

Measuring Artificial Intelligence Literacy in Higher Education: Validation of the ECAE-AI Scale

Medición de la alfabetización en inteligencia artificial en educación superior: Validación de la escala ECAE-IA

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ABSTRACT

The accelerated integration of artificial intelligence (AI) into higher education has increased the need for valid instruments capable of assessing AI literacy beyond technical skills, including attitudinal and ethical dimensions. Despite growing international interest in AI literacy, validated instruments adapted to Latin American undergraduate contexts remain scarce, limiting evidence-based educational interventions and institutional AI policies. This study aimed to validate the factorial structure of the ECAE-AI scale, a 14-item instrument designed to assess knowledge, attitudes, and ethical awareness regarding AI use among university students. A non-experimental, cross-sectional, instrumental design was applied to 408 undergraduate students from a northeastern Mexican university. Confirmatory factor analysis (CFA) using the DWLS estimator confirmed an excellent fit for the three-factor correlated model (CFI = .997; TLI = .996; RMSEA = .057; SRMR = .048). Standardised factor loadings ranged from .607 to .894. Reliability was excellent at both the global ($\omega = .915$; $\alpha = .917$) and dimensional levels. Convergent and discriminant validity were also supported. The findings support the ECAE-AI as a psychometrically robust instrument for assessing AI literacy in higher education, integrating cognitive, attitudinal, and ethical dimensions within a single framework. The scale provides practical value for diagnosing AI literacy profiles, designing evidence-based educational interventions, and supporting responsible AI integration policies in higher education institutions.

RESUMEN

La acelerada integración de la inteligencia artificial (IA) en la educación superior ha incrementado la necesidad de contar con instrumentos válidos capaces de evaluar la alfabetización en IA más allá de las habilidades técnicas, incorporando dimensiones actitudinales y éticas. A pesar del creciente interés internacional por la alfabetización en IA, siguen siendo escasos los instrumentos validados para contextos universitarios latinoamericanos, lo que limita el desarrollo de intervenciones educativas y políticas institucionales basadas en evidencia. El presente estudio tuvo como objetivo validar la estructura factorial de la escala ECAE-IA, un instrumento de 14 ítems diseñado para evaluar conocimientos, actitudes y conciencia ética sobre el uso de la IA en estudiantes universitarios. Se aplicó un diseño no experimental, transversal e instrumental a una muestra de 408 estudiantes de licenciatura de una universidad del noreste de México. El análisis factorial confirmatorio (AFC) mediante el estimador DWLS confirmó un excelente ajuste del modelo trifactorial correlacionado (CFI = .997; TLI = .996; RMSEA = .057; SRMR = .048). Las cargas factoriales estandarizadas oscilaron entre .607 y .894. La fiabilidad fue excelente tanto a nivel global ($\omega = .915$; $\alpha = .917$) como dimensional. Asimismo, se confirmó la validez convergente y discriminante. Los hallazgos respaldan al ECAE-IA como un instrumento psicométricamente robusto para evaluar la alfabetización en IA en educación superior, integrando dimensiones cognitivas, actitudinales y éticas en un único marco de evaluación. La escala ofrece utilidad práctica para diagnosticar perfiles de alfabetización en IA, diseñar

intervenciones educativas basadas en evidencia y fortalecer políticas institucionales orientadas a una integración responsable de la IA en la educación superior.

KEYWORDS | PALABRAS CLAVE

AI Literacy, Attitudes toward AI, Confirmatory Factor Analysis, Digital Ethics, Higher Education, Psychometric Validation. Actitudes hacia la IA, alfabetización en inteligencia artificial, análisis factorial confirmatorio, educación superior, ética digital, validación psicométrica.

