



7. Generative AI among university students in México: usefulness, trust, creativity, and emotions in public and private institutions

Inteligencia artificial generativa en estudiantes universitarios en México: utilidad percibida, confianza, creatividad y emociones en instituciones públicas y privadas

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ABSTRACT

Generative Artificial Intelligence (GenAI) has rapidly emerged as a transformative force in higher education, offering opportunities for innovation while potentially reinforcing existing inequalities. This study comparatively examines the perceptions of university students in Mexico from public and private institutions regarding GenAI across cognitive (perceived usefulness, ease of use), attitudinal (attitude, trust, creativity), and socio-emotional dimensions (enjoyment, positive and negative emotions). A quantitative cross-sectional design was employed with a sample of 274 students, using a validated questionnaire with high internal consistency ($\alpha > 0.80$). Data were analyzed through MANOVA and follow-up univariate ANOVAs. Findings reveal that students from private universities report significantly higher levels of perceived usefulness, ease of use, and attitude toward GenAI, although effect sizes were small, suggesting that institutional type explains only a limited portion of the variance. Emotional experiences, by contrast, were largely homogeneous across groups. These results partially support the notion that structural inequalities influence technological appropriation, though not uniformly across all dimensions. The study contributes empiri-

cal evidence from Mexico to the emerging literature on GenAI adoption in higher education and underscores the importance of strengthening technological infrastructure and advancing AI literacy to promote more equitable integration.

Keywords: Artificial intelligence; Higher education; Student perceptions; University students; Mexico; Educational innovation; Digital equity

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RESUMEN

La inteligencia artificial generativa (GenAI) se ha consolidado rápidamente como una fuerza transformadora en la educación superior, al ofrecer oportunidades para la innovación mientras podría reforzar desigualdades existentes. Este estudio analiza comparativamente las percepciones de estudiantes universitarios en México, provenientes de instituciones públicas y privadas, respecto a la GenAI en dimensiones cognitivas (utilidad percibida, facilidad de uso), actitudinales (actitud, confianza, creatividad) y socioemocionales (disfrute, emociones positivas y negativas). Se empleó un diseño cuantitativo transversal con una muestra de 274 estudiantes, utilizando un cuestionario validado con alta consistencia interna ($\alpha > 0.80$). Los datos se analizaron mediante MANOVA y ANOVAs univariados de seguimiento. Los resultados muestran que los estudiantes de universidades privadas reportan niveles significativamente más altos de utilidad percibida, facilidad de uso y actitud hacia la GenAI; no obstante, los tamaños del efecto fueron pequeños, lo que sugiere que el tipo de institución explica solo una proporción limitada de la varianza. En contraste, las experiencias emocionales se mantuvieron ampliamente homogéneas entre los grupos. Estos hallazgos respaldan parcialmente la idea de que las desigualdades estructurales influyen en la apropiación tecnológica, aunque no de manera uniforme en todas las dimensiones. El estudio aporta evidencia empírica desde México a la literatura emergente sobre adopción de GenAI en educación superior y subraya la importancia de fortalecer la infraestructura tecnológica y promover la alfabetización en IA para favorecer una integración más equitativa.

Palabras clave: inteligencia artificial; educación superior; percepción estudiantil; estudiantes universitarios; México; innovación educativa; equidad digital

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RESUMO

A Inteligência Artificial Generativa (GenAI) emergiu rapidamente como uma força transformadora no ensino superior, oferecendo oportunidades para inovação ao mesmo tempo em que pode reforçar desigualdades existentes. Este estudo analisa comparativamente as percepções de estudantes universitários no México, provenientes de instituições públicas e privadas, em relação à GenAI nas dimensões cognitivas (utilidade percebida, facilidade de uso), atitudinais (atitude, confiança, criatividade) e socioemocionais (prazer, emoções positivas e negativas). Foi adotado um desenho quantitativo transversal com uma amostra de 274 estudantes, utilizando um questionário validado com alta consistência interna ($\alpha > 0.80$). Os dados foram analisados por meio de MANOVA e ANOVAs univariadas complementares. Os resultados indicam que estudantes de universidades privadas apresentam níveis significativamente mais elevados de utilidade percebida, facilidade de uso e atitude em relação à GenAI; contudo, os tamanhos de efeito foram pequenos, sugerindo que o tipo de instituição explica apenas uma parcela limitada da variância. Em contraste, as experiências emocionais mostraram-se amplamente homogêneas entre os grupos. Esses achados sustentam parcialmente a noção de que desigualdades estruturais influenciam a apropriação tecnológica, embora não de forma uniforme em todas as dimensões. O estudo contribui com evidências empíricas do México para a literatura emergente sobre adoção da GenAI no ensino superior e ressalta a importância de fortalecer a infraestrutura tecnológica e promover a alfabetização em IA para uma integração mais equitativa.

