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Relative Advantage and Compatibility as Drivers of ChatGPT Adoption in Latin American Higher Education: A PLS SEM Study Towards Sustainable Digital Education

Juana Beatriz Vargas Bernuy ¹, Marco A. Nolasco-Mamani ², Norma C. Velásquez Rodríguez ³,
Renza L. Gambetta Quelopana ², Ana N. Martínez Valdivia ² and Sam M. Espinoza Vidaurre ^{2,*}

- ¹ Faculty of Civil Engineering, Architecture and Geotechnics, Jorge Basadre Grohmann National University, Tacna 23000, Peru; jvargasb@unjbgu.edu.pe
² Private University of Tacna, Tacna 23001, Peru; marnolasco@upt.pe (M.A.N.-M.); relgambetta@upt.pe (R.L.G.Q.); anamartinezv@upt.pe (A.N.M.V.)
³ Faculty of Economics and Commercial Sciences, Sedes Sapientiae Catholic University, Los Olivos 15301, Peru; nvelasquez@ucss.edu.pe
* Correspondence: samespinozav@upt.pe

Abstract

As Latin American universities pursue digitally and environmentally sustainable teaching models, understanding why students adopt generative AI is essential. We analyzed data from undergraduate students ($n = 792$) across five Latin American countries (Peru, Chile, Bolivia, Argentina, and Colombia). Grounded in the diffusion of innovations theory, the study evaluated the effects of relative advantage, compatibility, complexity, trialability, and observability on attitudes towards ChatGPT and examined the effect of attitude on intention to use among higher education students in the region. The reliability and validity of the measurement scale were confirmed, and structural relationships were tested using partial least squares structural equation modeling (PLS-SEM). The model explained 58.1% of the variance in attitude: relative advantage ($\beta = 0.247$) and compatibility ($\beta = 0.246$) exerted the largest effects, followed by trialability ($\beta = 0.223$) and observability ($\beta = 0.167$); complexity showed a weaker yet significant effect ($\beta = 0.118$). Attitude strongly predicted the intention to use ChatGPT ($\beta = 0.777$), accounting for 60.4% of its variance. All paths were significant ($p < 0.001$), and psychometric indicators exceeded recommended thresholds. These findings indicate that student adoption is driven more by perceived academic benefits and alignment with existing learning routines than by technical ease. Highlighting concrete, ethically delineated use cases and providing guided institutional spaces for experimentation may accelerate the responsible, long-term adoption of generative AI in quality higher education.

Keywords: ChatGPT; diffusion of Innovations; higher education; Latin America; technology adoption; SDG 4



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1. Introduction

Artificial intelligence (AI) has emerged as a technology of growing relevance across various sectors, including industry, economy, society, and education. Beyond its widespread adoption, AI has triggered a wave of innovation and has the potential to profoundly transform the educational landscape. At present, the education sector is undergoing significant transformations driven by rapid technological progress and characterized by an accelerated pace of change [1,2]. Within this context, the integration of AI has had a

considerable impact, redefining how students acquire knowledge, interact, and engage with educational resources [3,4].

The integration of AI is prompting significant transformations within universities, which are now challenged to modernize both their administrative and pedagogical structures to effectively incorporate this emerging technology [5–7]. In response to the increasing demands of the labor market, it is imperative that higher education institutions incorporate AI training into their curricula, extending beyond traditional computer science programs. This integration will enable students to develop technical and analytical strategies. AI's impact on the academic domain involves multiple dimensions, ranging from the formulation of institutional strategies and policies to the implementation of innovative pedagogical methods, all of which are aimed at fostering the efficient adoption of these advanced technological tools [8–10].

Recent developments in large language models (LLMs) such as ChatGPT have expanded the possibilities for integrating complex concepts across various disciplines, thereby enhancing comprehension among students with diverse academic backgrounds [11]. In this context, tools such as ChatGPT are redefining the generation of educational content by enabling the creation of adaptive and accessible materials that enhance personalized learning while enriching knowledge interaction in heterogeneous academic settings [9].

Regarding the use of large language models (LLMs), comparative studies have been conducted between ChatGPT and other AI-based tools, highlighting their performance in areas such as educational tasks and clinical contexts. [12] found that ChatGPT-4 achieved accuracy results equal to Claude 3, yet comparatively higher than Gemini 1.0 Pro. Similarly, [13] reported that ChatGPT provided more coherent responses than Gemini and Microsoft 365 Copilot in medical education contexts. In turn, [14], in a study encompassing seven models, ChatGPT was the most accurate for educational tasks across cognitive levels. These results position ChatGPT as a benchmark.

Therefore, despite the growing number of large-scale language models, such as Gemini (Google), Claude (Anthropic), Grok-1 (xAI), and Copilot (Microsoft), within the scope of this study, ChatGPT is selected as the object of analysis due to its broad data availability, public accessibility, and high level of adoption by students, instructors, and others since its launch to the present. To date, ChatGPT is among the first generative language models to achieve global mass adoption, making it one of the benchmark tools for studying perception, attitude, or intention to use in the context of generative AI [15,16].

Within this framework, it is essential to analyze the determinants that influence the adoption of AI models and LLMs in higher education. This study is grounded in the principles of the diffusion of innovations (DOI) theory, offering a robust conceptual framework to understand the underlying factors driving the adoption of disruptive technologies in academic environments [17–21].

Research on the adoption of innovations has been a central area of academic inquiry for an extended period [20], with the diffusion of innovations model emerging as one of the most influential and widely applied theoretical frameworks in the field. Numerous studies have highlighted the effectiveness of this theory in examining adoption processes both within higher education and across various educational contexts [22–26]. [20] emphasized that given the frequent presence of technological elements in diffusion studies, the terms technology and innovation may often be regarded as synonymous. The diffusion of innovations theory examines the factors influencing adoption, with particular emphasis on individual perceptions and the process by which innovations are disseminated through communicative interactions within a social system.

This study examines the factors that influence the adoption of artificial intelligence, focusing specifically on the use of ChatGPT among higher education students in Latin

America. Using the theoretical framework of the diffusion of innovations, the study analyzes the dimensions of relative advantage, compatibility, complexity, observability, and trialability to assess their impact on students' attitudes and behavioral intentions. The research aims to understand how integrating this technology can transform teaching and learning practices and contribute to sustainable educational development. The findings will provide a detailed understanding of the dynamics that influence acceptance of the technology and offer a solid basis for designing strategies that optimize its use. This will facilitate its successful and sustainable integration into learning environments.

We define sustainable digital education as the design and implementation of learning experiences mediated by digital technologies, including generative AI, aimed at verifiably improving educational quality under criteria of inclusion, efficiency, and integrity, through continuous monitoring of progress and real-time feedback to inform pedagogical and curricular decision-making [27,28]. Within this framework, the adoption of ChatGPT aligns with SDG 4 by enabling the continuous monitoring and optimization of learning and, through scalable integration into institutional environments, by strengthening educational infrastructure for equitable, efficient, and secure access [28,29]. Specifically, evidence shows that ChatGPT contributes to this quality through personalizing learning, supporting academic writing, and assisting with programming tasks, thereby reinforcing job-relevant competencies and more effective teaching practices [30–32]. Nevertheless, its effective use requires ethical governance that mitigates risks related to academic integrity, overreliance, and privacy, incorporating these safeguards as metrics for monitoring within a sustainable digital education approach [30,31].

In this context, the research poses the following question: What are the key factors influencing the adoption of ChatGPT among higher education students within the framework of diffusion of innovations theory? By analyzing these factors, the study aims to understand how such variables affect students' perceptions regarding the implementation of artificial intelligence technologies in academic settings.

The growing relevance of digital transformation in education makes it essential to understand how emerging technologies can effectively support teaching and learning; within this framework, focusing on Latin American students is pertinent for examining their perceptions and the barriers to adopting ChatGPT [33]. However, compared with North America and Europe, Latin America exhibits lower and more heterogeneous connectivity levels, with greater reliance on mobile access, less consolidated AI governance frameworks, and more limited device availability in educational settings [34,35]. Nevertheless, regional evidence shows specific gaps: global reviews and institutional analyses predominate, omitting student-level determinants of adoption and lacking systematic cross-country comparisons; the role of structural constraints, connectivity gaps, access to devices, and institutional heterogeneity that shape perceptions and use is insufficiently integrated; competency frameworks and guidelines for responsible use remain under development and are therefore scarcely operationalized; and the local sociotechnical and linguistic-cultural ecosystem, including regional initiatives, has received limited attention [31,36,37]. In this context, and given the limited empirical evidence available, the application of diffusion of innovations theory is, for now, exploratory in nature, which underscores the need for additional studies to confirm and extend initial findings. The present study addresses these gaps through an empirical and contextually grounded examination of ChatGPT adoption among Latin American university students.

Against this backdrop, the present study's focus on students in Latin America is highly relevant, as it enables a critical examination of their perceptions and the barriers they encounter when adopting ChatGPT. The study aims to expand the existing literature

and formulate recommendations for incorporating artificial intelligence competencies into curricula, preparing future professionals for a dynamic, technology-driven labor market.

1.1. Literature Review and Hypothesis Development

This section examines prior research on the adoption of artificial intelligence (AI) and large language models (LLMs) in higher education, contextualizing their relevance to the present study. The recent literature highlights key factors influencing their integration, particularly emphasizing their impact on teaching and learning processes. Within this framework, the review focuses on the use of ChatGPT as a pedagogical tool, drawing on diffusion of innovations theory to assess its influence on the adaptation of curricular content and the evolving dynamics of interaction between students and educational resources.

1.1.1. Diffusion of Innovations Theory

The diffusion of innovations (DOI) theory is one of the most popular ways to explain how new ideas move across a social system [19,38]. In this case, innovation is anything that a person or adoption unit sees as novel, whether it is a concept, a behavior, or an object. Diffusion, on the other hand, is the process by which information about the new idea is shared over time and through different channels between people in a social system. The DOI theory looks at when, where, and who adopted an innovation, which suggests that certain features of the innovation affect how quickly it is adopted [39,40]. This theoretical approach provides us with a solid base for looking at how people think and how they adopt new things, which is important for understanding how artificial intelligence can be used in schools [5,20,41–43].

The most important factors that can affect how quickly university students embrace ChatGPT are its relative benefit, compatibility, trialability, observability, complexity, and the attitude and intention towards innovation [44]. To figure out how the factors specified by the diffusion of innovations (DOI) theory affect the use of ChatGPT, we need to first explain what each of these factors means. [20] states that the core elements of DOI (see Table 1) are basic traits that, along with students' attitudes—shaped by both internal and external factors—are very important for how quickly and effectively new technologies are adopted [5,45–48].

Table 1. Key elements of the diffusion of innovations theory.

Component	Description
Relative advantage [5,20,49,50]	This refers to the degree to which an innovation is perceived as superior to the technology or practice it replaces.
Compatibility [5,20,49–51]	This measures the extent to which an innovation is congruent with the values, prior experiences, and needs of potential adopters, noting that innovations perceived as incompatible often require a shift in the value system.
Complexity [5,20,45,49–51]	This reflects the perceived difficulty of understanding and using the innovation.
Trialability [5,20,49–52]	This refers to the possibility of experimenting with the innovation on a limited basis before full adoption.
Observability [5,20,48–50,53]	This assesses the extent to which the results of the innovation are visible to others.