1. Introduction

Artificial intelligence (AI) literacy research has expanded rapidly in recent years; however, higher education institutions—particularly in Latin American contexts—still lack concise and psychometrically validated instruments capable of simultaneously assessing cognitive, attitudinal, and ethical dimensions of AI use. The rapid expansion of AI, particularly generative models, has profoundly reshaped educational environments, redefining the competencies students are expected to develop as future professionals (Gibson et al., 2023; İpek et al., 2023). AI-powered systems facilitate personalised learning, automated assessment, and academic support, while simultaneously raising critical concerns regarding authorship, academic integrity, algorithmic bias, and technological dependency (Abdallah et al., 2025; Fuchs & Aguilos, 2023). Within this landscape, preparing students to use AI critically, efficiently, and ethically has become a strategic priority for higher education institutions worldwide.

Responding to this challenge, AI literacy has emerged as a multidimensional competency framework integrating cognitive, attitudinal, and ethical dimensions related to AI use in educational settings. Recent research has highlighted the growing integration of AI into university teaching and learning processes, as well as the increasing need for validated assessment tools adapted to diverse educational contexts (Acosta-Enriquez et al., 2024). Nevertheless, most existing instruments have been developed for non-Latin American populations or focus primarily on technical competencies, limiting their usefulness for evidence-based educational interventions and institutional AI policy development in the region.

The present study addresses this gap by validating the factorial structure of the ECAE-AI (Scale of Competencies, Attitudes, and Ethics in the Use of Artificial Intelligence), an instrument developed by Girarte-Guillén et al. (2025) for undergraduate students. By providing empirical evidence of its validity and reliability, this study contributes to a theoretically grounded and psychometrically robust tool for diagnosing AI literacy across cognitive, attitudinal, and ethical dimensions in university contexts. Therefore, the objective of this study was to evaluate the factorial structure, reliability, and construct validity of the ECAE-AI scale among undergraduate students in a Latin American higher education context.

1.1. Artificial Intelligence in Contemporary Higher Education

Generative artificial intelligence (AI) systems such as ChatGPT, Gemini, and Copilot have rapidly transformed higher education by reshaping how students access information, produce academic content, and engage with learning processes (Gibson et al., 2023; Mora & Rizzo, 2023). Beyond simple technological assistance, AI systems are increasingly embedded in core educational practices such as tutoring, assessment, academic writing, feedback, and personalised learning support.

Recent empirical studies indicate that university students frequently perceive AI tools as useful for improving productivity, reducing workload, and supporting self-regulated learning (Acosta-Enriquez et al., 2024; Fuchs & Aguilos, 2023). However, the accelerated incorporation of AI into educational environments has also generated significant concerns regarding academic integrity, overreliance on automated systems, misinformation, algorithmic bias, and ethical responsibility in AI-assisted academic work (Abdallah et al., 2025; İpek et al., 2023).

Recent systematic reviews further suggest that higher education institutions remain unevenly prepared to address these challenges through coherent pedagogical and institutional strategies (Lo et al., 2024). While some higher education institutions have begun integrating AI literacy initiatives into curricula, many institutions still lack clear frameworks for responsible AI use, ethical regulation, and evidence-based educational implementation, particularly in developing and Latin American contexts (García Peñalvo et al., 2024). This situation has reinforced the need to understand AI literacy not only as technical proficiency, but also as a multidimensional competency involving critical understanding, attitudes, and ethical awareness in academic contexts.

From this perspective, AI literacy can be understood as an extension of media and digital literacy frameworks, activating critical, ethical, and communicative competencies required for responsible participation in technologically mediated societies (Ferrés & Piscitelli, 2012). Consequently, higher education institutions increasingly require validated assessment instruments capable of diagnosing students' AI literacy profiles in order to guide curriculum design, institutional policy development, and evidence-based educational interventions.

1.2. Dimensions of AI Literacy in Undergraduate Contexts

Recent research increasingly conceptualises AI literacy as a multidimensional construct that extends beyond technical knowledge to include attitudinal and ethical dimensions associated with the use of AI in educational settings (Ma et al., 2024). Rather than focusing exclusively on operational skills, contemporary approaches to AI literacy emphasise students' capacity to critically understand AI systems, evaluate their implications, and engage responsibly with AI-supported academic practices.