Palavras-chave: Inteligência artificial; Ensino superior; Percepção estudantil; Estudantes universitários; México; Inovação educacional; Equidade digital

L'intelligence artificielle générative chez les étudiants universitaires au Mexique : utilité perçue, confiance, créativité et émotions dans les établissements publics et privés

RÉSUMÉ

L'intelligence artificielle générative (GenAI) s'est rapidement imposée comme une force transformatrice dans l'enseignement supérieur, offrant

des opportunités d'innovation tout en risquant de renforcer les inégalités existantes. Cette étude analyse de manière comparative les perceptions des étudiants universitaires au Mexique, issus d'institutions publiques et privées, à l'égard de la GenAI selon des dimensions cognitives (utilité perçue, facilité d'utilisation), attitudinales (attitude, confiance, créativité) et socio-émotionnelles (plaisir, émotions positives et négatives). Un design quantitatif transversal a été adopté auprès d'un échantillon de 274 étudiants, à l'aide d'un questionnaire validé présentant une forte cohérence interne ($\alpha > 0,80$). Les données ont été analysées avec une MANOVA suivie d'ANOVA univariées. Les résultats montrent que les étudiants des universités privées déclarent des niveaux significativement plus élevés d'utilité perçue, de facilité d'utilisation et d'attitude envers la GenAI; toutefois, les tailles d'effet sont restées faibles, suggérant que le type d'institution n'explique qu'une part limitée de la variance. En revanche, les expériences émotionnelles se sont révélées largement homogènes entre les groupes. Ces résultats soutiennent partiellement l'idée que les inégalités structurelles influencent l'appropriation technologique, bien que de manière non uniforme selon les dimensions analysées. L'étude apporte des preuves empiriques issues du Mexique à la littérature émergente sur l'adoption de la GenAI dans l'enseignement supérieur et souligne l'importance de renforcer les infrastructures technologiques et de promouvoir la littératie en IA afin de favoriser une intégration plus équitable.

Mots clés: Intelligence artificielle; Enseignement supérieur; Perception étudiante; Étudiants universitaires; Mexique; Innovation éducative; Équité numérique

1. INTRODUCTION

The emergence of generative artificial intelligence (GenAI), driven by the launch of ChatGPT in November 2022, has substantially reshaped contemporary debates around higher education (Bahroun et al., 2023). The versatility of these technologies, capable of producing coherent texts, sustaining adaptive interactions, and responding to multiple contexts, has created a climate of ambivalent expectations, where enthusiasm and concern intertwine (Bansal et al., 2024). On the one hand, their potential to personalize learning processes, optimize academic productivity, and expand creative horizons is highlighted; on the other, the risks associated with academic integrity, the protection of intellectual property, and the widening of digital divides are emphasized (Pérez-Núñez, 2023).

At the international level, recent literature highlights the speed with which GenAI has been integrated into university settings, forcing a redesign of teaching practices, evaluation methodologies, and institutional policies (Chan & Colloton, 2024). However, this debate shows an evident geographic bias: while studies focused on North America, Europe, and Asia abound, there remains a clear shortage of empirical research in Latin America, a region where universities face specific challenges linked to structural inequality, the digital divide, and the heterogeneity of their educational systems (Okoye *et al.*, 2022). Similarly, existing evidence has predominantly prioritized broad analyses of artificial intelligence adoption, without systematically distinguishing between institutional types or integratively examining cognitive, attitudinal, and socio-emotional dimensions from the student perspective. This gap limits a comprehensive understanding of how structural inequalities shape the appropriation of Generative AI within Latin American higher education. It is an academic imperative to examine the experience of students in public and private institutions, categories that have historically reflected substantial differences in terms of access, resources, and educational quality (Andrade-Girón *et al.*, 2024).

Likewise, this research gap acquires greater relevance within the framework of the 2030 Agenda for Sustainable Development. SDG 4 emphasizes the need to guarantee inclusive, equitable, and quality education, while SDG 10 is oriented toward the reduction of inequalities in all their dimensions (Bhandari, 2024; Unterhalter, 2019). Along these lines, Galindo-Cuesta *et al.* (2025) warn that the integration of GenAI into Latin American higher education constitutes, at the same time, a strategic opportunity for pedagogical innovation and a latent risk of widening existing digital and socio-educational divides. Faced with this dilemma, initiatives such as the Higher Education and Society Nodes (NODESS), promoted by UNESCO IESALC, are configured as platforms aimed at strengthening links between universities, communities, and productive sectors, to promote innovation processes that combine academic excellence, social equity, and cultural relevance (Binagwaho *et al.*, 2022).

Within this ecosystem, the present study offers a comparative analysis of Mexican university students' perceptions of Generative AI, considering variables such as perceived usefulness, ease of use, attitudes towards AI, trust, creativity, enjoyment, and the positive and negative emotions associated with its integration into academic settings. By generating comparative empirical evidence across public and private institutions, the study enhances

understanding of the tensions between technological innovation and educational inequality. It also provides relevant insights for advancing Sustainable Development Goal 4 (Quality Education) and Sustainable Development Goal 10 (Reduced Inequalities) in Latin American higher education, with Mexico serving as the analytical case.

From this general objective, the following research questions are derived:

- Are there significant differences between students from public and private universities in the perceived usefulness and ease of use of GenAI?
- Are there contrasts in the attitude toward GenAI and in the level of trust placed in its application in university settings?
- What differences emerge in socio-emotional dimensions, such as creativity, enjoyment, positive emotions, and negative emotions?
- To what extent do these differences reflect structural inequalities in access, appropriation, and use of digital technologies in Latin America, and how are they connected to SDG 4 and SDG 10?

The expected contribution of this work is threefold. First, it seeks to generate comparative empirical evidence in a regional context that has been scarcely explored, broadening the understanding of the appropriation of GenAI in Latin American higher education. Second, it proposes to articulate cognitive, attitudinal, and emotional dimensions, going beyond traditional approaches that privilege only the instrumental performance of these technologies. Finally, it seeks to link academic analysis with international agendas of equity and sustainability, providing inputs for the formulation of public policies and the design of university strategies that contribute to closing the digital divide and consolidating the social role of higher education in the region.

