornell–Larcker criterion, the entries on the main diagonal, which are the square roots of the AVE for each construct, must be greater than the bivariate correlations between the respective construct and other constructs in the model [54]. According to the Fornell–Larcker criterion, the square root of the AVE for each construct was as follows: ASU = 0.953, ATU = 0.920, BIU = 0.939, PEU = 0.877, and PU = 0.792. As demonstrated, all of these values on the diagonal are higher than the corresponding off-diagonal correlations (results not shown for brevity), thereby confirming adequate discriminant validity.

Concerning the HTMT ratio, values below 0.85 are generally recommended to establish discriminant validity. Although the HTMT ratio between ATU and PEU slightly exceeds the 0.85 benchmark, it remains within the acceptable upper limit of 0.90 as suggested by Cheah et al. [52]. Overall, the remaining HTMT ratios satisfy the recommended threshold, providing further support for the discriminant validity of the proposed model.

Based on the Fornell–Larcker criterion and the HTMT ratio assessment, the structural model demonstrates acceptable discriminant validity, as evidenced by the sufficient distinctiveness of most constructs. This strengthens confidence in the validity of the proposed theoretical linkages between the constructs in the research framework.

The structural model, outlining the direct effects of multiple variables on the endogenous variables, is presented in Table 6. The model demonstrated substantial explanatory power for several endogenous variables. Specifically, PEU emerged as a highly significant and strong predictor of PU (β = 0.628, t = 13.71, p < 0.001), accounting for 39.44% of its variance (R^2 = 0.394) with a large effect size (f^2 = 0.650). ATU was significantly predicted by both PEU (β = 0.549, t = 12.17, *p* < 0.001) and PU (β = 0.305, t = 6.54, *p* < 0.001), with these two variables collectively explaining 60.6% of the variance in ATU (R2 =0.606). Regarding BIU, both PU (β = 0.284, t = 3.24, *p* < 0.01) and ATU (β = 0.216, t = 2.70, *p* < 0.01) exerted significant positive effects, explaining 20.8% of its variance (R^2 = 0.208). Finally, BIU demonstrated a very strong and highly significant direct effect on ASU (β = 0.767, t = 22.57, p < 0.001), explaining 58.83% of its variance (R^2 = 0.588) and exhibiting a remarkably large effect size (f^2 = 1.429). These results underscore the pivotal role of PEU and PU in shaping user attitudes, intentions, and subsequent actual engagement with the system and highlight the necessity of focusing on improving both the PEU and PU of AI to promote favorable attitudes, bolster usage intentions, and ultimately, achieve successful adoption.

The results of the structural model analysis, specifically concerning the proposed hypotheses, are summarized in Table 7. As

Table 5
Model validation – discriminant validity

	Fornell–Larcker criterion					Heterotrait–monotrait (HTMT) ratio				
	ASU	ATU	BIU	E	U	ASU	ATU	BIU	E	U
ASU	0.953									
ATU	0.301	0.92				0.351				
BIU	0.767	0.401	0.939			0.866	0.477			
E	0.302	0.741	0.365	0.877		0.344	0.888	0.425		
U	0.333	0.65	0.425	0.628	0.792	0.390	0.800	0.505	0.759	

Note: ASU = actual system use, ATU = attitude toward use, BIU = behavioral intention to use, E = perceived ease of use, and U= perceived usefulness.

Table 6
Effects on endogenous variables

Effects on endogenous variables	Direct effect	t-value	Percentile bootstrap 90% CI	Explained variance	f^2
Perceived usefulness ($R^2 = 0.394/Q^2 = 0.39$)					
Perceived ease of use (H_1)	0.628***	13.71	[0.532; 0.713] Sig	39.44%	0.650
Attitude toward use ($R^2 = 0.606/Q^2 = 0.544$)					
Perceived usefulness (H_2)	0.305***	6.541	[0.215; 0.396] Sig	19.83%	0.143
Perceived ease of use (H_3)	0.549***	12.171	[0.461; 0.637] Sig	40.68%	0.464
Behavioral intention to use ($R^2 = 0.208/Q^2 = 0.125$)					
Perceived usefulness (H_4)	0.284**	3.237	[0.109; 0.454] Sig	12.07%	0.059
Attitude toward use (H_5)	0.216***	2.703	[0.056; 0.037] Sig	8.66%	0.034
Actual system use ($R^2 = 0.588/Q^2 = 0.084$)					
Behavioral intention to use (H_6)	0.767***	22.571	[0.696; 0.827] Sig	58.83%	1.429

Note: Sig. denotes a significant direct effect at 0.05. Bootstrapping based on n = 1000 subsamples. * p < 0.005.