Note: Prepared by the authors based on the literature.

The diffusion of innovations theory provides a comprehensive framework for examining the adoption of AI within organizations. AI-based tools have led to substantial transformations in recent educational practices, enabling the incorporation of new dynamics and possibilities in the teaching–learning process [17,19,23]. A summary of the key studies applying this theoretical framework to ChatGPT adoption in higher education is presented in Table 2. At the same time, the advancement of generative artificial intelligence (GenAI) has significantly reshaped pedagogical methodologies in education. ChatGPT and other language models have demonstrated strong potential to enhance teaching and learning across various educational levels and disciplines [9,10,54]. The adoption of emerging technologies in academic settings is redefining traditional teaching methods and catalyzing a disruptive transformation in educational approaches [55–62].

Table 2. The key literature on diffusion of innovations (DOI) theory and ChatGPT in higher education.

Reference	Objective	Theory Used	Study Constructs	Main Findings
[5]	This study aimed to present an innovative approach, grounded in the diffusion of innovations (DOI) theory, to explore the adoption of ChatGPT by students in the fields of administration and management.	The theoretical framework encompassed key constructs of the DOI.	Relative advantage, compatibility, complexity, trialability, observability, and students' attitudes towards ChatGPT.	The findings indicate that students' attitudes towards the integration of ChatGPT for educational and knowledge acquisition purposes are overwhelmingly positive.
[63]	This study explored the adoption and social implications of an emerging technology—Chat Generative Pre-Trained Transformer (ChatGPT)—among higher education students. Employing a mixed-methods framework, the research integrated Rogers' diffusion of innovations theory with sentiment analysis.	Diffusion of innovations (DOI) theory.	Relative advantage, compatibility, ease of use, observability, and trialability.	The results suggest that five innovation attributes significantly influence the adoption rates and perceptions of ChatGPT, indicating its potential for transformative social change within the educational sector.
[37]	This study employed the diffusion of innovations theory to examine the adoption strategies of generative AI in higher education across 40 universities in six global regions.	Diffusion of innovations (DOI) theory.	The study explored the innovation of generative AI, including aspects such as compatibility, trialability, and observability, while also analyzing communication channels and stakeholder roles.	The findings revealed that universities proactively approached the integration of generative AI by emphasizing academic integrity, enhancing teaching and learning practices, and promoting equity.
[64]	This study investigated the factors influencing university students' inclination to use AI-based application tools, specifically chatbots, for educational purposes.	Extended diffusion of innovations theory.	Relative advantages, compatibility, trialability, trust, perceived usefulness, perceived ease of use, and behavioral intention.	The findings confirm the hypotheses regarding the relative advantages, compatibility, trialability, perceived usefulness, and trust in chatbots.
[65]	The aim of the study was to identify new variables that could enhance a proposed integrative model (PIM) for the adoption of ChatGPT. The PIM was, in turn, grounded in three well-established theoretical frameworks: the technology acceptance model (TAM), the diffusion of innovations (DOI) theory, and the cognitive moral development theory (CMDT).	TAM (technology acceptance model), DOI (diffusion of innovations theory), and CMDT (cognitive moral development theory).	The variables examined include accessibility, access to connectivity, trust in technology, creativity, entertainment, expectations, prior experience, feedback and continuous improvement, perceived innovation, integration with existing systems, time savings, personalization, workload reduction, perceived risk, satisfaction, and safety.	A total of sixteen new variables were identified as potentially influential in the use of ChatGPT: accessibility, access to connectivity, trust in technology, creativity, entertainment, expectations, prior experience, feedback and continuous improvement, perceived innovation, integration with existing systems, time savings, personalization, workload reduction, perceived risk, satisfaction, and safety.
[44]	This narrative review synthesized and analyzed empirical studies on the adoption and acceptance of ChatGPT in higher education, addressing the need to understand the key factors that influence its use by students and educators.	The technology acceptance model (TAM), the unified theory of acceptance and use of technology (UTAUT), the diffusion of innovations (DOI) theory, the technology–organization–environment (TOE) framework, and the theory of planned behavior (TPB) were all considered.	The main dimensions related to the diffusion of innovations theory include relative advantage, compatibility, complexity, trialability, observability, perceived relative risk, and design novelty.	The findings reveal that while traditional technology adoption models offer valuable insights, there is a pressing need to further explore contextual and psychological factors.

Table 2. Cont.

Reference	Objective	Theory Used	Study Constructs	Main Findings
[66]	The main objective of this article was to provide a quantitative assessment of early perceptions of tools such as ChatGPT among faculty and students within a higher education setting.	Diffusion of innovations (DOI) theory and the technology acceptance model (TA).	Awareness and general understanding; opinions of ChatGPT; benefits and implications; limitations of ChatGPT; work productivity when using ChatGPT; ChatGPT and plagiarism; the future of ChatGPT; usage, trust, and perceived benefits; and responses to ChatGPT-generated outputs.	Participants reported not using ChatGPT for plagiarism purposes, although they acknowledged that others might do so. When evaluating the accuracy of the outputs generated by the tool, more than half of the respondents were unable to detect errors, often judging inaccurate answers as correct or partially correct. These findings varied according to participants' demographic characteristics, including age, gender, and occupation.

Note: The reviewed literature on the adoption of ChatGPT and artificial intelligence technologies in higher education is primarily grounded in the diffusion of innovations (DOI) theory, both in its classical and extended versions, which highlight key attributes such as relative advantage, compatibility, complexity, trialability, and observability.

1.1.2. Relative Advantage (RA)

Relative advantage is the level at which people think an invention is better than the technology or practices it is meant to replace [20]. This idea is important for figuring out what makes people accept new ideas, since it shows how users see how useful it is for improving their performance [67]. The apparent relative advantage is a big reason why university students use ChatGPT. Emerging technologies have been shown to function as a powerful educational catalyst, outperforming traditional approaches by enhancing critical thinking, decision-making, and learning outcomes [51,68–72]. According to [63] and [9], if students think that ChatGPT is better than other tools, they might be more likely to use it as an academic resource. Accordingly, the following hypothesis is proposed:

H1. *The perception of relative advantage has a significant positive effect on students' attitudes towards ChatGPT.*

1.1.3. Compatibility (CB)

Compatibility is how well an invention fits with consumers' ideals, past experiences, and unique demands. This is a big part of why people accept it. When an innovation is seen as incompatible, among its pros and cons is often the issue of whether adopters need to change their values or not, which might make it harder for them to integrate and absorb it [20]. For ChatGPT to be popular with college students, it needs to be able to match their perceived learning needs. More students will utilize the tool if they think that it fits with their learning aims and approaches [5,48,50,51,73].

Thus, compatibility means how well the new ideas fit with the user's wants, values, and situations. People are more likely to employ new technologies if they seem to fit in with their daily lives [63,74]. Based on this reasoning, the following hypothesis is formulated:

H2. *Perceived compatibility positively influences students' attitudes towards the use of ChatGPT.*

1.1.4. Complexity (CX)

[20] defines complexity as the perceived difficulty associated with understanding and using an innovation. While Rogers asserts that higher complexity reduces the likelihood of adoption, recent studies have challenged this assumption. In a study conducted with university students familiar with the use of AI, the authors of [5] found a positive relationship between complexity and attitude. This suggests that confidence in using AI can alter the traditional negative effect of complexity, reframing it not as a barrier but as a formative challenge. In this context, complexity emerges as a key determinant in users'

willingness to adopt ChatGPT, exerting a significant influence on its integration into the learning process [17,48,50,51,75]. Accordingly, the following hypothesis is proposed:

H3. *The perception of complexity positively influences students' attitudes towards the use of ChatGPT.*

1.1.5. Trialability (TR)

Trialability is the level to which an innovation can be tested in a controlled setting before it is fully implemented [20]. This quality has been shown to be very important for increasing the desire to use, as it helps potential users become familiar with the technology better, which lowers the fear and uncertainty that come with adopting it [50]. Trialability is very important for using new technologies such as ChatGPT in higher education [17,19]. Research has demonstrated that enhancing testing capacity has a substantial positive effect on the adoption of artificial intelligence in educational settings [51,63]. Based on these findings, the following hypothesis is proposed:

H4. *Trialability has a significant positive effect on students' attitudes towards ChatGPT.*

1.1.6. Observability (OB)

Observability is defined as the extent to which the outcomes of an innovation are perceived as visible to others [20]. As a central construct in diffusion of innovations theory, it is regarded as a pivotal factor shaping the adoption rate of emerging technologies such as ChatGPT. The greater the visibility of an innovation's benefits and applications, the more likely users are to adopt it [5,51].

University students who use ChatGPT may feel better about themselves academically, since it is linked to digital skills and being able to adapt to new technologies. People who think positively about ChatGPT are likely to use it more in school, which will make it even more important in higher education. Furthermore, public talks about the supposed benefits of new technologies make them more visible and usable, which leads to more people using them in schools [5,51,63]. Based on this rationale, the following research hypothesis is proposed:

H5. *Observability has a significant positive effect on students' attitudes towards ChatGPT.*

1.1.7. Student Attitudes Towards ChatGPT Adoption (AT)

The attitudes of students, which are influenced by both intrinsic and extrinsic factors, play a fundamental role in the adoption and effective use of emerging technologies such as ChatGPT [61,76,77]. The analysis of these attitudes is crucial to identify the necessary modifications in the teaching of artificial intelligence, facilitating its efficient integration into educational processes [78,79]. Recent findings suggest that the adoption of ChatGPT is significantly influenced by students' attitudes and behavioral intentions, with positive attitudes leading to dedication and effort in acquiring new knowledge [5,76].

In this context, students' favorable attitude towards ChatGPT suggests that the tool could be successfully implemented in academic settings [57]. The following research hypothesis is therefore proposed:

H6. *Students' attitudes towards ChatGPT positively affect their intention to adopt it.*

1.1.8. ChatGPT Usage Intention (IU)

Students' tendency to adopt and make use of this tool in their academic activities is referred to as the intention to use ChatGPT in the context of higher education environments.

Perceived utility, simplicity of use, and expectations regarding the academic benefits it may provide are some of the aspects that influence this intention [80,81]. However, according to [81], it is evident that usage intention is influenced by students' positive perceptions of ChatGPT's ability to simplify tasks, improve academic performance, and facilitate access to relevant information. Nevertheless, this intention may also be subject to influence from ethical considerations and potential repercussions on creativity and critical thinking [82].

2. Materials and Methods

2.1. Design

A correlational explanatory and cross-sectional survey design was utilized for this study, which adopted a quantitative approach to data collection [83,84]. We aimed to conduct a study that would analyze the relationships between the dimensions of the diffusion of innovations theory, which include relative advantage, compatibility, trialability, observability, and complexity, and the attitudes of university students towards the adoption of ChatGPT. Additionally, the study's objective was to determine the influence of these dimensions on the students' intention to incorporate this technology into educational settings in Latin America. This application of the DOI theory takes on an exploratory character because there is only a small amount of empirical knowledge in the region. To provide baseline data on the early adoption of generative AI, a cross-sectional design was utilized to collect the perceptions and behavioral patterns of the sample at a certain point in time. Accordingly, the study provides an explanatory framework that can be used to gain a better understanding of the factors that are driving the incorporation of ChatGPT into university education in Latin America.