To respond to the research questions posed, this article is organized as follows: first, the reference framework that guides the analysis is presented; second, the methodology followed in the study is described; third, the results and their discussion are presented; and finally, the conclusions and implications are developed.

2. REFERENCE FRAMEWORK

The study of GenAI adoption in higher education requires grounding in robust theoretical frameworks that explain the processes through which

individuals accept, use, or reject new technologies (Sackstein et al., 2022). In this sense, it is essential to articulate consolidated models of technology adoption with recent approaches that integrate attitudinal, cognitive, and emotional factors. This section, therefore, develops the main constructs that guide the research, analyzing their theoretical foundations, recent empirical evidence, and relevance in the Latin American context.

2.1. The Technology Acceptance Model (TAM)

Historically, the Technology Acceptance Model (TAM), formulated by Davis (1989), has become one of the most influential conceptual frameworks for explaining the adoption of digital innovations in educational and organizational settings (Al-Nuaimi & Al-Emran, 2021). This model proposes that perceived usefulness and perceived ease of use constitute the main predictors of the intention to adopt technology, establishing a direct link between individual perceptions and usage behavior (Alsyof et al., 2023). Over time, TAM has undergone multiple extensions that incorporate additional variables such as attitude, enjoyment, and self-efficacy, which have strengthened its explanatory power and ensured its relevance for analyzing the appropriation of emerging technologies, including GenAI (Shao et al., 2024).

Currently, various authors confirm that TAM remains fully valid as an analytical framework to examine the adoption of GenAI tools in higher education. For example, Kanont et al. (2024) point out that expected benefits, perceived usefulness, and attitude toward technology emerge as determinants in the integration of these tools, although they warn that ease of use does not significantly increase the perception of usefulness. Additionally, although Hao's (2024) study is situated within the healthcare sector (where technological accuracy assumes especially critical implications), its findings offer a valuable analytical reference for understanding how variables such as enjoyment and self-efficacy may shape the acceptance of Generative AI. However, its transferability to educational settings should be considered cautiously, given the differences in usage objectives and the nature of human-technology interaction.

It is important to note that, according to the literature review conducted by the authors in databases such as Scopus and Web of Science (September 16, 2025), most of the research on TAM and its variables has been carried out in advanced economies, while studies in Latin America are still incipient. Moreover, differences between public and private universities have been virtually unexplored, even though these categories reflect structural

inequalities in access and resources. In this regard, instead of presuming the neutrality of the model, the present study recognizes that theoretical frameworks predominantly developed in advanced economies may not adequately capture the sociotechnical specificities of contexts marked by deeper structural inequalities. Consequently, TAM is employed not as a rigid explanatory scheme but as an analytical foundation to be critically examined in relation to the Latin American context. This research gap reinforces the relevance and value of the present study, which seeks to provide empirical evidence in a regional context that has been scarcely explored.

Nevertheless, TAM has long been subject to critique. Benbasat and Bar-ki (2007) contend that the model has historically prioritized perceptual variables while affording comparatively limited attention to the technological artefact and the contextual conditions of its use, potentially constraining its explanatory capacity in environments shaped by disruptive innovations such as Generative AI. Recognizing these limitations is therefore critical to preventing an unreflective application of the model and to fostering interpretations more closely aligned with the Latin American educational context.

2.2. Trust

Trust in technology constitutes an essential component for the adoption and sustained use of digital innovations in higher education (Almaiah *et al.*, 2022). In the specific case of GenAI, this construct goes beyond mere technical usability, as it incorporates perceptions related to transparency, ethics, fairness, and the reliability of generated results (Dhar *et al.*, 2023). In practical terms, it implies users' willingness to delegate cognitive and creative tasks to algorithms, accepting the uncertainty that such a transfer of control entails (Nylund *et al.*, 2023).

Recent empirical evidence confirms that trust in GenAI is closely linked to the success of its integration in university settings. Shahzad *et al.* (2024), for example, show that trust exerts a positive effect on academic performance, suggesting that the potential benefits of GenAI are mediated by the level of credibility students attribute to the system. Complementarily, Song (2024) demonstrated that trust levels in GenAI-based chatbots differ significantly between students at public and private universities, revealing that trust is not a static attribute but rather a dynamic construct conditioned by institutional and contextual factors. Beyond its functional dimension, trust in Generative AI also reflects students' willingness to rely on algorithmic systems

in contexts characterized by uncertainty, particularly within academic environments where credibility, integrity, and ethical considerations are gaining increasing prominence.

2.3. Creativity

Creativity has historically been recognized as one of the fundamental competencies of higher education, as it enables the generation of original ideas, the resolution of complex problems, and innovation with social impact (Morawska-Jancelewicz, 2021). Within this framework, the emergence of GenAI has reshaped debates about the role of human creativity in educational settings, positioning the discussion between its potential as an enhancer of divergent thinking and the tensions it raises around authenticity and algorithmic dependence (Vartiainen & Tedre, 2023; Lin & Chen, 2024).

Faced with this challenge, Zhu and Zou (2024) argue that access to ChatGPT can increase student satisfaction and strengthen creative self-efficacy, although in certain cases, a decrease in creative performance is observed compared to those who do not use these tools. Along the same lines, Habib *et al.* (2023) contend that GenAI can stimulate key dimensions of creative thinking (such as fluency, flexibility, and originality), but they caution that its impact may be ambivalent, since without adequate pedagogical support, it could erode students' creative confidence. In this scenario, creativity should not be understood solely as the generation of original ideas but also as the capacity to co-create with intelligent systems, thereby redefining the traditional boundaries between human and technological agency within learning processes.

