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Validation of an Instrument to Measure the Academic Use of Generative Artificial Intelligence (GenAI) in University Students

Validación de un instrumento para medir el uso académico de la IAGen en estudiantes universitarios

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ABSTRACT

This study aimed to design and validate an instrument for measuring the academic use of Generative Artificial Intelligence (GenAI) among higher education students. The research was conducted at Universidad Tecnológica de la Selva, located in southeastern Mexico, using a purposive sample of 905 students from various academic divisions. The initial instrument emerged from a theoretical framework on digital competence and artificial intelligence, that was evaluated by nine expert judges, and pilot-tested. Exploratory and confirmatory factor analyses were subsequently performed to determine the underlying structure of the instrument.Results revealed a seven-dimension solution comprising 42 items that explained 64% of total variance, with satisfactory goodness-of-fit indices (CFI = .90; TLI = .90; RMSEA = .06; SRMR = .04) and high internal consistency (α = .84, ω = .94). The findings indicate that the instrument demonstrates adequate validity and reliability; however, replication studies in different institutional contexts are recommended to examine factorial invariance and temporal stability.

RESUMEN

Este estudio tuvo como objetivo diseñar y validar un instrumento para medir el uso académico de la Inteligencia Artificial Generativa (IAGen) en estudiantes de educación superior. La investigación se desarrolló en la Universidad Tecnológica de la Selva, en el sureste de México, con una muestra intencionada de 905 estudiantes de diversas divisiones académicas. El instrumento inicial fue elaborado a partir de un marco teórico sobre competencias digitales e inteligencia artificial, sometido al juicio de nueve expertos y a una prueba piloto. Posteriormente, se aplicaron análisis factorial exploratorio y confirmatorio para determinar la estructura del instrumento. Los resultados evidenciaron una solución de siete dimensiones con 42 ítems, que explicó el 64 % de la varianza total, con índices de ajuste adecuados (CFI = .90; TLI = .90; RMSEA = .06; SRMR = .04) y una alta consistencia interna (α=.84 y ω=.94). Se concluye que el instrumento presenta validez y confiabilidad satisfactorias, aunque se recomienda replicar el estudio en diferentes contextos institucionales para examinar la invariancia factorial y la estabilidad temporal.

KEYWORDS · PALABRAS CLAVES

Artificial Intelligence; Educational Technology; Higher Education; Measurement Instrument; Perception.
Inteligencia Artificial; Tecnología Educativa; Educación Superior; Instrumento De Medida; Percepción.

1. Introduction

In recent years, Artificial Intelligence (AI) tools have transformed multiple domains, including education, where they are used to enhance teaching, learning, and institutional management (Bond et al., 2024; Xia et al., 2024). Russell and Norvig (2021) define AI as a field of study aimed at developing systems capable of carrying out tasks that require human intelligence, such as reasoning, perception, and natural language understanding. Within this field, Generative Artificial Intelligence (GenAI) constitutes a subset capable of producing new content such as text, images, music, or code from previously trained data (Jovanović & Campbell, 2022). Its transformative potential in higher education has been widely recognized (Peres et al., 2023; Ursavaş et al., 2025), offering opportunities for personalization and creativity in teaching and learning processes (Fan et al., 2025; Francis et al., 2025).

Tools such as ChatGPT, Gemini, and Copilot have gained considerable presence in universities due to their ability to generate academic content and support knowledge management. However, they also pose ethical and regulatory challenges that require critical reflection on their educational impact (Romeu et al., 2025; Castaño, 2024). Despite this growing relevance, empirical literature on how university students perceive and use these technologies remains limited, making it difficult to fully understand the extent of their adoption and their potential effects on academic development (Niño-Carrasco et al., 2025; Ruiz et al., 2024).

Recent systematic reviews highlight that GenAI can foster personalized learning and the development of advanced digital competencies, but it also involves risks related to technological dependency and the quality of generated information (Giannakos et al., 2024). In Latin America, this research field is still emerging, although interest is increasing in validating psychometrically robust instruments that assess perceptions and attitudes toward GenAI (Álvarez-Rebolledo et al., 2019; Maldonado-Suárez & Santoyo-Telles, 2024; Silgado-Tuñón & López-Flores, 2025).

Within this context, the present study was conducted at Universidad Tecnológica de la Selva (UTSelva), located in southeastern Mexico, with students enrolled in Higer University Technitian (TSU) and bachelor's degree programs across the academic divisions of Information Technologies, Administration, Agrobiotechnology, Tourism and Gastronomy, in a face-to-face modality. This institutional setting offers a relevant scenario for exploring the academic adoption of GenAI in regional or similar environments.