The cognitive dimension involves understanding the basic principles, applications, and limitations of AI technologies. Previous studies indicate that students with greater familiarity with AI concepts tend to demonstrate more informed and critical interactions with AI tools, although literacy levels often vary according to disciplinary background and prior technological exposure (Amiri et al., 2024; Laupichler et al., 2024). The attitudinal dimension refers to students' perceptions, acceptance, and willingness to use AI in academic contexts. Empirical research consistently reports generally positive attitudes toward educational AI, particularly when students perceive AI systems as useful for improving learning efficiency and academic performance (Lo et al., 2024; Ma et al., 2024). However, concerns related to dependency, privacy, and academic integrity may negatively influence technology acceptance and critical engagement.

The ethical dimension has gained increasing relevance due to the growing integration of generative AI into academic work. This dimension involves recognising issues such as algorithmic bias, responsible AI use, data privacy, transparency, and academic honesty (UNESCO, 2021). Recent studies suggest that ethical awareness is closely associated with both AI knowledge and students' attitudes toward technology use, reinforcing the need to assess AI literacy through integrated rather than isolated dimensions (Laupichler et al., 2024; Ng et al., 2023). From this perspective, multidimensional assessment instruments provide a more comprehensive understanding of students' AI literacy profiles and offer stronger evidence for curriculum development and institutional decision-making in higher education.

1.3. Attitudes Toward AI and Ethical Dimensions

University students generally report favourable attitudes toward the educational use of AI, particularly when AI systems are perceived as useful for improving productivity, personalising learning, and supporting academic tasks (Acosta-Enriquez et al., 2024; Gibson et al., 2023). Positive perceptions of AI are often associated with greater willingness to adopt emerging technologies in learning environments and to experiment with AI-assisted academic practices. Nevertheless, recent studies also warn that excessive dependence on AI tools may reduce critical engagement, weaken independent problem-solving, and normalise passive consumption of automatically generated content (İpek et al., 2023).

In this context, ethical awareness has become an essential component of responsible AI use in higher education. Ethical AI literacy involves recognising the limitations and risks associated with AI-generated content, including issues related to bias, transparency, misinformation, privacy, and academic integrity (Kong & Zhu, 2025; UNESCO, 2021). Students with stronger ethical awareness are more likely to critically evaluate AI outputs, verify information accuracy, and maintain responsible academic practices. Consequently, the ethical dimension not only complements attitudinal dispositions toward AI but also conditions the quality and responsibility of AI-mediated learning experiences in university contexts.

1.4. Psychometric Validity of AI Literacy Instruments

In recent years, several instruments have been developed to assess AI literacy, attitudes toward AI, and ethical awareness in educational contexts. However, many of these scales have been designed for specific disciplinary populations, focus predominantly on technical competencies, or provide limited evidence regarding construct validity and cross-context applicability (Almaraz-López et al., 2023). These limitations are particularly relevant in Latin American higher education contexts, where culturally and educationally adapted assessment tools remain scarce.

Recent validation studies support the multidimensional assessment of AI literacy through cognitive, attitudinal, and ethical dimensions. For example, Ng et al. (2023) validated an AI literacy questionnaire based on affective, behavioural, cognitive, and ethical dimensions, while Kong and Zhu (2025) developed an ethical awareness scale for secondary and university students. Similarly, Laupichler et al. (2024) reported differentiated AI literacy profiles associated with disciplinary background and prior technological exposure.

Together, these studies reinforce the need for psychometrically robust instruments capable of capturing the complexity of AI literacy in diverse educational settings.

Within this context, confirmatory factor analysis (CFA) has become one of the most widely used approaches for evaluating the structural validity of multidimensional educational instruments, as it allows theoretical models to be empirically tested against observed data (Brown, 2015; Kline, 2016). The present study applies CFA to evaluate the factorial structure of the ECAE-AI instrument, contributing empirical evidence regarding its validity and reliability for undergraduate students in a Latin American higher education context.