2.4. Positive and negative emotions in AI-mediated contexts

Emotions constitute a contemporary and decisive element in university learning, as they influence motivation, engagement, and the construction of knowledge (Shafait *et al.*, 2021). The incorporation of GenAI in classrooms not only transforms cognitive processes but also significantly reshapes students' emotional experiences (Guo & Wang, 2024).

On the positive side, GenAI can contribute to creating more participatory and stimulating learning environments by offering personalized interactions, immediate feedback, and adaptive pedagogical dynamics (Yaseen *et al.*, 2025). Recent empirical evidence confirms that the use of AI for emotional management in educational settings enhances student satisfaction, improves teaching quality, and fosters higher levels of involve-

ment (Ellikkal & Rajamohan, 2024). However, the literature also warns of potential adverse emotional effects. Alessandro et al. (2024) caution that intensive exposure to GenAI's capabilities may trigger anxiety, distrust, and perceptions of threat associated with the possible replacement of human skills or the loss of control over academic processes. This emotional duality is especially salient in contexts of technological innovation, where enthusiasm for emerging learning opportunities may coexist with tensions linked to adaptation and change. From this perspective, emotions may function as either enablers or barriers to students' willingness to adopt Generative AI.

In summary, the study of GenAI adoption in higher education demands an integrative approach that articulates consolidated theoretical frameworks, such as TAM, with emerging constructs related to trust, creativity, and emotions. While TAM offers a robust explanation of the cognitive determinants of technology acceptance (perceived usefulness and ease of use), trust introduces the relational and ethical dimensions, indispensable in contexts where AI's transparency and reliability are under scrutiny. At the same time, creativity stands as a strategic competency for pedagogical innovation and transformative learning, whereas positive and negative emotions highlight the socio-affective complexity that GenAI imprints on the student experience.

The integration of these variables into a joint analytical framework is particularly relevant in Latin America, where structural inequalities between public and private universities require comparative evidence to illuminate both gaps and opportunities (Galindo-Cuesta et al., 2025). This distinction is grounded in the recognition that these institutional types frequently operate under structurally unequal conditions with respect to funding, technological infrastructure, and innovation capacity, factors that may differentially shape students' experiences with emerging technologies such as Generative AI. In this way, the present study not only seeks to contribute to the empirical understanding of GenAI adoption but also aims to provide critical inputs for the design of institutional policies and practices aligned with SDGs 4 and 10, as well as with regional initiatives such as NODESS, thereby consolidating an academic agenda with social relevance and long-term sustainability.

3. METHOD

The research is framed within a quantitative approach, aimed at identifying differences in student perceptions of GenAI according to the type of university institution (public or private). Data were collected between January and July 2025 through an online questionnaire, facilitating the comparison of responses from students attending public and private institutions in Mexico. The following subsections present the design, participants, instrument, procedure, and analysis.

3.1. Research design

A cross-sectional and comparative design was adopted, suitable for examining perceptions at a single point in time and contrasting groups of interest in heterogeneous contexts (Ato et al., 2013). This type of design facilitates the identification of GenAI adoption patterns in higher education and, at the same time, allows for the recognition of inequalities associated with access to and use of these technologies. Its relevance lies in the fact that, in Latin America, empirical studies on GenAI remain incipient, which reinforces the need to generate evidence that engages with the Sustainable Development Goals (SDGs 4 and 10).

3.2. Participants

The sample consisted of 274 university students from different higher education institutions in Latin America, who voluntarily participated in the study. Of the total, 55.5% were women and 44.5% men, with an average age of 21.3 years (SD = 2.4). Regarding the type of institution, 51.8% of participants came from public universities, while 48.2% were from private universities. The complete sociodemographic distribution of the sample can be found in Table 1, which presents the frequencies and percentages of the main variables: gender, age, and type of university.

Table 1. Sociodemographic profile of participants			
Variable	Category	N	%
Gender	Female	152	55.50%
	Male	122	44.50%
University type	Public	142	51.80%
	Private	132	48.20%
Age (years)		M = 21.3 (SD = 2.4)	

Source: Own elaboration.

Note: Percentages were calculated over the total sample (N = 274). Age is presented with the mean and standard deviation.

3.3. Instrument

For data collection, a structured questionnaire was used, designed based on previously validated scales in the international literature on technology adoption and learning experiences mediated by generative AI. The instrument included eight main constructs: perceived usefulness, perceived ease of use, enjoyment, attitude toward AI, trust, creativity, positive emotions, and negative emotions.

Each construct consisted of between 4 and 12 items, evaluated using a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). The internal reliability of the scales was adequate, with Cronbach's α coefficients above 0.80 in all cases, indicating acceptable internal consistency according to classical psychometric criteria (Nunnally & Bernstein, 1994). Although perception-based surveys are well-suited to capturing students' subjective evaluations, they remain susceptible to self-report bias. As such, the findings are best interpreted as reflecting perceived experiences rather than objective indicators of technological behavior.

Table 2 presents the details of the constructs, items, the reliability values obtained, and the sources of the scales, all of which are drawn from recent research published in indexed journals.