The instrument's design was grounded in a theoretical model based on digital literacy, technological ethics, and AI-assisted autonomous learning, incorporating references from the DigCompEdu framework (Redecker, 2017) and AI literacy (Long & Magerko, 2020). These foundations gave rise to the seven dimensions of the questionnaire: comprehensive academic use, content creation and editing, perceived self-efficacy, ethical use, access and inequalities, environmental impact, and dependence or addiction. This model enables the assessment not only of the degree of GenAI adoption but also of students' critical and reflective maturity regarding its educational integration.

Thus, the validation of this instrument aims to contribute to the field of educational innovation by providing a robust tool for diagnosing and guiding institutional policies on the responsible academic use of generative artificial intelligence in higher education.

2. Methodology

2.1. Research Design

The study followed a quantitative, instrumental research design aimed at analyzing the psychometric properties of the questionnaire (Ato et al., 2013). The process adhered to international standards for educational and psychological testing (American Educational Research Association, American Psychological Association & National Council on Measurement in Education, 2018), which included a theoretical review, expert judgment, and empirical validation through factorial analyses.

2.2. Participants

The sample consisted of 905 students (460 men, 439 women, and 6 unspecified) from Universidad Tecnológica de la Selva, a public institution in southeastern Mexico offering Higer University Technitian (HUT) and bachelor's degree programs in face-to-face modality. Participants belonged to the academic divisions of Information Technologies, Administration, Agrobiotechnology, Tourism and Gastronomy. A purposive non-probabilistic sampling strategy was used. Inclusion criteria were: enrollment during 2025, voluntary participation, and completion of the questionnaire. Incomplete or duplicate responses were excluded.

2.3. Instrument

The initial instrument consisted of 47 items distributed across 9 dimensions, developed from the theoretical model described in the Introduction. After being evaluatedevaluation by nine experts (Escobar-Pérez & Cuervo-Martínez, 2008), items with Aiken's V < .80, or considered redundant or ambiguous, were removed. As a result, a revised version of 45 items was retained for the pilot test.

Subsequently, the exploratory factor analysis (EFA) suggested a seven-factor structure with 42 items, which was maintained in the final version (Table 1). The response scale was a 5-point Likert format (1 = Strongly disagree, 2 = Disagree, 3 = Neither agree nor disagree, 4 = Agree, 5 = Strongly agree).

Table 1

Instrument Version Traceability

Stage	Number of items	Number of dimensions	Criteria for Modification	Main Outcome
Initial version	47	9	Theoretical review and initial drafting based on DigCompEdu and AI literacy	First conceptual proposal

Stage	Number of items	Number of dimensions	Criteria for Modification	Main Outcome
Expert Judgment	45	9	Elimination of items with V < .80 and redundant items; wording adjustments; item reclassification	Version for pilot testing
Pilot Test (EFA)	45	9 → 7	Grouping of conceptually related factors and removal of items with loadings < .40	Adjusted empirical structure
Final Version	42	7	Model confirmation through CFA and internal consistency analysis	Validated instrument

Note: *Arranged by the authors.*

2.4. Validated Procedure

Phase 1. Content Validity: The initial 47-item questionnaire was evaluated by a panel of nine expert judges: five men and four women; seven from Mexico and two from Colombia. Six held doctoral degrees and three held master's degrees. Their research areas included data mining, artificial intelligence, educational innovation, generative AI, ICTs, and data science. Professional experience ranged from 12 to 38 years, and scientific publications from 4 to 25, indicating a group with extensive academic and research backgrounds.

Experts evaluated each item in terms of clarity, relevance, pertinence, and sufficiency, using a four-point scale, and provided qualitative feedback through a rubric adapted from Escobar-Pérez & Cuervo-Martínez (2008). Aiken's Content Validity Coefficient (V) (Aiken, 1985; Escurra, 1988) was calculated using the following formula (Martín-Romera & Molina, 2017):

$$V = \frac{\bar{x} - l}{c - 1}$$

Where: $\bar{x}$ mean rating of judges

l lowest possible score

c number of scale categories

Phase 2. Pilot test: The sample size used is justified based on psychometric standards. However, when conducting factor analyses, several authors recommend between 5 and 10 participants per item (Hair et al., 2019; Lloret-Segura et al., 2014). Considering the 45 initial items, the ideal sample should range between 230 and 450 cases. In this study, data were collected from 905 students, which ensures a robust level of reliability. Likewise, the use of the JASP software enabled the application of maximum likelihood models and the computation of goodness-of-fit indices widely employed in the literature, with the advantage of being an open-access tool that promotes reproducibility.