1.5. Theoretical Framework

The ECAE-AI is grounded in the conceptualisation of AI literacy as a multidimensional construct integrating cognitive, attitudinal, and ethical dimensions of AI use in educational contexts. The cognitive dimension is informed by constructivist perspectives on learning, which emphasise that students actively develop understanding through interaction with digital technologies and prior knowledge (Gibson et al., 2023). Within this perspective, AI literacy involves not only recognising how AI systems function, but also understanding their educational applications, limitations, and implications in academic environments.

The attitudinal dimension draws primarily on the Technology Acceptance Model (TAM), which explains technology adoption through perceived usefulness and ease of use (Lo et al., 2024; Ma et al., 2024). In higher education, students' attitudes toward AI influence their willingness to incorporate AI systems into learning processes and shape the extent to which these technologies are perceived as supportive or potentially problematic. At the same time, ethical awareness has become increasingly central to AI literacy frameworks due to growing concerns regarding bias, transparency, privacy, authorship, and academic integrity in AI-mediated learning environments (UNESCO, 2021).

Together, these perspectives support the understanding of AI literacy as a theoretically integrated construct in which cognitive understanding, attitudinal dispositions, and ethical responsibility interact dynamically in students' engagement with AI technologies. Based on this framework, the ECAE-AI was designed to provide an integrated assessment of these dimensions within higher education contexts.

2. Material and Methods

This study adopted a non-experimental, cross-sectional, instrumental design (León & Montero, 2020) to evaluate the psychometric properties of the ECAE-AI scale, an instrument designed to assess AI literacy among undergraduate students through cognitive, attitudinal, and ethical dimensions. Given the growing integration of AI into higher education and the limited availability of validated instruments for Latin American university contexts, an instrumental approach was considered appropriate to examine the factorial structure, reliability, and construct validity of the scale. The ECAE-AI comprises 14 Likert-type items rated on a five-point scale (1 = strongly disagree to 5 = strongly agree), organised into three theoretically grounded dimensions: Knowledge (4 items), Attitudes (6 items), and Ethics (4 items). Following recommendations for scale validation studies, the analysis combined exploratory and confirmatory procedures to evaluate the internal structure and psychometric consistency of the instrument.

2.1. Participants

The final sample comprised 408 undergraduate students enrolled in multiple academic programmes at a university in northeastern Mexico during the 2024–2025 academic year. The diversity of disciplinary backgrounds was considered relevant given the multidimensional and interdisciplinary nature of AI literacy in higher education contexts. Prior to analysis, 28 multivariate outliers (6.4%) and one researcher test case were excluded using Mahalanobis distance ($p < .001$), following recommendations by Hair et al. (2019) and Kline (2016).

Female participants represented 62.0% of the sample and male participants 37.7%, with one missing response for gender. The most represented academic programmes were Law (26.0%), Business Administration (23.8%), and Software Engineering (17.2%). Participants from other disciplines, including Logistics and Trade and additional undergraduate programmes, were also represented. The most frequent age ranges were 28–32 years (19.6%) and 33–37 years (19.9%). Detailed sociodemographic information is presented in Table 1.

Table 1: Sociodemographic Characteristics of Participants (N=408).

Variable	Category	n	%
Gender	Female	253	62.0
	Male	154	37.7
Age	18-22	24	5.9
	23-27	53	13.0
	28-32	80	19.6
	33-37	81	19.9
	38-42	62	15.2
	43-47	42	10.3
	48-52	38	9.3
	53+	28	6.9
Marital status	Married	185	45.3
	Single	142	34.8
	Cohabiting	54	13.2
	Divorced	26	6.4
	Widowed	1	0.2
Degree programme	Law	106	26.0
	Business Administration	97	23.8
	Software Engineering	70	17.2
	Logistics & Trade	43	10.5
	Other programmes	92	22.5
Semester	1st	102	25.0
	2nd	51	12.5
	3rd	52	12.7
	4th-9th	203	49.8

Note. 'Other programmes' groups five programmes with individual representation below 5%.