Given that the instrument was composed of previously validated scales, a confirmatory factor analysis (CFA) was conducted to verify the theoretical structure of the constructs within the present sample. The eight-factor correlated model demonstrated an adequate fit to the data: $\chi^2/df = 1.89$, CFI = .93, TLI = .92, RMSEA = .057 (90% CI [.048, .065]), and SRMR = .061. These indices meet the conventional thresholds recommended in the literature (CFI and TLI $\geq .90$; RMSEA and SRMR $\leq .08$), indicating satisfactory construct validity and factorial stability (Hu & Bentler, 1999; Kline, 2016). Therefore, the CFA results provide empirical support for the adequacy of the measurement model in this population.

3.4. Procedure

Data collection was carried out between January and July 2025 through a digital questionnaire administered via the Google Forms platform. Participation invitations were disseminated via institutional email and academic social networks, with the support of program coordinators and faculty members across multiple public and private universities in Mexico.

Table 2. Measurement instruments, items, sources, and reliability			
Construct	Items used	Source	Cronbach's α
Perceived Usefulness	1. AI allows me to perform certain tasks more quickly.	(Davis, 1989)	0.899
	2. AI would improve my performance as a student.		
	3. AI would increase my productivity as a student.		
	4. AI would enhance my effectiveness as a student.		
	5. Using AI can be useful for my student activities.		
Perceived Ease of Use	6. I think interacting with AI is simple and easy to understand.	(Davis, 1989)	0.902
	7. I think using AI is easy.		
	8. I believe one can quickly grasp how AI works.		
	9. I find interacting with AI clear and understandable.		
	10. I think interacting with AI does not require much mental effort.		
Perceived Enjoyment	11. Using AI is a pleasure.	(Venkatesh, 2000)	0.889
	12. I enjoy using AI.		
	13. The time I spend using AI is enjoyable.		
	14. AI provides me with entertainment.		
Attitude Toward Use	15. I believe AI can help improve things.	(Davis et al., 1989)	0.843
	16. I believe interesting opportunities may arise from using AI.		
	17. I am confident that using AI is a good choice.		
Positive Emotions	18. I feel proud to be able to use AI in my classes.	(Pekrun et al., 2010)	0.926
	19. I am excited to be able to use AI in my classes.		
	20. I feel inspired by the potential use of AI in my classes.		
	21. I feel energized when I consider using AI.		
	22. I look forward to going to university when I think about using AI.		
Negative Emotions (Anxiety)	23. I feel empowered when I think about using AI.	(Pekrun et al., 2010)	0.938
	24. I feel sensitive when people talk about using AI.		
	25. I find it difficult to relax when using AI.		
	26. I think I tend to overreact when someone mentions using AI.		
Self-efficacy / Confidence	27. I feel uncomfortable when someone talks about using AI.	(Compeau & Higgins, 1995)	0.942
	28. I feel confident when learning new AI-based technologies.		
	29. I am confident in my ability to use AI applications in my area of study.		
	30. I find it easy to adapt to new AI systems as they change or are updated.		
	31. I am confident I can solve complex problems using AI tools.		
	32. I can identify the best way to apply AI to improve task efficiency.		
	33. If I encounter a problem in an AI system, I am confident I can find an effective solution.		
	34. I feel capable of learning new AI-related concepts.		
	35. I believe I can continuously improve my skills in using AI technologies over time.		
	36. I am confident in my ability to acquire advanced knowledge of AI if I set my mind to it.		
	37. I feel comfortable interacting with AI systems.		
Creativity	38. If an AI system does not work properly, I know how to handle the situation.	(Zhou & George, 2001)	0.926
	39. I feel confident using AI systems for specific tasks without additional supervision.		
	40. I show creativity in my assignments and tasks when given the opportunity.		
	41. I develop appropriate plans and schedules for implementing new ideas in my courses and projects.		
	42. I propose creative solutions to problems that arise in my school projects.		
	43. I am a good source of creative ideas.		
	44. I suggest new ways to achieve goals or objectives in my courses.		
	45. I propose new and practical ideas to improve my academic performance.		
	46. I suggest new ways to improve the quality of school projects.		

Source: Own elaboration, based on cited authors.

Participation was completely voluntary, and no financial or academic incentives were offered for completing the questionnaire.

Before administration, participants were presented with an electronic informed consent form, which explained the purpose of the study, the anonymous and confidential nature of the responses, and the possibility of withdrawing at any time. The research was conducted in accordance with the ethical principles of social research established by the Belmont Report in 1979 and reconceptualized by Shore (2006), as well as the classic methodological recommendations for survey studies in higher education (Hair *et al.*, 2010).

The questionnaire was available online for a period of five months and was designed to be completed in an estimated time of 15 to 20 minutes. After data collection, a preliminary cleaning process of the database was carried out to remove incomplete or inconsistent records, following methodological guidelines for data management in quantitative studies (Kerlinger & Lee, 2000).

3.5. Data Analysis

Statistical processing of the data was conducted using SPSS software (version 29). In the preliminary phase, the database was cleaned by removing incomplete cases and outliers, and the reliability of each construct was assessed using Cronbach's α coefficient, with values above 0.70 considered acceptable (Nunnally & Bernstein, 1994).

For the main analysis, although the independent variable "type of university" comprised only two levels (public and private), a multivariate analysis of variance (MANOVA) was applied instead of limiting the study to Student's *t*-tests. This decision is justified by the fact that MANOVA allows for the simultaneous evaluation of the effect of university type on a set of correlated dependent variables, reducing the risk of Type I error. Providing a more integrated view of the results. The methodological choice is supported by both classical and contemporary references: Fisher (1925) laid the foundations of analysis of variance, while Keppel and Wickens (2004) and Tabachnick and Fidell (2019) highlight the usefulness of MANOVA for studies with multiple related dependent variables. Furthermore, it is worth noting that a one-factor ANOVA with two levels is statistically equivalent to Student's *t*-test (Field, 2018), but it has the advantage of reporting effect sizes (η^2) and aligning more naturally with multivariate frameworks.