The instrument was administered to students from the Universidad Tecnológica de la Selva over a two-week period through a Google Forms survey. It is worth noting that the first section of the form emphasized the principles of anonymity, confidentiality, and the scientific managment of the data.

Phase 3. Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) were applied to validate construct structure. The process followed internationally recognized psychometric standards (American Educational Research Association et al., 2018). Additionally, the instrument was aligned with contemporary research emphasizing the need to measure self-efficacy, digital ethics, environmental impact, and technological dependence in academic contexts involving GenAI (Giannakos et al., 2024; Silgado-Tuñón & López-Flores, 2025).

Phase 4. Reliability: Internal consistency was calculated using Cronbach's α and McDonald ω.

Phase 5. Final instrument: The final validated instrument assesses students' experiences, skills, and perceptions regarding the academic use of GenAI in higher education.

Although analyses of factorial invariance and temporal stability (test–retest) were not included in the present study, future research will incorporate these components using broader and more diverse samples. These analyses would assess whether the factorial structure remains stable across groups (e.g., gender, academic area) and over time. Future studies will also explore convergent and discriminant validity to compare the constructs with theoretically related or distinct measures. Incorporating these analyses will enhance the instrument's validity, generalizability, and psychometric robustness.

3. Analysis and results

Content validity assessed through Aiken's V showed adequate values for most items, with coefficients ranging from .80 to .95, evidencing clarity, relevance, and appropriateness in item wording (Table 2).

Table 2

Aiken's V Coefficients by Category and Item

Dimension	item	Clarity	Coherence	Relevance	Sufficiency
1. Information Search and Management	1	0.93	0.93	0.89	0.89
	2	0.81	0.85	0.89	
	3	0.85	0.81	0.85	
	4	0.81	0.81	0.89	
	5	0.89	0.89	0.93	
	6	0.93	0.93	0.96	
	7	0.96	0.93	0.89	
2. Academic Tutoring and Assistance	8	0.85	0.85	0.85	0.89
	9	0.93	0.89	0.96	
	10	0.93	0.96	0.89	

Dimension	item	Clarity	Coherence	Relevance	Sufficiency
	11	0.85	0.85	0.85	
3. Content Creation and Editing	12	0.93	0.85	0.96	0.93
	13	0.93	0.78*	0.85	
	14	0.89	0.85	0.93	
	15	0.96	0.93	0.93	
4. Perceived Self-Efficacy	16	0.81	0.85	0.89	0.96
	17	0.93	0.96	0.96	
	18	0.85	0.89	0.89	
	19	0.93	0.93	0.93	
	20	0.89	0.93	0.96	
	21	0.93	0.89	0.85	
	22	0.93	0.93	0.93	
5. Ethical Use	23	0.93	0.96	1.00	1.00
	24	0.93	0.96	0.93	
	25	0.85	0.89	0.89	
	26	1.00	0.96	1.00	
	27	1.00	0.96	0.96	
	28	0.96	0.89	0.93	
	29	0.93	0.89	0.96	
6. Limitations and Barriers	30	0.85	0.85	0.89	0.93
	31	0.89	0.89	0.85	
	32	0.81	0.81	0.81	
7. Accessibility and Equity	33	0.85	0.89	0.89	0.93
	34	0.85	0.93	0.89	
	35	0.85	0.89	0.78*	
	36	0.85	0.85	0.85	
8. Environmental Impact	37	0.89	0.96	0.89	0.96
	38	0.85	0.78*	0.85	
	39	0.85	0.85	0.85	
	40	0.85	0.85	0.85	
	41	0.81	0.85	0.85	
	42	0.74*	0.78*	0.81	
9. Dependence or Addiction	43	0.85	0.81	0.81	0.96
	44	0.81	0.78*	0.81	
	45	0.81	0.81	0.78*	
	46	0.78*	0.74*	0.81	
	47	0.74*	0.74*	0.74*	

Note: Asterisks (*) indicate items with Aiken's V < .80 in at least one category, later revised in wording.

Based on expert feedback and Aiken's V results, items 2 and 44 were removed due to conceptual redundancy. Item 13, which scored slightly below .80 in coherence, was rewritten in the refinement stage. Item 47 was removed due to values below .80 in three categories. Item 6 was reassigned to the Content Creation and Editing dimension, while items 13, 35, 38, and 42 were reformulated based on expert recommendations. The resulting 45-item version was applied in the pilot test with 905 students.