2.2. Participants

The study involved a total of 906 undergraduate students from seven Latin American countries: Peru, Chile, Bolivia, Argentina, Colombia, Ecuador, and Mexico. Participants were selected through non-probability convenience sampling, guided by accessibility, availability, and expressed willingness to contribute to the research. This approach ensured the inclusion of a heterogeneous group, rich in geographic, disciplinary, and institutional diversity [85].

Eligibility criteria included the following: active enrollment during the academic term in which data were collected, being of legal adult age, and the provision of informed consent. Exclusion criteria encompassed participants who did not meet these requirements, as well as cases invalidated by ethical, legal, or methodological inconsistencies. Notably, records from Ecuador and Mexico were excluded due to limited representation, culminating in a final sample of 792 valid cases.

Data collection unfolded through an online survey instrument distributed via official university channels, namely institutional email accounts and WhatsApp groups, thereby maximizing digital outreach and accessibility. Adhering strictly to ethical protocols, the study guaranteed confidentiality, anonymity, and the voluntary nature of participation. Informed consent was obtained electronically prior to engagement.

The sociodemographic and academic composition of the sample is set out in Table 3. This provides the contextual background against which subsequent analyses are set to be conducted.

Table 3. Sociodemographic and academic characteristics.

Category	Group (N = 792)	Frequency	%
Country	Argentina	108	13.6%
	Bolivia	85	10.7%
	Chile	165	20.8%
	Colombia	123	15.5%
	Peru	311	39.3%
Type of university	Private	341	43.1%
	Public	451	56.9%
Mode of study	In-person	595	75.1%
	Virtual	21	2.7%
	Hybrid	176	22.2%
Gender	Male	351	44.3%
	Female	441	55.7%
Age	Mean	21.8	
	STDEV	3.81	
	Min	18	
	Max	39	

Note: The table presents the sociodemographic and academic characteristics of the participants (N = 792) based on data collected through the survey. Frequencies and percentages are reported for categorical variables, while measures of central tendency and dispersion are provided for age.

Table 3 displays the sociodemographic and academic characteristics of the 792 university students included in this study. Regarding country of origin, the highest proportion of participants was from Peru (39.3%), followed by Chile (20.8%), Colombia (15.5%), Argentina (13.6%), and Bolivia (10.7%). With respect to the type of institution, 56.9% of the students were enrolled in public universities, while 43.1% were attending private universities. The present study encompasses a variety of university settings, thus allowing for the analysis of potential differences in the perception and adoption of AI tools depending on the institutional context.

Regarding the study modality, 75.1% of the students were enrolled in face-to-face programs, 22.2% in hybrid modalities, and 2.7% in fully online programs. The sample consisted of 55.7% female students, while male students represented 44.3% of the total. This distribution enables the identification of potential gender-based disparities and aligns with broader demographic trends observed in the higher education landscape of Latin America. Additionally, the average age of the participants was 21.8 years, with a standard deviation of 3.81%.

Within the framework of this study, the characterization of the sample enables the identification of key conditions for determining the adoption of artificial intelligence tools. The predominant average age suggests that students within this age group are more familiar with the use of digital technologies. Moreover, being at the university stage facilitates the adoption of ChatGPT at a significantly earlier age, as posited by the diffusion of innovations theory. However, it is worth noting that a high proportion of students choose face-to-face learning modalities, which could represent a limiting factor in promoting direct and frequent access to artificial intelligence environments and tools. Nevertheless, this analysis is essential when considering the increasing presence of tools such as ChatGPT in Latin American university classrooms, within a context characterized by heterogeneous technological infrastructure across countries in the region.

2.3. Measurement Instrument

To ensure the content validity of the instrument, the items incorporated into this study were meticulously drawn from previously validated research instruments. These selections were made to guarantee that the scales employed adequately reflect the constructs under investigation, aligning with the overarching goal of producing generalizable and methodologically robust inferences [5,49,86]. The instrument was structured as a comprehensive questionnaire composed of three main sections.

The first section provided participants with informed consent documentation and gathered foundational demographic data, including gender, age, academic program, year of study, and type of institution. This section served to contextualize the respondent profile and establish a baseline for interpreting variance within the sample. The second section evaluated dimensions related to ChatGPT usage, systematically grouped under seven theoretical constructs derived from the diffusion of innovations theory: relative advantage, compatibility, complexity, trialability, observability, students' attitudes towards ChatGPT, and their intention to use the tool. This section included 31 items, each measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). This scaling strategy facilitated nuanced assessments of agreement, allowing for both intensity and directionality in response patterns.

The third section adopted a dichotomous format to explore participants' exposure to artificial intelligence training. Respondents were asked whether they had received any form of training in AI. If affirmative, follow-up questions were posed regarding the type, duration, and perceived quality of such training. This segment enabled the researchers to examine whether prior engagement with AI might influence attitudes or intention to adopt ChatGPT. To refine the instrument and ensure psychometric rigor, three successive pilot studies were conducted, involving a cumulative total of 150 undergraduate students from universities located in Tacna and Lima. These pilots were instrumental in estimating the reliability of the instrument and identifying any linguistic, semantic, or structural ambiguities. The final refinement process was completed through expert validation, wherein three domain specialists reviewed the instrument for clarity, objectivity, and theoretical coherence. The development and adaptation of the survey are summarized in Table 4, which presents the origin and distribution of each construct and its corresponding items.

Table 4. Research instrument.

No.	Component	Item	References
1	Relative advantage	1. ChatGPT contributes to the development of students' competencies. 2. I can save time by using ChatGPT. 3. I can save effort by using ChatGPT. 4. ChatGPT helps me to be more effective.	[5,20,49,50]
2	Compatibility	5. The use of ChatGPT aligns with all aspects of my life. 6. ChatGPT is well suited to my current circumstances. 7. I have invested considerable time and effort in engaging with ChatGPT. 8. I am concerned about the potential misuse of ChatGPT.	[5,20,49–51]
3	Complexity	9. The ChatGPT interface is intuitively designed and user-friendly, encompassing elements such as layout, menus, buttons, and the display of responses. 10. The output provided by ChatGPT is expressed in a clear and easily understandable manner. 11. Operating ChatGPT does not necessitate prior technical expertise. 12. The use of ChatGPT does not involve a considerable cognitive load. 13. Engaging in interaction with ChatGPT is unlikely to generate confusion on my part.	[5,20,45,49–51]

Table 4. *Cont.*

No.	Component	Item	References
4	Trialability	14. I have been familiar with ChatGPT since its initial development phases. 15. I typically find it engaging to explore and test emerging tools like ChatGPT. 16. Before incorporating ChatGPT into my learning process, I prefer to evaluate its practical value through experimentation. 17. The university sets forth specific guidelines governing the use of ChatGPT in academic learning prior to its adoption.	[5,20,49–52]
5	Observability	18. The presence of ChatGPT is noticeable across my university environment. 19. It is anticipated that my peers will express interest in ChatGPT upon observing my engagement with it. 20. My use of ChatGPT is likely to be perceived by others. 21. I am more likely to use ChatGPT due to its adoption by my peers.	[5,20,48–50,53]
6	Attitude towards ChatGPT	22. Utilizing ChatGPT would represent a beneficial decision—for instance, in facilitating information retrieval, enhancing the quality of academic writing, or assisting in the planning of lesson and assignments. 23. Employing ChatGPT would be considered a judicious and well-informed choice. 24. I hold a favorable perception regarding the use of ChatGPT in my academic endeavors. 25. I would feel enthusiastic about integrating ChatGPT into my academic activities. 26. I would derive satisfaction from the use of ChatGPT in my scholarly work. 27. The integration of ChatGPT would contribute significantly to the advancement of my professional career.	[5,45,87]
7	Intention to use ChatGPT	28. I am open to utilizing ChatGPT for academic or professional purposes. 29. I would consider using ChatGPT, provided that its use is authorized within the given context. 30. I would be willing to permit ChatGPT to assist me in carrying out a range of tasks. 31. I plan to incorporate ChatGPT into my activities in the near future.	[5,45,87]

Note: Prepared by the authors based on a review of the specialized literature.

2.4. Data Collection Procedure

The data collection was carried out using self-administered questionnaires distributed through the Google Forms platform. Prior to distribution, the study's documentation was submitted to the rectors of the universities included in the sample. These authorities were provided with comprehensive information about the research objectives and procedures and were requested to support the dissemination of the instrument. Furthermore, collaboration was secured by faculty members at these institutions, who assisted in facilitating the distribution of the online form. Students who expressed interest in participating received an invitation to complete the questionnaire via email and the WhatsApp application.

Of the 906 questionnaires distributed, 55 were excluded at the outset because the respondents were not enrolled in an active academic semester at their respective universities. Additionally, 10 responses were filtered out due to participants being under the age of 18, and 16 were discarded for lacking informed consent. A total of 25 surveys from countries with limited representation (Ecuador and Mexico) were also excluded, along with 8 responses from students over the age of 40, following established methodological criteria. Consequently, the final data set comprised 792 valid responses from five Latin American countries. Participation was entirely voluntary and anonymous, with data confidentiality assured throughout the study. The survey instrument remained open during March and April 2025, which constituted the data collection period.

2.5. Statistical Analysis

Two specialized software tools were utilized to perform the data analysis. Descriptive statistical analyses were conducted using SPSS Statistics (version 29.0), while the structural model was developed with SmartPLS 4 (version 4.1.1.2) [88]. The procedures for partial least squares structural equation modeling (PLS-SEM) adhered to the methodological recommendations outlined by [89]. In the initial stage of the analysis, the measurement model was examined to evaluate the reliability and validity of the constructs through Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) indicators. Dis-

criminant validity was assessed using the heterotrait–monotrait ratio (HTMT) and the Fornell–Larcker criterion.

In the subsequent phase, the structural model was estimated, and hypothesis testing was performed via bootstrapping, focusing on the analysis of path coefficients (β), t-statistics, and corresponding *p*-values. Additionally, the coefficient of determination (R^2) was reported to assess the explanatory power of the model in relation to the intention to use ChatGPT within the context of higher education in Latin America [90,91].

To verify the validity of cross-country comparisons, we applied the MICOM (measurement invariance of composites) procedure, following the recommendations of [92]. This procedure assesses invariance in three stages; in our analysis, most constructs satisfied the first two steps. However, the construct trialability did not achieve compositional invariance in certain pairwise country comparisons; consequently, partial invariance was established across all pairwise comparisons, and it was therefore unnecessary to perform the third step (equality of means and variances). We subsequently conducted a multigroup analysis (MGA) to determine differences between countries [93].

3. Results

3.1. Descriptive Results

Prior to engaging in the structural model analysis, a series of descriptive variables concerning the adoption and experiential engagement with artificial intelligence tools, specifically ChatGPT, were meticulously examined. This foundational layer aimed not only to contextualize the study’s analytical dimensions but also to elucidate patterns in users’ familiarity, motivations, usage frequency, and self-perceived proficiency (see Table 5).

Table 5. Variables related to the use of artificial intelligence.