Before the analysis, statistical assumptions were verified: (a) multivariate normality was assessed using the standardized skewness and kurtosis values for all items, which ranged from -1.91 to 1.84 , thereby remaining within the acceptable threshold of ± 2 ; (b) homogeneity of variances, assessed with Levene's test ($p > .05$ in most cases, without compromising the robustness of the analysis); and (c) homogeneity of covariances, tested with Box's M ($F = 1.32$, $p = .17$). These results suggest that no substantial violations occurred that would compromise the multivariate analysis (Cohen, 1988; Field, 2018).

Subsequently, univariate ANOVAs were conducted to identify in which specific constructs significant differences existed between students from public and private universities, complementing the overall findings of the MANOVA.

4. RESULTS

To address the stated objective and research questions, several statistical analyses were performed to examine both the overall effect of university type (public vs. private) on the set of dependent variables and the specific differences in each construct evaluated. The results are presented in three sections: first, the findings of the multivariate analysis of variance (MANOVA); second, the results of the univariate analyses (ANOVAs) for each variable; and finally, a comparative visualization of the means obtained across the different constructs.

It is important to note that the following analyses reflect differences observed within the sampled institutions and should be interpreted as context-specific rather than as representative of all public and private universities in Mexico.

4.1. Results of the multivariate analysis (MANOVA)

With the intention of evaluating the overall effect of university type (public vs. private) on the eight constructs analyzed, a one-factor MANOVA was applied, a technique recommended when the dependent variables are intercorrelated and the goal is to reduce the Type I error associated with multiple univariate tests (Fisher, 1925; Tabachnick & Fidell, 2019).

The results showed a statistically significant multivariate effect in both the Wilks' Lambda test ($\Lambda = 0.953$, $F(8, 265) = 1.66$, $p = .045$) and Pillai's Trace test

($V = 0.047$, $F(8, 265) = 1.66$, $p = .045$). The convergence of both tests, frequently recommended as the most robust in designs with moderate sample sizes (Olson, 1971; Stevens, 1946), supports the reliability of this result.

This finding indicates that, when the dependent variables are considered jointly (perceived usefulness, perceived ease of use, enjoyment, attitude toward AI, trust, creativity, positive emotions, and negative emotions), there are significant differences between students from public and private universities. In other words, the overall patterns of perception regarding the use of GenAI in higher education differ depending on the type of institution. The results of these analyses are presented in Table 3.

Table 3. MANOVA results (public vs. private universities)			
Multivariate test	Value	F (df)	p
Wilks' Lambda	0.953	$F(8, 265) = 1.66$	0.045
Pillai's Trace	0.047	$F(8, 265) = 1.66$	0.045

Source: Own elaboration.
Note: The full model, including the eight constructs, was significant; therefore, univariate ANOVAs were conducted as follow-up analyses.

Since the multivariate model reached significance, and following the recommendations of Keppel and Wickens (2004) to identify the location of the effects, univariate ANOVAs were conducted as follow-up analyses.

4.2. Results of the univariate analyses (ANOVAs)

Subsequently, univariate ANOVAs were conducted with the purpose of identifying the specific constructs in which differences were found between students from public and private universities. The complete results are presented in Table 4, which reports the F values, statistical significance (p), effect size (η^2), and the direction of the observed differences. Although the overall model reached statistical significance, the observed effect sizes were predominantly small; therefore, the findings should be interpreted with caution regarding their practical significance.

The analyses show that the most consistent differences are concentrated in the instrumental and attitudinal dimensions. First, a significant effect was identified for perceived usefulness ($F(1, 272) = 6.37$, $p = .012$, $\eta^2 = .023$), with

Table 4. Univariate ANOVA results for differences between public and private universities				
Construct	F	P value	η^2	Observed difference
Perceived Usefulness	6.37	0.012	0.023	Private > Public
Perceived Ease of Use	4.50	0.035	0.016	Private > Public
Attitude toward AI	5.47	0.020	0.020	Private > Public
Confidence	3.00	0.085	0.011	Private $\approx$ Public (trend)
Creativity	3.18	0.076	0.012	Private $\approx$ Public (trend)
Perceived Enjoyment	1.25	0.265	0.005	No difference
Positive Emotions	1.80	0.181	0.007	No difference
Negative Emotions	0.90	0.342	0.003	No difference

Source: Own elaboration.

students from private universities reporting a higher degree of perceived usefulness of GenAI to support their academic activities. Although the effect size was small, the difference is relevant, as it points to a systematic pattern in how the potential of the technology is valued in differentiated institutional contexts. Although the effect size was small ($\eta^2 = .023$), the difference points to a systematic pattern in how the potential of the technology is evaluated across differentiated institutional contexts.

Similarly, perceived ease of use showed significant differences ($F(1, 272) = 4.50, p = .035, \eta^2 = .016$), again in favor of students from private universities, which corresponds to a small effect size. This result suggests that the perception of accessibility and ease of learning of GenAI tools tends to be more positive in private contexts, which could be linked to greater opportunities in technological infrastructure and training.