Table 7
Hypothesis support resume

Hypothesis	Relationship	Path coefficient	Interpretation	Support
H_1	Perceived ease of use → perceived usefulness	0.628	Ease of use increases perceived usefulness	Yes
H_2	Perceived ease of use → attitude toward use	0.549	Ease of use strengthens attitude	Yes
H_3	Perceived usefulness → attitude toward use	0.305	Usefulness enhances positive attitude	Yes
H_4	Perceived usefulness → behavioral intention	0.284	Usefulness enhances intention to use AI	Yes
H_5	Attitude toward use → behavioral intention	0.216	Attitude increases intention to use AI	Yes
H_6	Behavioral intention → actual system use	0.767	Intention strongly predicts actual AI use	Yes

hypothesized, all six direct relationships were found to be positive and statistically significant, thereby providing full support for H_1 to H_6. Consistent with the theoretical framework, PEU significantly influenced PU (H_1). Both PEU (H_2) and PU (H_3) were significant determinants of ATU. Furthermore, PU (H_4) and ATU (H_5) positively predicted BIU. Notably, BIU emerged as a very strong predictor of ASU (H_6), exhibiting the highest path coefficient ($\beta = 0.767$) among all relationships. These findings collectively validate the proposed theoretical model and confirm the hypothesized pathways influencing the adoption of AI.

4.2. Use of AI among university students

To gain deeper insights into how university students use AI, two-word clouds were generated based on the responses to the open-ended questions included in the survey instrument. Figure 2 illustrates the most commonly used AI tools among students. ChatGPT® emerged as the most frequently mentioned, followed by Microsoft Bing® AI and ChatPDF®, the latter being favored for its capacity to process and summarize long documents. This indicates a clear preference for GAI tools that support comprehension, information retrieval, and writing assistance.

Additionally, students were asked to describe how they specifically use AI in their academic activities. As shown in Figure 3, the predominant uses include searching for information to improve academic reports, generating summaries, and refining research outcomes. These responses reflect a pattern of instrumental use, where AI serves as a support tool for academic enhancement rather than as a replacement for critical thinking or original content creation.

These insights enrich the quantitative results of the structural model by illustrating the practical ways in which students are integrating AI into their learning routines. They also highlight the relevance of GAI for supporting academic productivity, suggesting that students are actively exploring and appropriating these technologies within the constraints of their educational environment.

5. Discussion

The results obtained through PLS-SEM fully support the six hypotheses derived from the TAM. Specifically, H1 and H2 are confirmed by the significant and strong effect of PEU on both PU ($\beta = 0.628$, $p < 0.001$) and ATU ($\beta = 0.549$, $p < 0.001$), highlighting the importance of intuitive design in AI interfaces. H3 and H4 show that PU contributes positively to both attitude ($\beta = 0.305$, $p < 0.001$) and behavioral intention ($\beta = 0.284$, $p < 0.01$), emphasizing students' recognition of AI tools' potential to improve academic performance. H5 is supported by the positive relationship between attitude and behavioral intention ($\beta = 0.216$, $p < 0.01$), confirming the mediating role of affective evaluation. Finally, H6 reveals that behavioral intention is a strong predictor of actual AI use ($\beta = 0.767$, $p < 0.001$), explaining nearly 59% of its variance, consistent with theoretical expectations from TAM-based studies [47, 48]. These results reinforce the relevance of TAM constructs for explaining AI adoption among students and validate their predictive strength in a Latin American higher education setting.