Category	Group (N = 792)	Frequency	%
Familiarity in use	Very low	34	4.3%
	Low	111	14.0%
	Average	330	41.7%
	High	192	24.2%
	Very high	125	15.8%
Main motivation	Improve the quality of work	191	24.1%
	Save time	196	24.7%
	Access to information	307	38.8%
	Inspiration	63	8.0%
	Nothing in particular	35	4.4%
Frequency of use	Never	29	3.7%
	Every day	128	16.2%
	Three days a week	128	16.2%
	Occasionally	437	55.2%
	Once a week	70	8.8%
Ability to use	Nothing advanced	110	13.9%
	Somewhat advanced	119	15.0%
	Intermediate	366	46.2%
	Advanced	133	16.8%
	Very advanced	64	8.1%
AI training	Yes	309	39.0%
	No	483	61.0%

Note: The table presents the frequencies and percentages of variables related to the use of artificial intelligence (N = 792), including level of familiarity, primary motivation, frequency of use, perceived skill level, and prior AI training among university students.

With respect to familiarity, a significant portion of respondents (41.7%) reported a moderate level of knowledge regarding ChatGPT, while 24.2% considered their familiarity

to be high. These findings suggest a notable level of exposure to generative AI tools, although this exposure varied in depth and regularity. When asked about the motivations driving their use of ChatGPT in academic contexts, the most frequently cited purpose was access to information (38.8%), followed closely by time-saving benefits (24.7%) and the desire to enhance the quality of academic output (24.1%). This triad of motivations underscores the instrumental logic guiding most students' engagement with the tool. These observations reflect a pragmatic orientation among students—one rooted in the recognition of AI's instrumental value in enhancing academic efficiency, decision-making, and output quality. Rather than being grounded in its novelty or because they are following a trend, their interaction with ChatGPT appears to be grounded in its purposeful academic utility.

Regarding the usage frequency, occasional use was reported by most participants (55.2%), establishing it as the prevailing behavioral pattern. This was followed by daily usage (16.2%) and use three times per week (16.2%), indicating that although ChatGPT is not yet embedded in routine academic behavior for most students, it is nonetheless a recurring resource. Such trends may be interpreted as reflective of evolving user confidence, institutional norms, and pedagogical practices. Participants were also prompted to self-assess their level of proficiency with ChatGPT. Here, 46.2% rated themselves as intermediate users, while 16.8% identified as advanced and 8.1% described themselves as very advanced. These figures suggest that a substantial segment of the student population already possesses functional mastery of the platform, although advanced competencies remain limited. Such variance in digital fluency may shape not only patterns of adoption but also the depth of critical engagement with AI-generated content.

Finally, regarding exposure to formal instruction, 39% of students reported having received some form of training in artificial intelligence, while 61% had not. This highlights a pressing imperative within higher education: to bridge the gap between the widespread availability of AI tools and the structured pedagogical guidance necessary to foster their ethical and effective use. Together, these results paint a nuanced portrait of student engagement with ChatGPT—marked by growing familiarity, selective adoption, and a recognition of its academic utility yet tempered by significant variation in skill level and formal instruction. As generative AI technologies become increasingly woven into the academic fabric, these preliminary findings serve as both a snapshot of the present and a call to shape the trajectory of future educational strategies.

3.2. Measurement Model Evaluation

The results of the measurement model validation are displayed in Table 6 and were carried out in accordance with the PLS-SEM approach. The findings confirm the validity and consistency required for exploratory research, thereby supporting the application of the model within the framework of the diffusion of innovations (DOI) theory for the Latin American context. Consequently, the composite reliability coefficient (CR) was utilized to assess the constructs; the reported data exceeded the recommended minimum threshold of 0.70 [89], signifying adequate internal consistency of the indicators.

Observability (CR = 0.788) was found to be the construct with the lowest CR, while attitude towards ChatGPT (CR = 0.929) was identified as the construct with the highest CR. Consequently, it can be posited that the indicators employed in this study are reliable for measuring each construct. Convergent validity was analyzed using AVE, for which the values for all constructs were greater than 0.50, the minimum required in the scientific literature. In accordance with the CR, the observability variable exhibited the lowest AVE coefficient, registering at 0.558, while the intention to use variable demonstrated the highest AVE, at 0.752. For most constructs, Cronbach's alpha (α) exceeded the threshold, although certain constructs, including complexity, trialability, and observability, exhibited coefficients

that were below the threshold. These have been compensated for by adequate levels of CR and AVE, which are considered primary indicators in measurement models with a PLS-SEM approach [89,94].

Table 6. Evaluation of the measurement model.

Construct	Items	Factor Loading	α	CR	AVE	R ²	VIF
Relative advantage	RA01	0.747	0.768	0.849	0.586		1.396
	RA02	0.787					1.778
	RA03	0.679					1.537
	RA04	0.840					1.639
Compatibility	CB05	0.879	0.709	0.836	0.636		1.833
	CB06	0.881					1.765
	CB07	0.599					1.174
Complexity	CX09	0.779	0.639	0.807	0.586		1.417
	CX10	0.853					1.528
	CX13	0.650					1.139
Trialability	TR15	0.908	0.521	0.797	0.666		1.142
	TR16	0.712					1.142
Observability	OB18	0.654	0.611	0.788	0.558		1.167
	OB19	0.884					1.341
	OB21	0.682					1.231
Attitude towards ChatGPT	AT22	0.777	0.907	0.929	0.685	0.581	2.014
	AT23	0.868					2.916
	AT24	0.830					2.345
	AT25	0.866					3.172
	AT26	0.860					3.100
	AT27	0.758					1.828
Intention to use ChatGPT	IU28	0.898	0.889	0.924	0.752	0.604	3.190
	IU29	0.897					3.267
	IU30	0.847					2.167
	IU31	0.823					1.937

Note: The table shows the statistical indicators of the measurement model estimated using PLS-SEM. Output from SmartPLS 4 software (version 4.1.1.2).

Regarding the factor loadings of the individual indicators for each construct, the majority display values in excess of 0.70, which is widely regarded as the recommended threshold. This outcome aligns with the methodological tenets that ensure the maintenance of each indicator's internal reliability. However, certain indicators with loadings falling below the established threshold were identified. Given that these indicators contributed to the reliability of the CR and convergent validity (AVE), it was decided to maintain them in the theoretical model, as they are part of the structure and make a significant contribution to the measurement model.

Regarding the levels of collinearity between the study variables, the results of the preliminary discriminant validity, as represented by the VIF, are reported in Table 6. A thorough examination of the available data reveals that all indicators fall below the stipulated threshold of 3.3. It is noteworthy that this threshold can be elevated to as high as 5.0, as indicated in the work of [89]. Therefore, it can be deduced that multicollinearity problems are not present, since the highest value reported falls on the IU29 indicator with a VIF of 3.267, which is within the acceptable thresholds.

3.3. Discriminant Validity

As illustrated in Table 7, the HTMT matrix does not reveal any relationships that could be indicative of critical correlations between the study variables. It is therefore observed that the coefficients remain within acceptable levels as outlined in the relevant literature. The relationship between the factor of attitude towards ChatGPT and intention to use ChatGPT has an HTMT index of 0.863; however, this is within acceptable margins without compromising differences between both study variables. Conversely, the index is pertinent given the theoretical framework that establishes a close relationship between both variables within the explanatory models of intention to use.

Table 7. HTMT matrix.

	AT	CB	CX	IU	OB	RA	TR
Attitude towards ChatGPT							
Compatibility	0.750						
Complexity	0.666	0.651					
Intention to use ChatGPT	0.863	0.661	0.661				
Observability	0.653	0.606	0.539	0.577			
Relative advantage	0.738	0.736	0.747	0.700	0.652		
Trialability	0.782	0.684	0.683	0.719	0.660	0.711	

Note: Output from SmartPLS 4 software (version 4.1.1.2).

As demonstrated in Table 8, the Fornell–Larcker matrix reveals relationships that demonstrate the suitability of the measurement model. The various correlations between the study variables remained below the diagonal of correlations between the same variables, which in turn remained more associated than the others. For instance, the variable entitled “attitude towards ChatGPT” has a value of 0.828, which is higher than the values obtained by the other variables, including “compatibility” (0.620), “complexity” (0.508), “intention to use ChatGPT” (0.777), “observability” (0.514), “relative advantage” (0.637), and “trialability” (0.564). This pattern is maintained with all other variables, even those where there is a theoretical approximation, such as relative advantage and compatibility. Therefore, the existence of empirical differentiation is postulated.

Table 8. Fornell–Larcker matrix.

	AT	CB	CX	IU	OB	RA	TR
Attitude towards ChatGPT	0.828						
Compatibility	0.620	0.797					
Complexity	0.508	0.465	0.765				
Intention to use ChatGPT	0.777	0.544	0.502	0.867			
Observability	0.514	0.429	0.344	0.449	0.747		
Relative advantage	0.637	0.592	0.526	0.592	0.459	0.765	
Trialability	0.564	0.453	0.399	0.514	0.395	0.474	0.816

Note: Output from SmartPLS 4 software (version 4.1.1.2).

3.4. Structural Model

Table 9 and Figure 1 present the results of the structural model estimation. The analysis confirms all the hypotheses proposed in this research, with each path demonstrating a statistically significant relationship ($p < 0.001$). The standardized path coefficients (β) align with findings reported in the prior literature. Among the predictors, relative advantage (RA) ($\beta = 0.247$; $t = 5.494$) and compatibility (CB) ($\beta = 0.246$; $t = 6.235$) exhibit the strongest effects on attitude towards ChatGPT. These outcomes suggest that students recognize clear

benefits associated with the use of the ChatGPT platform and perceive its application as congruent with their personal values, thereby fostering more favorable attitudes.

Table 9. Path coefficients and hypotheses.

Hypotheses	Path	β	M	STDEV	t	p	Validation
H1	RA $\rightarrow$ AT	0.247	0.249	0.045	5.494	0.000	Accepted
H2	CB $\rightarrow$ AT	0.246	0.246	0.039	6.235	0.000	Accepted
H3	CX $\rightarrow$ AT	0.118	0.118	0.033	3.542	0.000	Accepted
H4	TR $\rightarrow$ AT	0.223	0.221	0.039	5.768	0.000	Accepted
H5	OB $\rightarrow$ AT	0.167	0.167	0.033	5.037	0.000	Accepted
H6	AT $\rightarrow$ IU	0.777	0.778	0.017	46.191	0.000	Accepted

Note: Data obtained through the use of SmartPLS 4 software (version 4.1.1.2).