A significant effect was also observed for attitude toward AI ($F(1, 272) = 5.47, p = .020, \eta^2 = .020$), which corresponds to a small effect size, indicating that students from private universities exhibit a more favorable disposition toward the integration of GenAI in higher education. This finding reinforces the idea that positive attitudes toward technology are related not only to individual experiences but also to the institutional context in which learning takes place.

In contrast, other constructs did not reach the conventional threshold of significance ($p < .05$), although they showed marginal effects that suggest

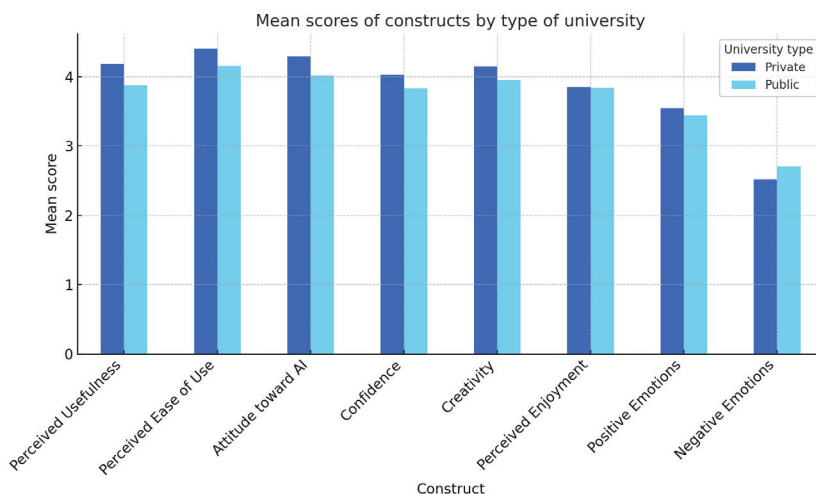
interesting trends. Such is the case of trust ($p = .085$, $\eta^2 = .011$) and creativity ($p = .076$, $\eta^2 = .012$), both with small effect sizes, where students from private universities reported slightly higher scores. Although these differences cannot be considered conclusive from a statistical standpoint, their proximity to the significance threshold allows them to be interpreted as emerging gaps, whose consolidation could depend on additional factors such as institutional policies supporting AI use or digital literacy programs.

Finally, no differences were found in the emotional dimensions. Neither enjoyment, positive emotions, nor negative emotions showed significant differences between groups ($p > .05$). This finding suggests that, regardless of the type of institution, the emotional experiences associated with the use of GenAI are shared in a relatively homogeneous way among university students.

4.3. Comparative visualization of means

With the aim of more clearly illustrating the patterns of differences between public and private universities, a graphical representation of the means obtained for each of the constructs evaluated was developed. Figure 1 presents the visual comparison, differentiating students from private universities (dark blue) and public universities (light blue).

Figure 1. Mean scores of constructs by type of university



Source: Own elaboration.

As can be observed, students from private universities present consistently higher scores in the constructs of perceived usefulness, ease of use, and attitude toward AI, results that coincide with the statistically significant differences reported in the univariate analyses. In addition, in the dimensions of trust and creativity, the bars show a slight advantage for the private sector, reinforcing the presence of the marginal effects previously noted, even though they did not reach conventional statistical significance.

In contrast, the differences are notably reduced in emotional dimensions. Both enjoyment and positive emotions appear with practically equivalent means in both groups, while negative emotions show a slight tendency to be higher in public universities, although without statistical significance. This suggests that the affective factors associated with the use of GenAI are transversal and less dependent on the type of institution.

Taken together, the results show that although student perceptions of GenAI are largely similar between public and private universities, relevant differences exist in the instrumental and attitudinal dimensions. Students from private institutions report greater perceived usefulness, higher ease of use, and a more favorable attitude toward AI, while the differences in trust and creativity appear marginal. In turn, the emotional variables display a homogeneous pattern across both groups, indicating that affective experiences related to the use of these technologies transcend the type of institution. These findings enable a broader discussion on equity in access, technological appropriation, and the implications for advancing Sustainable Development Goals 4 and 10 within Latin American higher education, with Mexico serving as the empirical reference.

5. DISCUSSION

The results of this study directly address the overarching objective of conducting a comparative analysis of students' perceptions of Generative AI across public and private universities in Mexico, considering cognitive, attitudinal, and socio-emotional dimensions.

First, the significance of the multivariate model indicates that the type of university constitutes a differentiating factor across the set of variables studied, confirming that perceptions of GenAI are not homogeneous across institutional contexts. This finding answers the first research question and is consistent with previous studies that emphasize how conditions of access to digital

infrastructure and pedagogical support influence perceptions of usefulness and usability of new technologies (Kanont et al., 2024; Shao et al., 2024). However, these findings should be interpreted with caution. Although statistically significant differences were identified, the effect sizes were small, indicating that the type of university explains only a limited proportion of the variance in student perceptions. This suggests that the adoption of Generative AI may also be shaped by additional individual and contextual factors.

Specifically, the univariate analyses showed significant differences in perceived usefulness, ease of use, and attitude toward GenAI, with higher scores among students from private universities. These results suggest that environments with greater institutional resources foster not only the technical integration of these tools but also the attitudinal disposition toward their adoption. In contrast, trust and creativity showed marginal effects, which may be interpreted as indications of emerging gaps that have not yet achieved statistical robustness but could consolidate depending on institutional policies or accumulated user experience.