The findings reinforce previous research suggesting that the intuitive design and accessibility of AI interfaces are critical for positive perceptions and sustained usage [21, 39]. The strength of the relationship

Figure 2
Most commonly used AI tools (based on students' responses to open-ended survey items)

Figure 3
AI empirical use (based on student-provided textual input)

between PEU and both PU and ATU highlights that technological fluency and user experience remain central to GAI adoption, especially among students with diverse academic backgrounds.

Additionally, the positive influence of PU on both attitude and behavioral intention underscores the importance of demonstrating the tangible benefits of GAI for academic performance. This includes its value in enhancing productivity, creativity, and access to high-quality information sources [1]. Moreover, the actual use of AI tools such as ChatGPT® and ChatPDF®—as evidenced by the students' open-ended responses—confirms their practical relevance for summarizing, drafting, and refining academic content.

Although students express enthusiasm for AI tools, their acceptance is not unconditional. Many still rely on human instruction, especially for nuanced tasks that require empathy, ethical judgment, and disciplinary expertise. This tension between automation and human mentoring should be addressed in future implementations of AI in education [3].

In summary, this study expands the theoretical scope of the TAM by confirming its applicability in the Peruvian higher education context and by integrating empirical insights on real-world usage. Practically, it provides a foundation for designing policies and support systems that align with students' attitudes and behavioral patterns. Institutions should invest in user training, ethical guidelines, and accessible design to maximize AI's pedagogical value and minimize barriers to adoption.

6. Conclusion

The structural model tested in this study validated all six hypotheses derived from the TAM, confirming the sequential influence of PEU, PU, ATU, and behavioral intention on actual AI use among university students. The strongest effects were observed in H1 (PEU → PU) and H6 (BIU → ASU), emphasizing the importance of intuitive and beneficial AI tools in driving real usage. These findings reinforce TAM's relevance as a robust framework to explain students' adoption of GAI tools in educational settings. The model also demonstrates acceptable explanatory power, with behavioral intention explaining 58.8% of the variance in ASU. By empirically validating the theoretical relationships and contextualizing them in a Latin American university, the study contributes both to the academic literature and to institutional efforts seeking to guide responsible and effective AI integration in higher education.

From a theoretical perspective, this study confirms the continued relevance of the TAM in the context of emerging AI technologies and enriches the model by validating it in a Latin American context, specifically among Peruvian students. It highlights the central role of usability and perceived benefits in shaping the adoption of digital tools, even amid the complex ethical and pedagogical challenges posed by GAI.

Practically, the results suggest that institutions of higher education should invest in user-centered design, training initiatives, and support systems to enhance students' confidence and competence in using AI tools. The observed reliance on tools such as ChatGPT®, Gemini®, and ChatPDF® for summarizing and content generation points to an immediate need for academic policies that guide ethical, effective, and pedagogically sound use of GAI.

One important limitation of this study lies in the exclusive reliance on self-reported data, which may not fully capture the nuances of students' actual interaction with AI systems. Although this approach aligns with the theoretical foundation of the TAM, which emphasizes subjective evaluations, it does not account for real-time decision-making or behavioral responses triggered by direct system use. Future studies may benefit from incorporating experimental or scenario-based designs, allowing participants to interact with GAI tools and respond to structured prompts or tasks. This would enhance ecological validity and offer a more comprehensive understanding of user attitudes and preferences.

In conclusion, this study reaffirms that AI adoption in education is not merely a function of technological availability but of students' beliefs, motivations, and the institutional structures that support them. Understanding and addressing these factors are essential for harnessing the full potential of AI to enhance learning outcomes and prepare students for a digitally transformed academic and professional world.

Ethical Statement

The procedures used in this study adhere to the ethical tenets of the Declaration of Helsinki. Formal institutional ethical approval was not required as the research involved anonymous surveys and posed minimal risk to participants. Informed consent was obtained from all individual participants included in the study.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Mildher Ugaz-Rivero: Validation, Data curation. **Yulissa Navarro-Castillo:** Methodology, Formal analysis, Visualization. **Janet Corzo-Zavaleta:** Investigation, Writing – original draft. **Alberto Urueña:** Conceptualization, Writing – review & editing, Supervision.

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