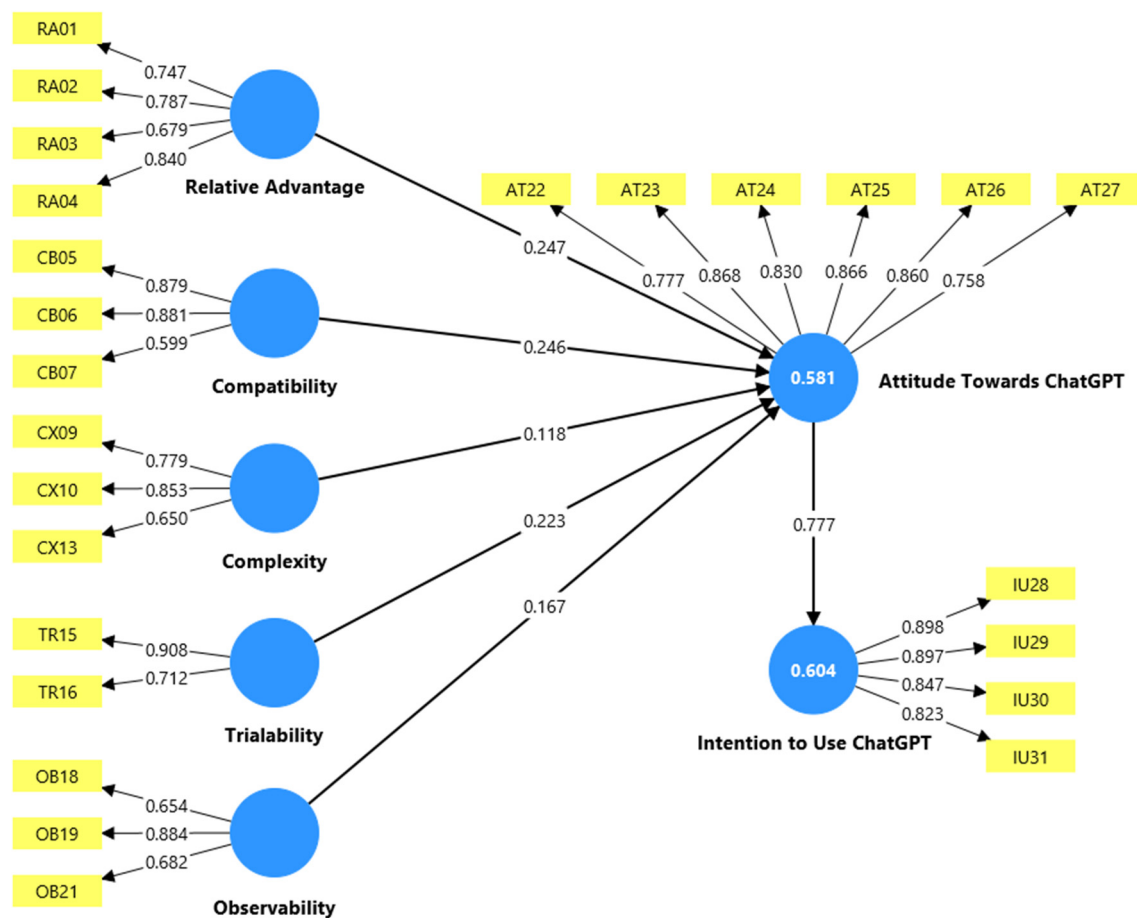


Figure 1. Estimation of the structural model. Note: Structural model analysis results. Output generated using SmartPLS 4 software (version 4.1.1.2).

In addition, trialability (TR) ($\beta = 0.223$; $t = 5.768$) significantly influences attitude towards ChatGPT, indicating the importance that students assign to the possibility of experimenting with the tool before full-scale implementation. This variable plays a pivotal role, as the results reflect positive perceptions regarding trial opportunities. Observability (OB) ($\beta = 0.167$; $t = 5.037$) and complexity (CX) ($\beta = 0.118$; $t = 3.542$) also exert positive, albeit weaker, effects on attitude towards ChatGPT. These findings indicate that both the visibility of the benefits and the perceived ease of use contribute—though to a lesser degree—to the formation of favorable attitudes towards the adoption of the tool among university students.

Moreover, the model highlights a particularly strong association between attitude towards ChatGPT and intention to use ChatGPT (AT) ($\beta = 0.777$; $t = 46.191$), emphasizing the central role of attitude as a mediating variable. This finding corroborates the findings of previous studies rooted in technology acceptance frameworks, which posit attitude as a critical antecedent of behavioral intention [95].

3.5. Explained Variance

The structural model depicted in Figure 1 reveals an R^2 value of 0.581 for attitude towards ChatGPT and of 0.604 for intention to use ChatGPT. These numbers, which are bright spots in the explanatory analysis architecture, show that the model captures almost 60% of the variance in usage intention, which is a powerful indication of the model's predictive range. According to the subtle rules of PLS-SEM research, this level of explained variance is in the moderate range [89]. It is evident that the factors under scrutiny have been demonstrated to form a robust theoretical framework with the potential to predict the intention to utilize artificial intelligence tools such as ChatGPT. Consequently, these factors emerge as pivotal determinants within the structural model and possess considerable predictive capacity, being influenced by attitude in the context of higher education in Latin America.

3.6. Compositional Invariance

To assess the feasibility of conducting multigroup comparisons, we applied the MICOM procedure proposed by Henseler [92], specifically Step 2, which evaluates compositional invariance via permutation tests ($n = 5000$) with 10 pairwise comparisons between the five countries included in this study: Argentina, Bolivia, Chile, Colombia, and Peru. The results presented in Table 10 indicate that across all country pairs, in most cases, at least five to six constructs yielded p -values > 0.05 , thereby satisfying the partial invariance condition recommended for proceeding with multigroup analysis (MGA). The constructs of attitude towards ChatGPT, intention to use, and complexity exhibited robust invariance in nearly all comparisons. By contrast, constructs such as trialability and compatibility showed a lower degree of consistency in certain specific country pairs.

Table 10. Compositional invariance testing across countries using the MICOM approach.

Comparison	AT	CB	CX	IU	OB	RA	TR
Argentina–Bolivia	0.819	0.233	0.431	0.313	0.666	0.811	0.008
Argentina–Chile	0.560	0.005	0.060	0.631	0.384	0.337	0.000
Argentina–Colombia	0.496	0.486	0.216	0.671	0.684	0.212	0.000
Argentina–Peru	0.918	0.576	0.331	0.837	0.951	0.772	0.002
Bolivia–Chile	0.805	0.106	0.360	0.461	0.024	0.186	0.860
Bolivia–Colombia	0.907	0.750	0.701	0.593	0.160	0.579	0.647
Bolivia–Peru	0.946	0.373	0.885	0.403	0.283	0.577	0.817
Chile–Colombia	0.267	0.015	0.469	0.953	0.961	0.034	0.367
Chile–Peru	0.511	0.000	0.447	0.843	0.375	0.973	0.877
Colombia–Peru	0.392	0.795	0.977	0.722	0.660	0.065	0.417

Note: Values ≤ 0.05 are shown in bold, indicating that compositional invariance is not met for that construct. Partial invariance ($\geq 50\%$ of constructs with $p > 0.05$) permits proceeding with multigroup analysis (MGA).

3.7. Multigroup Analysis

To assess structural invariance across the countries in the sample, we conducted a multigroup analysis (MGA) using bootstrapping on the coefficients of the model's structural relationships. Implementing this procedure enabled us to determine whether the structural relationships of the measurement model differ across countries [94].

The results presented in Table 11 indicate that most structural coefficients do not exhibit statistically significant differences between countries ($p > 0.05$), which supports the

comparability of the model and allows the results to be generalized to the Latin American context. However, it is important to note that some statistically significant differences ($p < 0.05$) were observed in certain relationships—namely, between complexity and attitude towards ChatGPT, between observability and attitude towards ChatGPT, and between trialability and attitude towards ChatGPT—particularly in comparisons involving Peru and Bolivia. While these differences reflect the importance of these factors for perceptions and intentions regarding the adoption of AI tools such as ChatGPT, they also suggest that some predictors may carry different weights depending on the cultural or educational context, without affecting the model’s overall structure.

Table 11. Multigroup analysis of structural coefficients by country.

	ARG BOL	ARG CHI	ARG COL	ARG PER	BOL CHI	BOL COL	BOL PER	CHI COL	CHI PER	COL PER
Attitude towards ChatGPT → intention to use ChatGPT	0.654	0.825	0.516	0.378	0.810	0.318	0.229	0.394	0.274	0.871
Compatibility → attitude towards ChatGPT	0.682	0.523	0.518	0.276	0.853	0.828	0.525	0.965	0.622	0.681
Complexity → attitude towards ChatGPT	0.026	0.408	0.058	0.927	0.072	0.531	0.016	0.165	0.358	0.033
Observability → attitude towards ChatGPT	0.279	0.801	0.833	0.558	0.103	0.153	0.038	0.976	0.656	0.682
Relative advantage → attitude towards ChatGPT	0.905	0.428	0.513	0.666	0.516	0.608	0.559	0.867	0.098	0.151
Trialability → attitude towards ChatGPT	0.374	0.279	0.830	0.399	0.036	0.473	0.847	0.164	0.019	0.515

Note: Bold p -values indicate statistically significant differences ($p < 0.05$); ARG—Argentina, BOL—Bolivia, CHI—Chile, COL—Colombia, and PER—Peru.

4. Discussion

Framed within the diffusion of innovations theory, the results clearly answer the research question on the main factors affecting the adoption of ChatGPT among university students. Table 9 shows statistically significant and favorable correlations between all the proposed hypotheses, therefore validating them. Emphasizing the key roles of relative advantage, compatibility, and trialability as fundamental characteristics supporting technology adoption, these results show the validity and applicability of [20] the theoretical model in educational environments supplemented by artificial intelligence. Particularly among Latin American college students, these qualities are crucial, since they significantly influence their views on using ChatGPT and, consequently, their probability of using it.

A comparison of the results of the present study with the findings reported in [5] reveals clear convergence in the recognition of the growing relevance of artificial intelligence (AI) within education. This finding serves to reinforce the prevailing argument that students’ attitudes towards ChatGPT are characterized by a pronounced inclination to adopt the tool, which is predominantly informed by positive perceptions. Collectively, participants exhibited an optimistic, enthusiastic, and confident outlook regarding the future benefits of using ChatGPT. Such perspectives underscore the perceived value of ChatGPT regarding the relative advantage, compatibility, and trialability, thereby indicating a favorable context for its progressive integration into educational settings.

The findings of this study corroborate the pertinence of the technological attributes proposed by the diffusion of innovations theory in elucidating university students’ attitudes and adoption intentions towards ChatGPT. Our results in Latin America confirm the centrality of the DOI attributes, relative advantage, compatibility, and trialability as facilitators of students’ attitude towards and intention to use ChatGPT; in contrast, perceived complexity exhibits a positive but weak effect on attitude ($\beta = 0.118$), and observability shows a moderate effect ($\beta = 0.167$), while the attitude–intention relationship is strong ($\beta = 0.777$;

$R^2 = 0.604$). In contrast, the findings reported by [63], based on a university population in India, model the five DOI attributes as direct predictors of intention and indicate that ease of use directly influences intention, additionally highlighting observability and gender differences (distinct prioritization of attributes between male and female students). In sum, our findings converge on the overall relevance of DOI attributes but diverge by prioritizing practical benefits, academic congruence, and the possibility of trial over usability/visibility, underscoring the moderating role of the Latin American context in students' adoption of ChatGPT.