Exploratory Factor Analysis (EFA) confirmed data suitability (KMO = excellent; Bartlett's test = significant), indicating strong factorability. Although the theoretical model proposed nine dimensions, EFA suggested a seven-factor solution, explaining 64% of total variance. Three items (25, 33, and 36) were removed due to low factor loadings (< .40). Item 14 was reassigned to the Perceived Self-Efficacy dimension. The factors "Limitations and Barriers" and "Accessibility and Equity" merged into a single dimension.

Factor loadings ranged from .44 to .96, using oblique rotation (Promax), with no significant cross-loadings (> .30). Communalities ranged from .41 to .79, indicating solid contribution of items to their respective factors.

Subsequently, the Confirmatory Factor Analysis (CFA) compared the original nine-factor model with the empirically derived seven-factor model. Results indicated superior global fit for the seven-dimension model (CFI = .90; TLI = .90; RMSEA = .06; SRMR = .04); these results confirm the construct validity of the revised seven-dimension model, reflecting students' experiences and perceptions regarding the academic use of GenAI more accurately than the original formulation.

The internal consistency was raised to Cronbach's α and McDonald's ω ranged from .84 to .94, demonstrating high internal consistency and measurement stability.

Taken together, the analyses support that the final structure comprising seven dimensions and 42 items constitutes a parsimonious and robust representation of the construct Academic Use of Generative Artificial Intelligence among University Students (Table 3). Each modification—whether item removal, relocation, or merging—was guided by statistical and conceptual criteria, with the aim of maximizing the instrument's theoretical coherence and empirical validity.

Table 3

Final Version of the Instrument

Dimension	Item
Comprehensive Academic Use	1. I use of GenAI tools to search for academic information.
	2. I use of GenAI tools to analyze academic materials such as PDF reports, videos, statistical data, and others.
	3. I use of GenAI tools to cite and/or generate bibliographic references in APA, MLA, Chicago, IEEE, or Vancouver formats.
	4. I use of GenAI tools to translate and understand academic texts in other languages.
	5. I use of GenAI tools to generate or structure ideas, outlines, or arguments for academic assignments.
	6. I use of GenAI tools on a daily basis to address academic questions.

Dimension	Item
	7. I use of GenAI tools to check grammar, spelling, and writing style in my academic work. 8. I use of GenAI tools to solve or request help with complex topics when studying independently. 9. I use of GenAI tools to prepare for exams.
Content creation adn editing	10. I use GenAI tools to create summaries of academic texts. 11. I use GenAI tools to generate ideas, texts, or slides for academic presentations. 12. I use GenAI tools to write and/or edit academic assignments. 13. I use GenAI tools to generate multimedia content (videos, images, audio) for academic activities.
Perceived Self-Efficacy	14. I adapt and combine GenAI-generated responses with my own ideas when completing academic assignments. 15. I feel confident using GenAI tools to search for information, write texts, or solve academic questions. 16. I can learn to use new GenAI tools quickly if necessary. 17. I trust my ability to solve academic problems using GenAI tools. 18. I feel competent in using GenAI tools to improve my learning. 19. I can use GenAI tools to enhance the quality of my academic work. 20. I feel capable of evaluating the quality of information generated by GenAI tools. 21. I trust my ability to effectively integrate GenAI tools into my study routine.
Ethical Use	22. I understand how to use GenAI tools appropriately and ethically in my studies. 23. I verify the reliability of information and sources generated by GenAI tools. 24. I evaluate whether the use of GenAI tools improves my learning. 25. I consider GenAI a complementary tool rather than a substitute. 26. I recognize that GenAI tools may produce incorrect results or interpretations. 27. I am aware of the risks that GenAI tools may pose in academic contexts. 28. I am aware of the risks that GenAI tools may pose in personal contexts.
Access and inequality	29. I have experienced technical limitations when using GenAI tools for my studies (e.g., connectivity issues, device compatibility, lack of licenses, platform access failures). 30. I have encountered language barriers when using GenAI tools. 31. Lack of knowledge on how to use or configure GenAI tools is a barrier for me.