With respect to the socio-emotional dimensions, the results revealed no differences in enjoyment, positive emotions, or negative emotions. This finding is particularly relevant, as it indicates that affective experiences associated with the use of GenAI are shared by students regardless of the type of university. Such uniformity aligns with the literature emphasizing the transversal nature of emotional responses in AI-mediated contexts, where both enthusiasm and anxiety are widely distributed phenomena (Guo & Wang, 2024; Yaseen et al., 2025).

1. Taken together, these results allow the research questions to be answered as follows:
2. Yes, there are significant differences in perceived usefulness and ease of use, favoring students from private universities.
3. Contrasts are also observed in attitude toward GenAI, although trust remains marginal.
4. Socio-emotional dimensions, by contrast, do not show significant differences, except for creativity, which presents an incipient trend.
5. The differences partially reflect structural inequalities, concentrated in instrumental and attitudinal dimensions, while emotional dimensions remain homogeneous; this demonstrates an uneven influence that limits progress toward SDGs 4 and 10.

These findings suggest that structural inequalities in access to technology in Latin America are reflected mainly in instrumental and attitudinal perceptions, while emotional dimensions appear less sensitive to the type of institution. The study provides empirical evidence that enriches the understanding of GenAI adoption in Latin America, highlighting that gaps are not distributed uniformly across all the dimensions analyzed.

6. CONCLUSIONS

This study compared the perceptions of students attending public and private universities in Mexico regarding GenAI, considering cognitive dimensions (perceived usefulness, ease of use), attitudinal dimensions (attitude, trust, creativity), and socio-emotional dimensions (enjoyment, positive emotions, and negative emotions). The results show that the main differences are concentrated in the instrumental and attitudinal aspects, with higher averages in private universities, while emotional experiences appear homogeneous. In this way, the hypothesis that structural inequalities influence technological appropriation is partially confirmed, although not uniformly across all dimensions.

6.1. Theoretical implications

The findings reinforce the relevance of the Technology Acceptance Model (TAM) in the analysis of GenAI, highlighting perceived usefulness and ease of use as differential predictors in unequal contexts. However, the incorporation of emerging variables such as trust, creativity, and emotions reveals the need to expand classical models toward an integrative approach that considers both cognitive and socio-affective factors. This contribution is novel in the region, where comparative empirical studies in higher education remain scarce.

6.2. Practical and social implications

At the practical level, the findings suggest that private universities have managed to generate more favorable conditions for the instrumental appropriation of GenAI, while public institutions face greater limitations. This gap poses significant challenges for educational equity, since students' ability to integrate these tools depends not only on their individual competencies but also on the resources, support, and institutional policies available. From a social perspective, the findings highlight the need to ensure

institutional conditions that promote equitable access to GenAI and prevent structural limitations from translating into new forms of educational exclusion.

6.3. Implications for educational policies

The results of this study provide direct input for the design and implementation of educational policies in Latin America. Three priority lines of action are identified:

■ ***Ensuring infrastructure and equitable access:***

Ministries of education and public universities should invest in technological infrastructure (connectivity, equipment, AI platforms) that allows students to access GenAI under conditions like those of private institutions. This is essential to prevent the digital divide from translating into academic inequality.

■ ***Digital literacy and teacher training:***

It is recommended to develop national training programs on GenAI for both students and faculty. Training should not only focus on instrumental use but also address the ethical, critical, and creative aspects of AI. Advancing AI literacy is essential to enable both students and educators to understand these systems, use them critically, and promote ethical academic practices. This requires not only the development of technical competencies but also the adaptation of pedagogical strategies suited to AI-mediated learning environments.

■ ***Promotion of collaborative networks and regional articulation:***

Initiatives such as the Higher Education and Society Nodes (NODESS) should be strengthened and expanded to bring together public and private universities, communities, and productive sectors. These networks can become platforms for inclusive innovation that ensure collective (not only institutional) benefits.

These proposals shift the debate from technological adoption toward the construction of a digital equity agenda, explicitly linked to SDG 4 (quality education) and SDG 10 (reduction of inequalities). This implies that governments, international organizations, and universities must approach GenAI not only as a pedagogical tool but also as a strategic factor of social justice and educational sustainability in the region.

6.4. Limitations and future research directions

This study presents several limitations. First, it is based on a cross-sectional design that does not allow for the establishment of causal relationships; therefore, future research could adopt longitudinal approaches to observe how student perceptions evolve. Second, although the sample was broad and diverse, it was limited to Mexico, which means the results should be interpreted as exploratory and not generalizable to the entire Latin American region without additional studies. Importantly, the findings of this research cannot be generalized or applied to all public or private universities in Mexico. Generalization must be strictly restricted to the specific institutions included in the sample and to comparable institutional contexts. Therefore, replicating this study in other Latin American countries would be valuable for contrasting the findings and expanding the understanding of Generative AI adoption across diverse higher education systems. Finally, self-reports were used, which may involve social desirability bias or the overestimation of competencies.

For future lines of research, it is suggested to expand the analysis to include other actors in higher education, such as faculty members and university authorities; to explore cross-cultural comparisons with other regions of the world; and to employ mixed-method approaches integrating quantitative and qualitative data to capture the student experience with GenAI in greater depth.

6.5. Final reflection

GenAI represents a turning point for higher education in Latin America: it can become either a driver of innovation and educational justice or a factor of exclusion that amplifies historical inequalities. The future will not depend on technology itself but on the political and institutional will to recognize it as a strategic public good and to ensure inclusive access. These decisions will determine whether the region moves toward more equitable education aligned with the Sustainable Development Goals or deepens the very gaps it seeks to overcome.

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