2.2. Procedure

Data collection was conducted during the 2024–2025 academic year through an online questionnaire administered across multiple undergraduate programmes at a university in northeastern Mexico. Participation was voluntary, and informed digital consent was obtained from all participants prior to data collection. The study adhered to principles of confidentiality, anonymity, and responsible data management throughout the research process.

A total of 437 responses were initially obtained. Prior to analysis, one researcher test case was removed and 28 multivariate outliers were excluded based on Mahalanobis distance analysis ($p < .001$) to improve the robustness of the factorial analyses, resulting in a final sample of 408 participants. The administration process was designed to facilitate broad participation across disciplinary areas and to ensure adequate representation of students with diverse academic backgrounds.

2.3. Data Analysis

All analyses were conducted using JASP (version 0.19.1). Given the ordinal nature of the Likert-type items and the absence of multivariate normality, confirmatory factor analysis (CFA) was performed using the Diagonally Weighted Least Squares (DWLS) estimator, which is recommended for ordinal data in psychometric validation studies (Li, 2016). A three-factor correlated model was specified, comprising the dimensions Knowledge (items 1–4), Attitudes (items 5–10), and Ethics (items 11–14).

Model fit was evaluated using commonly accepted goodness-of-fit indicators: chi-square/degrees of freedom ratio ($\chi^2/df < 3$), Comparative Fit Index ($CFI \geq .95$), Tucker-Lewis Index ($TLI \geq .95$), Root Mean Square Error of Approximation ($RMSEA \leq .06$), and Standardised Root Mean Square Residual ($SRMR \leq .08$) (Hu & Bentler, 1999). Standardised factor loadings were considered acceptable at $\lambda \geq .50$ (Hair et al., 2019).

Internal consistency was assessed using McDonald's omega (ω) and Cronbach's alpha (α), with values above .70 indicating acceptable reliability (Dunn et al., 2014). Convergent validity was examined through Average Variance Extracted ($AVE \geq .50$), while discriminant validity was evaluated using the Fornell-Larcker criterion (Fornell & Larcker, 1981).

Prior to CFA, sampling adequacy was assessed using the Kaiser-Meyer-Olkin (KMO) index and Bartlett's Test of Sphericity. An exploratory factor analysis (EFA) conducted on an independent subsample provided preliminary support for the three-factor structure before confirmatory testing, following the two-step validation approach proposed by Anderson and Gerbing (1988).

3. Results

3.1. Global Model Fit

The three-factor correlated model demonstrated an excellent fit to the data: $\chi^2(74) = 173.253$, $p < .001$; $\chi^2/df = 2.34$; CFI = .997; TLI = .996; RMSEA = .057, 90% CI [.046, .069], p-close = .131; and SRMR = .048. All fit indices met or exceeded the criteria recommended by Hu and Bentler (1999), supporting the adequacy of the proposed factorial structure (Table 2).

These findings are consistent with recent AI literacy validation studies reporting multidimensional structures in educational contexts. For example, Kong and Zhu (2025) reported CFI = .967 and RMSEA = .059 in the validation of an AI ethical awareness scale, while Laupichler et al. (2024) identified acceptable fit indices across AI literacy dimensions in university students. In comparison, the ECAE-AI demonstrated excellent fit with a concise 14-item structure, suggesting that the instrument adequately captures cognitive, attitudinal, and ethical dimensions of AI literacy in higher education.