In contrast with the institutional landscape described by [37], in which universities prioritize governance frameworks for generative AI, academic integrity, the redesign of authentic assessments, and AI literacy programs and explicitly promote trialability together with, to a lesser extent, observability—although gaps persist in data privacy, equity, and systematic evaluation—our PLS-SEM results (see Figure 1) based on Latin American students reveal a more behavioral dynamic: intention to use is mediated by attitude, and the innovation attributes contribute in a moderate, non-hierarchical manner; in particular, trialability and observability do not emerge as predominant drivers. This asymmetry suggests a “policy–practice” misalignment: while institutions establish guidelines and implementation pathways, diffusion among students appears to advance primarily through individual appraisals of perceived performance rather than through social mechanisms of visibility and institutional experimentation. The novelty of our study lies in documenting this gap and proposing that adoption strategies incorporate mechanisms that enhance observability, trialability, and bidirectional feedback with students. [5] documents that complexity is positively associated with attitudes towards ChatGPT, a result also observed in our data and one that departs from Rogers' classical prediction. This direction can be explained by participants' prior familiarization, through introductory materials and opportunities for trialability, which enhances self-efficacy and reframes difficulty as a formative challenge, thereby attenuating the traditional inhibiting effect. In our Latin American context, the positive effect appears moderate, suggesting that when digital literacy and guided practice are present, “complexity” functions more as an indicator of perceived competence than as a barrier. This implies that the effect of complexity depends on how the tool's use is defined and taught; therefore, future studies should make the direction of the items explicit and control for prior experience.

The PLS-SEM structural model (Figure 1) confirms that the five attributes proposed by diffusion of innovations theory exert significant effects on attitudes towards ChatGPT and that attitude acts as a powerful mediator of usage intention ($\beta = 0.777$; $R^2 = 0.604$). These results partially converge with those of the authors of [64], who also identified relative advantage, compatibility, and trialability as key facilitators of chatbot adoption in university settings. However, their model tested direct relationships with intention and did not include attitude as a mediating variable. The present study also considers complexity and observability, which were absent or non-significant in the South African research. The results show that although their effects are more modest ($\beta = 0.118$ and $\beta = 0.167$, respectively), they still make a substantial contribution to explaining variance in attitude ($R^2 = 0.581$). This extension suggests that in Latin American contexts, students' perceptions of the complexity and visibility of AI benefits shape their affective disposition and, consequently, their intention to adopt ChatGPT. It also underscores the need for institutional strategies that not only emphasize the tool's utility and alignment with academic tasks but also reduce perceived complexity and render its benefits tangible in practice.

From the results of the compositional invariance test, it was observed that most constructs maintained structural stability across each paired country in the sample. Nevertheless, some key variables of the structural model, such as trialability and complexity,

exhibited significant violations of invariance in certain comparisons. Accordingly, this finding indicates that students from different countries may interpret or value specific aspects related to the adoption of AI tools such as ChatGPT differently.

Moreover, the multigroup analysis conducted using a bootstrap-based MGA identified significant differences in structural effects between some countries, particularly for the paths of complexity and attitude towards ChatGPT, on the one hand, and of trialability and attitude towards ChatGPT, on the other hand. These differences, together with the compositional invariance results, suggest that the influence of complexity or trialability on attitudes towards using ChatGPT is not homogeneous across countries. This may be attributable to cross-national differences in digital literacy, organizational culture, or technological maturity, given that each country's context differs in these respects [96].

5. Conclusions

The accelerated digital transformation in education makes it imperative to understand the potential of emerging technologies such as ChatGPT to optimize teaching and learning. In this context, the present study, which focused on university students in Latin America, provides empirical evidence on perceptions and barriers to adoption. The structural model estimated with SmartPLS 4 corroborates the explanatory relevance of diffusion of innovations (DOI) theory: the five innovation attributes (relative advantage, compatibility, complexity, trialability, and observability) explain 58.1% of the variance in attitude towards the tool, a proportion considered moderate–high in the technology adoption literature.

Among the predictors, relative advantage and compatibility exhibit similar standardized coefficients ($\beta \approx 0.25$), underscoring the influence of perceived academic benefits and alignment with established study routines. Trialability ($\beta = 0.223$) and observability ($\beta = 0.167$) also contribute significantly, highlighting the importance of safe experimental environments and socially legitimizing signals. With respect to complexity, and contrary to DOI expectations, it does not operate as a barrier but is positively associated with attitude ($\beta = 0.118$); we propose that this sign reflects processes of prior familiarization and guided practice that enhance self-efficacy and establish boundary conditions under which the traditional negative effect is attenuated or even reversed. Based on these findings, we recommend integrating AI competencies into curricula to prepare future professionals for a dynamic, technology-intensive labor market, as well as developing clear ethical policies for the use of generative AI. In the absence of precise guidelines, ChatGPT adoption risks becoming ethically ambiguous, which could limit its sustained impact on digital educational transformation.

The present study corroborates the notion that students' attitudes towards ChatGPT represent a pivotal conduit between the innovation attributes—relative advantage, compatibility, complexity, observability, and trialability—and their behavioral intention to adopt the tool in Latin America. The structural model yielded a path coefficient of 0.777, accounting for 60.4% of the variance in usage intention. This finding serves to reinforce the premises of the technology acceptance model, demonstrating that cognitive-affective evaluations are decisive in translating technology perceptions into behavioral willingness to adopt. Psychometrically, most factor loadings exceed 0.70, while the few items ranging between 0.60 and 0.70 retain theoretical coherence, thereby supporting the constructs' convergent and discriminant validity, as well as the instrument's internal reliability. The findings of this study serve to further refine our comprehension of the factors that influence the adoption of artificial intelligence within the Latin American higher education sector. Moreover, they underscore the pivotal mediating role of attitude, thereby signifying this aspect as a promising avenue for future research endeavors.

The findings of this study show that the adoption of ChatGPT among Latin American university students is primarily determined by perceptions of relative advantage and compatibility: attitudes are more favorable when the tool's academic benefits are demonstrably evident and when its use aligns with established learning routines. Trialability and observability reinforce this dynamic by enabling low-risk experimentation in socially legitimized settings, thereby fostering familiarity and trust. The strong relationship between attitude and behavioral intention underscores the mediating role of cognitive-affective judgments, providing empirical support for the diffusion of innovations framework.

Taken together, these results offer a more nuanced understanding of the socio-cognitive mechanisms underpinning the adoption of generative AI in Latin American higher education and provide a validated, theory-guided model to inform institutional strategies for integration that are pedagogically sound and ethically sustainable.

6. Limitations and Future Directions

One of the limitations identified in this study concerns the variability in participation rates across countries. Notable differences in representativeness and response rates were observed between student samples from Argentina, Bolivia, Chile, and Colombia, which may have introduced bias affecting the cross-national comparability of the findings. This variability could constrain the generalizability of the results and highlights the importance of addressing such disparities in future research to ensure a more balanced and comparable representation across populations.

Additionally, a second methodological limitation pertains to the potential for self-reporting bias, which is inherent in the use of self-administered questionnaires as the principal data collection method. Such instruments are vulnerable to distortions driven by social desirability, whereby respondents may provide answers they perceive as socially acceptable rather than reflecting their true experiences or behavior. Although steps were carried out to mitigate these biases, their influence on the internal validity of the data cannot be completely dismissed. To overcome this limitation, future studies are encouraged to employ longitudinal research designs that facilitate the tracking of changes in user intentions and actual engagement with tools such as ChatGPT over time. Moreover, the integration of objective measures or triangulation with digital behavioral data could improve the precision and causal interpretation of technology adoption processes in educational contexts.

7. Implications

These outcomes are quite theoretically and practically relevant. Theoretically, this work adds to the increasing corpus of research confirming the applicability of the diffusion of innovations theory to the integration of generative artificial intelligence technologies within Latin American educational environments. Moreover, the findings offer a nuanced interpretation of Rogers' traditional attribute hierarchy, revealing that perceived usefulness and compatibility with existing academic practices surpassed simplicity in influencing adoption.

On the practical side, higher education institutions aiming to foster the responsible implementation of ChatGPT should underscore its pedagogical advantages, embed it within established instructional frameworks, create structured opportunities for guided experimentation to reinforce user self-efficacy, and develop clear guidelines that legitimize its ethical use. Such strategies will not only cultivate a favorable disposition towards the tool but also strengthen users' sustained intention to engage with it, thereby enhancing the integration of generative AI into educational practices.

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References

1. Bettayeb, A.M.; Abu Talib, M.; Altayasinah, A.Z.S.; Dakalbab, F. Exploring the impact of ChatGPT: Conversational AI in education. *Front. Educ.* **2024**, *9*, 1379796. [\[CrossRef\]](#)
2. Bin Arif, T.; Munaf, U.; Ul-Haque, I. The Future of Medical Education and Research: Is ChatGPT a Blessing or Blight in Disguise? *Med. Educ. Online* **2023**, *28*, 2181052. [\[CrossRef\]](#)
3. Abuhassna, H. The Information Age for Education via Artificial Intelligence and Machine Learning: A Bibliometric and Systematic Literature Analysis. *Int. J. Inf. Educ. Technol.* **2024**, *14*, 700–711. [\[CrossRef\]](#)
4. Williams, P. AI, Analytics and a New Assessment Model for Universities. *Educ. Sci.* **2023**, *13*, 1040. [\[CrossRef\]](#)
5. Abdalla, A.A.; Bhat, M.A.; Tiwari, C.K.; Khan, S.T.; Wedajo, A.D. Exploring ChatGPT Adoption among Business and Management Students through the Lens of Diffusion of Innovation Theory. *Comput. Educ. Artif. Intell.* **2024**, *7*, 100257. [\[CrossRef\]](#)
6. Brem, A.; Viardot, E.; Nylund, P.A. Implications of the Coronavirus (COVID-19) Outbreak for Innovation: Which Technologies Will Improve Our Lives? *Technol. Forecast. Soc. Change* **2021**, *163*, 120451. [\[CrossRef\]](#)
7. Gong, B.; Nugent, J.P.; Guest, W.; Parker, W.; Chang, P.J.; Khosa, F.; Nicolaou, S. Influence of Artificial Intelligence on Canadian Medical Students' Preference for Radiology Specialty: A National Survey Study. *Acad. Radiol.* **2019**, *26*, 566–577. [\[CrossRef\]](#) [\[PubMed\]](#)
8. Almaraz-Menéndez, F.; Maz-Machado, A.; López-Esteban, C.; Almaraz-López, C. (Eds.) *Strategy, Policy, Practice, and Governance for AI in Higher Education Institutions*; IGI Global: Hershey, PA, USA, 2022.
9. Semeraro, F.; Cascella, M.; Montomoli, J.; Bellini, V.; Bignami, E.G. Comparative Analysis of AI Tools for Disseminating CPR Guidelines: Implications for Cardiac Arrest Education. *Resuscitation* **2025**, *208*, 110528. [\[CrossRef\]](#) [\[PubMed\]](#)
10. Wickramasekara, A.; Breiting, F.; Scanlon, M. Exploring the Potential of Large Language Models for Improving Digital Forensic Investigation Efficiency. *Forensic Sci. Int. Digit. Investig.* **2025**, *52*, 301859. [\[CrossRef\]](#)
11. Einarsson, H.; Lund, S.H.; Jónsdóttir, A.H. Application of ChatGPT for Automated Problem Reframing across Academic Domains. *Comput. Educ. Artif. Intell.* **2024**, *6*, 100194. [\[CrossRef\]](#)
12. Zhao, F.-F.; He, H.-J.; Liang, J.-J.; Cen, J.; Wang, Y.; Lin, H.; Chen, F.; Li, T.-P.; Yang, J.-F.; Chen, L.; et al. Benchmarking the Performance of Large Language Models in Uveitis: A Comparative Analysis of ChatGPT-3.5, ChatGPT-4.0, Google Gemini, and Anthropic Claude3. *Eye* **2025**, *39*, 1132–1137. [\[CrossRef\]](#)
13. Bolgova, O.; Ganguly, P.; Mavrych, V. Comparative Analysis of LLMs Performance in Medical Embryology: A Cross-platform Study of ChatGPT, Claude, Gemini, and Copilot. *Anat. Sci. Educ.* **2025**, *18*, 718–726. [\[CrossRef\]](#)
14. Fedoruk, B.D. Cross-Evaluation of Large Language Model Assessment Behaviours in Educational Tasks by Cognitive Level. *J. Educ. Inform.* **2025**, *6*, 2–23. [\[CrossRef\]](#)
15. Shahzad, M.F.; Xu, S.; Javed, I. ChatGPT Awareness, Acceptance, and Adoption in Higher Education: The Role of Trust as a Cornerstone. *Int. J. Educ. Technol. High. Educ.* **2024**, *21*, 46. [\[CrossRef\]](#)