Dimension	Item
	32. I have had difficulties accessing GenAI tools due to subscription limitations.
	33. I know classmates who cannot use GenAI tools due to lack of adequate technology.
Enviromental impact	34. I am aware that intensive use of GenAI tools implies high electricity consumption.
	35. I inform myself about the environmental effects of using GenAI tools.
	36. I consider the ecological impact of intensive GenAI use.
	37. I reflect on how the academic use of GenAI tools may contribute to climate change.
	38. I agree with promoting responsible use to reduce the environmental impact of GenAI tools.
	39. I am willing to reduce my use of GenAI tools to lower their ecological footprint.
Dependence or addiction	40. I feel that I frequently rely on GenAI tools to complete academic tasks.
	41. I use GenAI tools even when they are not necessary for my academic activities.
	42. I have noticed that I spend more time than necessary using GenAI tools for my studies.

Note: *Arranged by the authors*.

4. Discussion

The results of the validation process provide strong evidence of the internal consistency and construct validity of the instrument designed to measure the academic use of generative artificial intelligence (GenAI) in higher education. The final structure of seven dimensions and 42 items reflects a parsimonious and theoretically coherent model, aligned with the digital competence and AI literacy frameworks proposed by Redecker (2017) and Long and Magerko (2020).

The dimensional reduction from nine to seven factors does not represent a conceptual loss but rather a theoretical consolidation that groups related components and enhances the interpretability of the instrument. For instance, the integration of the dimensions Limitations and Barriers with Accessibility and Equity suggests that both constructs converge on a shared notion of contextual conditions for the critical appropriation of GenAI, which is consistent with recent findings on digital inequality and technological access (Giannakos et al., 2024). Likewise, the strengthening of the Perceived Self-Efficacy dimension highlights the importance of technological competence beliefs in the responsible adoption of generative tools (Qadir, 2023).

From an applied perspective, the instrument makes it possible to diagnose the level of GenAI literacy and academic use among university students, offering valuable information for designing institutional strategies for ethical, technical, and reflective training in AI use. This potential for practical application aligns with the need for universities to regulate and guide the use of GenAI in educational and assessment processes (Bond et al., 2024; Holmes et al., 2019).

The importance of advancing toward studies that examine the factorial invariance of the instrument is also recognized, with the aim of determining whether the seven-dimension structure remains stable across different comparison groups such as gender, academic area, or educational level (Technical Degree and Bachelor's Degree). Incorporating these analyses—along with tests of convergent and discriminant validity—will allow for the evaluation of the model's metric and structural equivalence, strengthening evidence of external validity and result generalizability. Such procedures, widely recommended in contemporary psychometrics (Milfont & Fischer, 2010; Putnick & Bornstein, 2016), will consolidate the potential of the instrument as a standardized tool for comparative and longitudinal research in higher education.

Finally, the item refinement process and the establishment of a robust factor structure support the utility of the instrument as both a diagnostic and research tool. Its application can contribute to the empirical understanding of the role of GenAI in higher education, particularly in the development of critical digital competencies, ethical reasoning, and students' academic autonomy. In sum, the study offers a relevant methodological and conceptual advancement, albeit with the necessary caution regarding its scope and the need for additional validation efforts.

5. Conclusions

The present study successfully designed and validated a reliable and valid instrument to measure the academic use of generative artificial intelligence (GenAI) among higher education students. The final structure comprising 42 items across seven dimensions, demonstrated adequate factorial fit, internal consistency, and theoretical coherence, supporting its applicability for educational research and institutional management.

Operationally, the instrument allows for the calculation of dimension scores through the mean of responses from 1 to 5 on the Likert scale. The following interpretive ranges are recommended: 1.00 to 2.49 (low level), 2.50 to 3.49 (medium level), and 3.50 to 5.00 (high level). These scores may be used to identify strengths and areas for improvement in students' academic, ethical, and critical use of GenAI, as well as to inform training strategies or institutional policies related to digital literacy and technological ethics.

The instrument is suitable for institutional diagnostic studies, comparative evaluations across programs or academic divisions, and longitudinal monitoring of digital competence development. Its implementation can support decision-making in universities seeking to integrate AI responsibly into teaching and learning processes.

However, it is important to note that the study's findings are limited to a single technological university in southeastern Mexico. Therefore, results should not be generalized without caution to other educational contexts. Future research should incorporate factorial invariance testing, convergent and discriminant validity analyses, and temporal stability assessments to strengthen the generalizability and applicability of the instrument across diverse contexts.

In summary, this study offers a significant methodological and practical contribution to the field of educational innovation by providing a robust tool for understanding and promoting the reflective and ethical academic use of GenAI in higher education.

Suppelemntary material

The dataset used in this study is available upon reasonable request to the corresponding author.

Conflict of interest

The authors declare no conflict of interest..

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