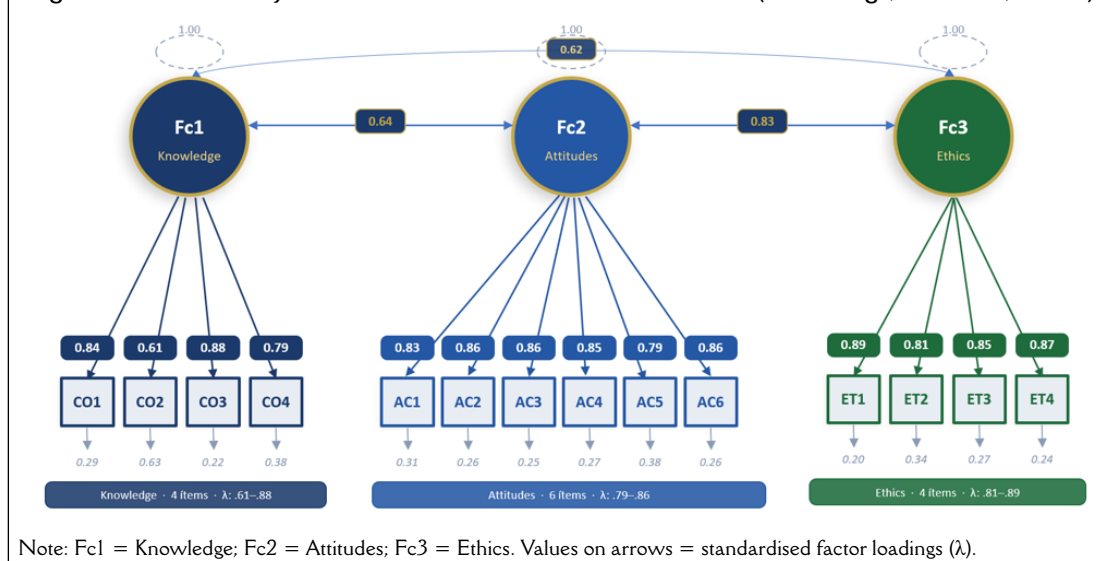
The standardised factor loadings were consistently strong across the three dimensions, particularly within the Ethics factor, supporting the internal coherence of the proposed model (Figure 1).

Table 2: Global Fit Indices for the Three-Factor CFA Model.

Index	Value	Criterion
χ^2 (df = 74)	173.253, $p < .001$	—
χ^2/df	2.34	< 3.00
CFI	.997	$\geq .95$
TLI	.996	$\geq .95$
RMSEA [90% CI]	.057 [.046, .069]	$\leq .06$
SRMR	.048	$\leq .08$

Note. CFA performed using DWLS estimator; N=408. df = degrees of freedom.

Figure 1: Confirmatory factor model of the ECAE-AI instrument (Knowledge, Attitudes, Ethics).



3.2. Factor Loadings

All standardised factor loadings were statistically significant ($p < .001$) and exceeded the minimum

recommended threshold of .50, ranging from .607 to .894 (Table 3). These results provide support for the factorial consistency of the proposed three-dimensional structure.

Within the Knowledge dimension, factor loadings ranged from .607 to .880. The lowest loading corresponded to item CON2, related to knowledge of natural language processing principles ($\lambda = .607$), which may reflect the greater technical specificity of this concept compared to the remaining items. Nevertheless, the loading remained above the acceptable threshold for construct representation. The Attitudes dimension showed consistently strong loadings between .786 and .864, while the Ethics dimension presented the highest loadings overall, ranging from .814 to .894.

Overall, the results indicate that the items adequately represent their respective latent constructs and support the internal coherence of the ECAE-AI scale across cognitive, attitudinal, and ethical dimensions.

Table 3: Standardised Factor Loadings of the ECAE-AI Scale.

Dimension	Item	Content	λ
Knowledge	CON1	I have knowledge of the basic concepts of AI.	.843
	CON2	I know the principles of natural language processing.	.607
	CON3	I know how AI can be applied to personalise learning.	.880
	CON4	I know ways in which AI is applied in academic assessment.	.787
Attitudes	ACT1	I believe AI can improve the teaching-learning process.	.831
	ACT2	I am willing to use AI tools in educational activities.	.859
	ACT3	I perceive that AI can reduce workload.	.864
	ACT4	I am motivated to learn about AI use.	.854
	ACT5	I feel confident using AI technologies.	.786
	ACT6	I believe AI can address individual learning needs.	.859
Ethics	ETIC1	I assume ethical responsibility for decisions when interacting with AI.	.894
	ETIC2	I believe AI should encourage honesty practices in academia.	.814
	ETIC3	I am responsible for verifying the accuracy of AI-generated work.	.854
	ETIC4	I consider myself responsible for the ethical use of AI tools.	.874

Note. λ = standardised factor loading. All loadings are significant at $p < .001$. Estimation via DWLS.