16. Polyportis, A.; Pahos, N. Understanding Students' Adoption of the ChatGPT Chatbot in Higher Education: The Role of Anthropomorphism, Trust, Design Novelty and Institutional Policy. *Behav. Inf. Technol.* **2025**, *44*, 315–336. [\[CrossRef\]](#)
17. Ali, M.; Wood-Harper, T.; Wood, B. Understanding the Technical and Social Paradoxes of Learning Management Systems Usage in Higher Education: A Sociotechnical Perspective. *Syst. Res. Behav. Sci.* **2023**, *41*, 134–152. [\[CrossRef\]](#)
18. Buraimoh, O.F.; Boor, C.H.M.; Aladesusi, G.A. Examining Facilitating Condition and Social Influence as Determinants of Secondary School Teachers' Behavioural Intention to Use Mobile Technologies for Instruction. *Indones. J. Educ. Res. Technol.* **2023**, *3*, 25–34. [\[CrossRef\]](#)
19. Dwivedi, Y.K.; Kshetri, N.; Hughes, L.; Slade, E.L.; Jeyaraj, A.; Kar, A.K.; Baabdullah, A.M.; Koohang, A.; Raghavan, V.; Ahuja, M.; et al. Opinion Paper: "So What If ChatGPT Wrote It?" Multidisciplinary Perspectives on Opportunities, Challenges and Implications of Generative Conversational AI for Research, Practice and Policy. *Int. J. Inf. Manag.* **2023**, *71*, 102642. [\[CrossRef\]](#)
20. Rogers, E.M. *Diffusion of Innovations*; Simon and Shuster Inc.: New York, NY, USA, 2003; Volume 5.
21. Zhang, K.; Aslan, A.B. AI Technologies for Education: Recent Research & Future Directions. *Comput. Educ. Artif. Intell.* **2021**, *2*, 100025. [\[CrossRef\]](#)
22. Greenhalgh, T.; Robert, G.; Macfarlane, F.; Bate, P.; Kyriakidou, O. Diffusion of Innovations in Service Organizations: Systematic Review and Recommendations. *Milbank Q.* **2004**, *82*, 581–629. [\[CrossRef\]](#)
23. Haman, M.; Školník, M. Using ChatGPT to Conduct a Literature Review. *Acc. Res.* **2024**, *31*, 1244–1246. [\[CrossRef\]](#)
24. Li, Y.; Sui, M. Literature Analysis of Innovation Diffusion. *Technol. Invest.* **2011**, *2*, 155–162. [\[CrossRef\]](#)
25. Murray, R.; Caulier-Grice, J.; Mulgan, G. *The Open Book of Social Innovation*; Nesta: London, UK, 2010; Volume 24.
26. Sahin, I.; Thompson, A. Using Rogers' Theory to Interpret Instructional Computer Use by COE Faculty. *J. Res. Technol. Educ.* **2006**, *39*, 81–104. [\[CrossRef\]](#)
27. Martin, F.; Dennen, V.P.; Bonk, C.J. A Synthesis of Systematic Review Research on Emerging Learning Environments and Technologies. *Educ. Technol. Res. Dev.* **2020**, *68*, 1613–1633. [\[CrossRef\]](#)
28. Bocean, C.G. Sustainable Development in the Digital Age: Harnessing Emerging Digital Technologies to Catalyze Global SDG Achievement. *Appl. Sci.* **2025**, *15*, 816. [\[CrossRef\]](#)
29. Peng, H.; Ma, S.; Spector, J.M. Personalized Adaptive Learning: An Emerging Pedagogical Approach Enabled by a Smart Learning Environment. *Smart Learn. Environ.* **2019**, *6*, 9. [\[CrossRef\]](#)
30. Naznin, K.; Al Mahmud, A.; Nguyen, M.T.; Chua, C. ChatGPT Integration in Higher Education for Personalized Learning, Academic Writing, and Coding Tasks: A Systematic Review. *Computers* **2025**, *14*, 53. [\[CrossRef\]](#)
31. Baig, M.I.; Yadegaridehkordi, E. ChatGPT in the Higher Education: A Systematic Literature Review and Research Challenges. *Int. J. Educ. Res.* **2024**, *127*, 102411. [\[CrossRef\]](#)
32. Yap, Y.-Y.; Tan, S.-H.; Choon, S.-W. Elderly's Intention to Use Technologies: A Systematic Literature Review. *Heliyon* **2022**, *8*, e08765. [\[CrossRef\]](#)
33. George-Reyes, C.; Avello Martínez, R.; Buenestado Fernández, M. Perceptions of ChatGPT and the Complexity of Its Impact Among Higher Education Students: Evidence Across Ten Countries of Latin America and Europe. *Educ. Process Int. J. (EDUPIJ)* **2025**, *15*, 1–26. [\[CrossRef\]](#)
34. Hankins, E.; Fuentes, P.; Martinescu, L.; Grau, G.; Rahim, R. *Government AI Readiness Index 2023*; Oxford Insights: Malvern, UK, 2023.
35. Andrés, L.; Beylis, G.; Rifon, P.; Fenwick, C. *A Multidimensional Approach to Assessing the Affordability of Internet Services in Latin America and the Caribbean*; World Bank: Washington, DC, USA, 2024.
36. Salas-Pilco, S.Z.; Yang, Y. Artificial Intelligence Applications in Latin American Higher Education: A Systematic Review. *Int. J. Educ. Technol. High. Educ.* **2022**, *19*, 21. [\[CrossRef\]](#)
37. Jin, Y.; Yan, L.; Echeverria, V.; Gašević, D.; Martinez-Maldonado, R. Generative AI in Higher Education: A Global Perspective of Institutional Adoption Policies and Guidelines. *Comput. Educ. Artif. Intell.* **2025**, *8*, 100348. [\[CrossRef\]](#)
38. Modgil, S.; Dwivedi, Y.K.; Rana, N.P.; Gupta, S.; Kamble, S. Has COVID-19 Accelerated Opportunities for Digital Entrepreneurship? An Indian Perspective. *Technol. Forecast. Soc. Change* **2022**, *175*, 121415. [\[CrossRef\]](#)
39. Lian, Y.; Tang, H.; Xiang, M.; Dong, X. Public Attitudes and Sentiments toward ChatGPT in China: A Text Mining Analysis Based on Social Media. *Technol. Soc.* **2024**, *76*, 102442. [\[CrossRef\]](#)
40. Lim, W.M.; Gunasekara, A.; Pallant, J.L.; Pallant, J.I.; Pechenkina, E. Generative AI and the Future of Education: Ragnarök or Reformation? A Paradoxical Perspective from Management Educators. *Int. J. Manag. Educ.* **2023**, *21*, 100790. [\[CrossRef\]](#)
41. Frei-Landau, R.; Muchnik-Rozanov, Y.; Avidov-Ungar, O. Using Rogers' Diffusion of Innovation Theory to Conceptualize the Mobile-Learning Adoption Process in Teacher Education in the COVID-19 Era. *Educ. Inf. Technol.* **2022**, *27*, 12811–12838. [\[CrossRef\]](#)
42. Lippert, S.K.; Forman, H. Utilization of Information Technology: Examining Cognitive and Experiential Factors of Post-Adoption Behavior. *IEEE Trans. Eng. Manag.* **2005**, *52*, 363–381. [\[CrossRef\]](#)