3.3. Reliability and Validity

Reliability estimates indicated strong internal consistency across all dimensions of the ECAE-AI scale and for the instrument as a whole (Table 4). Global reliability was excellent, with McDonald's omega ($\omega = .915$) and Cronbach's alpha ($\alpha = .917$) showing highly consistent results. At the dimensional level, reliability coefficients ranged from .810 to .881, supporting the stability of the Knowledge, Attitudes, and Ethics factors.

Table 4: Internal Reliability (ω , α) and Average Variance Extracted (AVE) by Dimension.

Dimension	ω	95% CI ω	α	95% CI α	AVE
Knowledge	.811	[.781, .841]	.810	[.768, .851]	.619
Attitudes	.881	[.862, .899]	.879	[.850, .909]	.710
Ethics	.880	[.861, .899]	.879	[.848, .911]	.739
Total scale	.915	[.903, .927]	.917	[.897, .937]	—

Note. ω = McDonald's omega; α = Cronbach's alpha; AVE = average variance extracted; CI = confidence interval.

Evidence of convergent validity was also observed. Average Variance Extracted (AVE) values exceeded the recommended .50 threshold across all dimensions, ranging from .619 for Knowledge to .739 for Ethics, indicating that the items adequately captured the variance of their respective constructs.

Table 5: Inter-Factor Correlations and Discriminant Validity (Fornell-Larcker Criterion).

Factor	Knowledge	Attitudes	Ethics
Knowledge	.787		
Attitudes	.642	.842	
Ethics	.620	.825	.860

Note. Diagonal values (bold) represent the square root of AVE for each construct. Off-diagonal values are Pearson inter-factor correlations. Discriminant validity is established when the square root of AVE exceeds all corresponding inter-factor correlations (Fornell & Larcker, 1981).

Discriminant validity was evaluated using the Fornell-Larcker criterion (Table 5). In all cases, the square root of the AVE for each construct exceeded the corresponding inter-factor correlations, supporting the empirical distinction between the cognitive, attitudinal, and ethical dimensions of AI literacy measured by the ECAE-AI.

4. Discussion

This study aimed to validate the factorial structure of the ECAE-AI instrument, designed to assess AI literacy across knowledge, attitudinal, and ethical dimensions in undergraduate students. The CFA results confirmed the three-factor theoretical structure with high factor loadings and excellent global fit, supporting the instrument's construct validity. These findings are consistent with recent research conceptualising AI literacy as an integrated competency requiring the articulation of cognitive, dispositional, and ethical components (Abdallah et al., 2025; Ma et al., 2024).

Regarding the Knowledge dimension, results suggest relatively homogeneous understanding of AI concepts across participants. This aligns with studies showing that, even without specialised training, undergraduates develop a functional understanding of AI through everyday exposure to intelligent tools (Amiri et al., 2024). The lower loading on item CON2 (natural language processing, $\lambda = .607$) reflects the greater technical specificity of this concept, consistent with findings from Laupichler et al. (2024), who similarly report lower levels of AI literacy among students from non-technical or less digitally intensive disciplines. This underscores the need for discipline-sensitive AI literacy curricula that address conceptual gaps without assuming programming expertise.

Despite the rapid growth of AI integration in higher education globally, the Latin American context presents specific challenges that demand locally validated instruments. Institutional frameworks for AI governance remain underdeveloped in many regional higher education institutions, and faculty preparation for AI-informed pedagogy is uneven across disciplines and institutions (García Peñalvo et al., 2024). In this context, AI literacy assessment tools calibrated for Latin American undergraduate populations fill a critical gap, enabling institutions to move beyond generalist diagnostics toward discipline-sensitive, evidence-based interventions. The ECAE-AI responds directly to this need, offering a compact yet comprehensive instrument for systematic AI literacy profiling across heterogeneous student populations.