43. Pinho, C.; Franco, M.; Mendes, L. Application of Innovation Diffusion Theory to the E-Learning Process: Higher Education Context. *Educ. Inf. Technol.* **2021**, *26*, 421–440. [\[CrossRef\]](#)
44. Al-kairy, M. Factors Impacting the Adoption and Acceptance of ChatGPT in Educational Settings: A Narrative Review of Empirical Studies. *Appl. Syst. Innov.* **2024**, *7*, 110. [\[CrossRef\]](#)
45. Acikgoz, F.; Elwalda, A.; De Oliveira, M.J. Curiosity on Cutting-Edge Technology via Theory of Planned Behavior and Diffusion of Innovation Theory. *Int. J. Inf. Manag. Data Insights* **2023**, *3*, 100152. [\[CrossRef\]](#)
46. Askarany, D. Attributes of Innovation and Management Accounting Changes. *Contemp. Manag. Res.* **2016**, *12*, 455–466. [\[CrossRef\]](#)
47. Salazar, E.; Perez, K.K.; Ashraf, M.; Chen, J.; Castillo, B.; Christensen, P.A.; Eubank, T.; Bernard, D.W.; Eagar, T.N.; Long, S.W.; et al. Treatment of Coronavirus Disease 2019 (COVID-19) Patients with Convalescent Plasma. *Am. J. Pathol.* **2020**, *190*, 1680–1690. [\[CrossRef\]](#)
48. Wang, Y.; Douglas, M.; Hazen, B. Diffusion of Public Bicycle Systems: Investigating Influences of Users' Perceived Risk and Switching Intention. *Transp. Res. Part A Policy Pract.* **2021**, *143*, 1–13. [\[CrossRef\]](#)
49. Fahad; Shahid, M. Exploring the Determinants of Adoption of Unified Payment Interface (UPI) in India: A Study Based on Diffusion of Innovation Theory. *Digit. Bus.* **2022**, *2*, 100040. [\[CrossRef\]](#)
50. Kaur, P.; Dhir, A.; Bodhi, R.; Singh, T.; Almotairi, M. Why Do People Use and Recommend M-Wallets? *J. Retail. Consum. Serv.* **2020**, *56*, 102091. [\[CrossRef\]](#)
51. Menzli, L.J.; Smirani, L.K.; Boulahia, J.A.; Hadjouni, M. Investigation of Open Educational Resources Adoption in Higher Education Using Rogers' Diffusion of Innovation Theory. *Heliyon* **2022**, *8*, e09885. [\[CrossRef\]](#)
52. Schuwer, R.; Janssen, B. Adoption of Sharing and Reuse of Open Resources by Educators in Higher Education Institutions in the Netherlands: A Qualitative Research of Practices, Motives, and Conditions. *Int. Rev. Res. Open Distrib. Learn.* **2018**, *19*, 151–171. [\[CrossRef\]](#)
53. Al Breiki, M.; Al Abri, A.; Al Moosawi, A.M.; Alburaiqi, A. Investigating Science Teachers' Intention to Adopt Virtual Reality through the Integration of Diffusion of Innovation Theory and Theory of Planned Behaviour: The Moderating Role of Perceived Skills Readiness. *Educ. Inf. Technol.* **2023**, *28*, 6165–6187. [\[CrossRef\]](#)
54. Ray, P.P. ChatGPT: A Comprehensive Review on Background, Applications, Key Challenges, Bias, Ethics, Limitations and Future Scope. *Internet Things Cyber-Phys. Syst.* **2023**, *3*, 121–154. [\[CrossRef\]](#)
55. Adeshola, I.; Adepoju, A.P. The Opportunities and Challenges of ChatGPT in Education. *Interact. Learn. Environ.* **2023**, *32*, 6159–6172. [\[CrossRef\]](#)
56. Bin-Hady, W.R.A.; Al-Kadi, A.; Hazaea, A.; Ali, J.K.M. Exploring the Dimensions of ChatGPT in English Language Learning: A Global Perspective. *Libr. Hi Tech* **2023**, *41*. [\[CrossRef\]](#)
57. Habibi, A.; Mukminin, A.; Octavia, A.; Wahyuni, S.; Danibao, B.K.; Wibowo, Y.G. ChatGPT Acceptance and Use through UTAUT and TPB: A Big Survey in Five Indonesian Universities. *Soc. Sci. Humanit. Open* **2024**, *10*, 101136. [\[CrossRef\]](#)
58. Hong, W.C.H. The Impact of ChatGPT on Foreign Language Teaching and Learning: Opportunities in Education and Research. *J. Educ. Technol. Innov.* **2023**, *5*, 37–45. [\[CrossRef\]](#)
59. Kasneci, E.; Sessler, K.; Küchemann, S.; Bannert, M.; Dementieva, D.; Fischer, F.; Gasser, U.; Groh, G.; Günemann, S.; Hüllermeier, E.; et al. ChatGPT for Good? On Opportunities and Challenges of Large Language Models for Education. *Learn. Individ. Differ.* **2023**, *103*, 102274. [\[CrossRef\]](#)
60. Kohnke, L.; Moorhouse, B.L.; Zou, D. ChatGPT for Language Teaching and Learning. *RELC J.* **2023**, *54*, 537–550. [\[CrossRef\]](#)
61. Liu, M.; Zhang, L.J.; Biebricher, C. Investigating Students' Cognitive Processes in Generative AI-Assisted Digital Multimodal Composing and Traditional Writing. *Comput. Educ.* **2024**, *211*, 104977. [\[CrossRef\]](#)
62. Sharples, M. Towards Social Generative AI for Education: Theory, Practices and Ethics. *Learn. Res. Pract.* **2023**, *9*, 159–167. [\[CrossRef\]](#)
63. Raman, R.; Mandal, S.; Das, P.; Kaur, T.; Sanjanasri, J.P.; Nedungadi, P. Exploring University Students' Adoption of ChatGPT Using the Diffusion of Innovation Theory and Sentiment Analysis with Gender Dimension. *Hum. Behav. Emerg. Technol.* **2024**, *2024*, 3085910. [\[CrossRef\]](#)
64. Ayanwale, M.A.; Ndlovu, M. Investigating Factors of Students' Behavioral Intentions to Adopt Chatbot Technologies in Higher Education: Perspective from Expanded Diffusion Theory of Innovation. *Comput. Hum. Behav. Rep.* **2024**, *14*, 100396. [\[CrossRef\]](#)
65. Torres Urdan, A.; Marson, C. Moralidade e Modelagem Da Intenção de Uso Da Tecnologia ChatGPT. *Int. J. Innov.* **2024**, *12*, e26378. [\[CrossRef\]](#)
66. Damiano, A.D.; Lauría, E.J.M.; Sarmiento, C.; Zhao, N. Early Perceptions of Teaching and Learning Using Generative AI in Higher Education. *J. Educ. Technol. Syst.* **2024**, *52*, 346–375. [\[CrossRef\]](#)
67. Suliman, M.A.E.; Zhang, W.; Sleiman, K.A.A. Factors Affecting Students' Intention to Use m-Learning: Extending the Technology Acceptance Model (TAM). *Innov. Educ. Teach. Int.* **2024**, *61*, 1184–1199. [\[CrossRef\]](#)
68. Al-ghazali, B.; Rasli, A.; Yusoff, R.; Mutahar, A. Antecedents of Continuous Usage Intention of Mobile Banking Services from the Perspective of DeLone and McLean Model of Information System Success. *Int. J. Econ. Financ. Issues* **2015**, *5*, 13–21.

69. Al-Jabri, I.; Sadiq, M. Mobile Banking Adoption: Application of Diffusion of Innovation Theory. *J. Electron. Commer. Res.* **2012**, *13*, 379–391.
70. Bhaskar, P.; Tiwari, C.K.; Joshi, A. Blockchain in Education Management: Present and Future Applications. *Interact. Technol. Smart Educ.* **2021**, *18*, 1–17. [[CrossRef](#)]
71. Li, J.; Woods, J.; Wu, D. The Impact of Accounting Training on Small Business Performance and New Technology Adoption. *Int. J. Manag. Pract.* **2020**, *13*, 23–46. [[CrossRef](#)]
72. Tiwari, C.K.; Bhat, M.A.; Khan, S.T.; Subramaniam, R.; Khan, M.A.I. What Drives Students toward ChatGPT? An Investigation of the Factors Influencing Adoption and Usage of ChatGPT. *Interact. Technol. Smart Educ.* **2024**, *21*, 333–355. [[CrossRef](#)]
73. Mohamed, K.; Yousef, M.; Medhat, W.; Mohamed, E.H.; Khoriba, G.; Arafa, T. Hands-on Analysis of Using Large Language Models for the Auto Evaluation of Programming Assignments. *Inf. Syst.* **2025**, *128*, 102473. [[CrossRef](#)]
74. Ahad, T.; Busch, P. Exploring the Factors Influencing Mobile-Based Ubiquitous System Adoption in the Bangladesh RMG Sector: A View through DOI and TOE. *Electron. J. Inf. Syst. Dev. Ctries.* **2024**, *90*, e12291. [[CrossRef](#)]
75. Kim, H.J.; Hong, A.J.; Song, H.-D. The Roles of Academic Engagement and Digital Readiness in Students' Achievements in University e-Learning Environments. *Int. J. Educ. Technol. High. Educ.* **2019**, *16*, 21. [[CrossRef](#)]
76. Bitzenbauer, P. ChatGPT in Physics Education: A Pilot Study on Easy-to-Implement Activities. *Contemp. Educ. Technol.* **2023**, *15*, ep430. [[CrossRef](#)]
77. Yilmaz, H.; Maxutov, S.; Baitekov, A.; Balta, N. Student Attitudes towards Chat GPT: A Technology Acceptance Model Survey. *Int. Educ. Rev.* **2023**, *1*, 57–83. [[CrossRef](#)]
78. Almaraz-López, C.; Almaraz-Menéndez, F.; López-Esteban, C. Comparative Study of the Attitudes and Perceptions of University Students in Business Administration and Management and in Education toward Artificial Intelligence. *Educ. Sci.* **2023**, *13*, 609. [[CrossRef](#)]
79. Espinoza Vidaurre, S.M.; Velásquez Rodríguez, N.C.; Gambetta Quelopana, R.L.; Martinez Valdivia, A.N.; Leo Rossi, E.A.; Nolasco-Mamani, M.A. Perceptions of Artificial Intelligence and Its Impact on Academic Integrity Among University Students in Peru and Chile: An Approach to Sustainable Education. *Sustainability* **2024**, *16*, 9005. [[CrossRef](#)]
80. Al-Emran, M.; Mezhyuev, V.; Kamaludin, A. Technology Acceptance Model in M-Learning Context: A Systematic Review. *Comput. Educ.* **2018**, *125*, 389–412. [[CrossRef](#)]
81. Bonsu, E.M.; Baffour-Koduah, D. From the Consumers' Side: Determining Students' Perception and Intention to Use ChatGPT in Ghanaian Higher Education. *J. Educ. Soc. Multicult.* **2023**, *4*, 1–29. [[CrossRef](#)]
82. Hu, G. Challenges for Enforcing Editorial Policies on AI-Generated Papers. *Acc. Res.* **2023**, *31*, 978–980. [[CrossRef](#)] [[PubMed](#)]
83. Creswell, J.W.; Creswell, J.D. *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches*; Sage Publications: Thousand Oaks, CA, USA, 2017.
84. Hernández, R.; Mendoza, C. *Metodología de la Investigación: Las Rutas Cuantitativa, Cualitativa y Mixta*; McGraw Hill México: Mexico City, Mexico, 2018.
85. Creswell, J.W. *Educational Research: Planning, Conducting, and Evaluating Quantitative and Qualitative Research*; Pearson: Upper Saddle River, NJ, USA, 2015.
86. Kerlinger, F.N.; Lee, H.B. *Foundations of Behavioral Research*, 4th ed.; Harcourt College Publishers: Fort Worth, TX, USA; London, UK, 2000; ISBN 0155078976.
87. Davis, F.D. Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Q.* **1989**, *13*, 319–340. [[CrossRef](#)]
88. Ringle, C.M.; Wende, S.; Becker, J.M. *Bönningstedt: SmartPLS*; SmartPLS GmbH: Boenningstedt, Germany, 2024.
89. Hair, J.F.; Hult, G.T.; Ringle, C.M.; Sarstedt, M. *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 3rd ed.; Sage Publications: Thousand Oaks, CA, USA, 2021.
90. Aldás, M.; Uriel, J. *Análisis Multivariante Aplicado Con R*; Ediciones Paraninfo: Madrid, Spain, 2017.
91. Anderson, J.C.; Gerbing, D.W. Structural Equation Modeling in Practice: A Review and Recommended Two-Step Approach. *Psychol. Bull.* **1988**, *103*, 411–423. [[CrossRef](#)]
92. Henseler, J.; Ringle, C.M.; Sarstedt, M. Testing Measurement Invariance of Composites Using Partial Least Squares. *Int. Mark. Rev.* **2016**, *33*, 405–431. [[CrossRef](#)]
93. Beltrão, G.; Sousa, S.; Lamas, D. Assessing the Measurement Invariance of the Human–Computer Trust Scale. *Electronics* **2025**, *14*, 1806. [[CrossRef](#)]
94. Henseler, J.; Ringle, C.M.; Sinkovics, R.R. The Use of Partial Least Squares Path Modeling in International Marketing. In *New Challenges to International Marketing*; Emerald Group Publishing Limited: Leeds, UK, 2009; pp. 277–319.

95. Venkatesh, V.; Morris, M.; Davis, G.; Davis, F. User Acceptance of Information Technology: Toward a Unified View. *MIS Q.* **2003**, *27*, 425–478. [\[CrossRef\]](#)
96. Budhathoki, T.; Zirar, A.; Njoya, E.T.; Timsina, A. ChatGPT Adoption and Anxiety: A Cross-Country Analysis Utilising the Unified Theory of Acceptance and Use of Technology (UTAUT). *Stud. High. Educ.* **2024**, *49*, 831–846. [\[CrossRef\]](#)

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