The Attitudes dimension demonstrated outstanding reliability ($\omega = .881$) and a highly stable structure, consistent with literature documenting positive student dispositions toward educational AI use (Acosta-Enriquez et al., 2024; Lo et al., 2024). Perceived usefulness, efficiency, and personalised support drive this positivity, though excessive optimism may compromise critical engagement and foster over-reliance (İpek et al., 2023). The Ethics dimension also showed strong psychometric properties, which is particularly relevant given the global push for responsible AI use in education. Notably, the high correlation between Attitudes and Ethics ($r = .825$) reflects a well-documented pattern: students with more positive AI dispositions tend to display greater ethical sensitivity (Laupichler et al., 2024). This finding supports the feasibility of interdisciplinary AI literacy models that cultivate both positive engagement and ethical judgment simultaneously (Ng et al., 2023).

The three-dimensional conceptualisation of AI literacy has gained robust empirical support across diverse educational settings. Ng et al. (2023) propose an ABC+E framework — Affective, Behavioural, Cognitive, plus Ethical — that maps directly onto the ECAE-AI structure: Knowledge corresponds to the cognitive and behavioural dimensions, Attitudes to the affective dimension, and Ethics to the ethical dimension. This alignment underscores the theoretical coherence of the ECAE-AI as an operationalisation of established AI literacy theory. Furthermore, the instrument's Likert format and concise 14-item structure make it particularly suitable for integration into institutional assessment systems, where efficiency and cross-programme comparability are priorities.

Convergent and discriminant validity results confirm the empirical distinctiveness of the three factors while maintaining theoretically meaningful inter-correlations. This supports conceptual models of AI literacy as a structured yet integrated competency, where technical knowledge shapes attitudes, which in turn condition ethical judgment (Brown, 2015; Kline, 2016). From a practical standpoint, the ECAE-AI provides institutions with a valid diagnostic tool for identifying AI literacy gaps across knowledge, attitudinal, and ethical dimensions, enabling targeted curriculum interventions grounded in psychometric evidence.

Several limitations should be acknowledged. The sample was drawn from a single Mexican university, limiting generalisability. The non-probabilistic sampling procedure may introduce representation bias. Future research should extend validation efforts to more diverse institutional and national contexts, implement multi-group analyses by gender, age, and academic discipline, and explore longitudinal designs to track AI literacy development over time.

5. Conclusions

This study provided empirical evidence supporting the factorial validity, reliability, and construct coherence of the ECAE-AI scale as a multidimensional instrument for assessing AI literacy in higher education. The confirmatory factor analysis confirmed a theoretically consistent three-factor structure integrating cognitive, attitudinal, and ethical dimensions, while reliability and validity indicators demonstrated strong psychometric performance across all constructs. These findings reinforce current perspectives that conceptualise AI literacy not merely as technical proficiency, but as an integrated competency involving critical understanding, responsible attitudes, and ethical awareness in the use of AI technologies.

The study also contributes to the limited availability of validated AI literacy instruments adapted to Latin American higher education contexts. In regions where institutional strategies for AI integration and ethical governance are still developing, the ECAE-AI offers a concise and psychometrically robust tool capable of supporting evidence-based curriculum design, institutional assessment, and educational decision-making. Its multidimensional structure facilitates the identification of strengths and gaps in students' AI literacy profiles, enabling higher education institutions to design targeted interventions that promote both critical engagement and responsible AI use.

Several limitations should nevertheless be acknowledged. The cross-sectional design does not allow examination of changes in AI literacy over time, and the use of self-report measures may introduce response bias, particularly in ethical dimensions. In addition, data were collected from a single university context, which may limit broader generalisability. Future studies should therefore examine the scale across more diverse institutional and cultural settings, incorporate longitudinal approaches, and evaluate measurement invariance across demographic and disciplinary groups.

Despite these limitations, the ECAE-AI represents a meaningful methodological contribution to emerging AI literacy research in higher education. Its alignment with contemporary theoretical frameworks and its practical applicability in university contexts position the instrument as a useful resource for future research, institutional evaluation, and the responsible integration of AI within higher education systems.

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