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Artificial intelligence literacy in in-person and virtual study modalities among university students

Alfabetización en inteligencia artificial en modalidades de estudio presencial y virtual entre estudiantes universitarios

Alfabetização em inteligência artificial nas modalidades de estudo presencial e virtual entre estudantes universitários

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■ **Abstract.** The incorporation of artificial intelligence into educational processes has transformed teaching and learning dynamics in both in-person and virtual environments. However, questions remain about the differences in learning this technology depending on the educational modality. The primary objective of this research was to compare artificial intelligence learning in in-person and virtual study modalities among Ecuadorian university students. The methodology employed a quantitative and explanatory approach to analyze observed and latent variables related to AI. The sample included 432 students from various higher education institutions, distributed as 56% in the virtual modality and 44% in the in-person modality. Analyses were conducted using SPSS version 25 and AMOS 24, utilizing the AI Literacy Questionnaire, which encompasses affective, behavioral, cognitive, and ethical dimensions. The multivariate analysis of factorial invariance, based on multigroup analysis, demonstrated excellent reliability for the questionnaire (α=0.960 and Ω=0.959), with higher scores among students in the virtual modality. The model fit indices were highly satisfactory (X^2=2.647, NFI=0.904, RFI=0.897, IFI=TLI=0.934, CFI=0.938, RMSEA=0.064). It was concluded that in-person and virtual modalities show equivalence in the use of artificial intelligence, as evidenced by configural, metric, scalar, and strict invariance, with no significant differences in the means of the analyzed dimensions. These findings underscore the effectiveness of both modalities for AI learning in Ecuadorian educational contexts.

Keywords: Artificial intelligence, Learning, Scientific statistics, Educational clustering.

■ **Resumen.** La incorporación de la inteligencia artificial en los procesos educativos ha transformado las dinámicas de enseñanza y aprendizaje en entornos presenciales y virtuales. No obstante, persisten interrogantes sobre las diferencias en el aprendizaje de esta tecnología según la modalidad educativa. El objetivo principal de esta investigación fue comparar el aprendizaje de inteligencia artificial en las modalidades de estudio presencial y virtual entre estudiantes universitarios ecuatorianos. La metodología utilizó un enfoque cuantitativo y explicativo para analizar variables observadas y latentes relacionadas con la IA. La muestra incluyó a 432 estudiantes de diversas instituciones de educación superior, distribuidos en un 56% en la modalidad virtual y un 44% en la modalidad presencial. Los análisis se realizaron con SPSS versión 25 y AMOS 24, empleando el Cuestionario de Alfabetización en IA, que abarca dimensiones afectivas, conductuales, cognitivas y éticas. El análisis multivariado de invarianza factorial, basado en análisis multigrupo, mostró una excelente fiabilidad del cuestionario (α=0.960 y Ω=0.959), con puntajes más altos entre los estudiantes de la modalidad virtual. Los índices de ajuste del modelo fueron altamente satisfactorios (X^2=2.647, NFI=0.904, RFI=0.897, IFI=TLI=0.934, CFI=0.938, RMSEA=0.064). Se concluyó que las modalidades presencial y virtual son equivalentes en el uso de inteligencia artificial, evidenciado por la invarianza configural, métrica, escalar y estricta,

sin diferencias significativas en las medias de las dimensiones analizadas. Estos hallazgos destacan la efectividad de ambas modalidades para el aprendizaje de IA en contextos educativos ecuatorianos.

Palabras clave: Inteligencia artificial, Aprendizaje, Estadísticas científicas, Agrupación educativa.

Resumo. A incorporação da inteligência artificial nos processos educacionais transformou a dinâmica de ensino e aprendizagem em ambientes presenciais e virtuais. Porém, persistem questionamentos sobre as diferenças no aprendizado dessa tecnologia dependendo da modalidade educacional. O objetivo principal desta pesquisa foi comparar a aprendizagem de inteligência artificial nas modalidades de estudo presencial e virtual entre estudantes universitários equatorianos. A metodologia utilizou uma abordagem quantitativa e explicativa para analisar variáveis observadas e latentes relacionadas à IA. A amostra contou com 432 estudantes de diversas instituições de ensino superior, distribuídos 56% na modalidade virtual e 44% na modalidade presencial. As análises foram realizadas no SPSS versão 25 e AMOS 24, por meio do AI Literacy Questionnaire, que abrange dimensões afetivas, comportamentais, cognitivas e éticas. A análise multivariada de invariância fatorial, baseada na análise multigrupo, mostrou excelente confiabilidade do questionário (α=0,960 e Ω=0,959), com maiores pontuações entre os estudantes da modalidade virtual. Os índices de ajuste do modelo foram altamente satisfatórios (X^2=2,647, NFI=0,904, RFI=0,897, IFI=TLI=0,934, CFI=0,938, RMSEA=0,064). Concluiu-se que as modalidades presencial e virtual são equivalentes no uso da inteligência artificial, evidenciadas pela invariância configural, métrica, escalar e estrita, sem diferenças significativas nas médias das dimensões analisadas. Estas descobertas destacam a eficácia de ambas as modalidades para a aprendizagem de IA em contextos educacionais equatorianos.

Palavras-chave: Inteligência artificial, Aprendizagem, Estatística científica, Agrupamento educacional.

INTRODUCTION

Currently, online learning transforms and manages every aspect of educational processes and learning management compared to in-person education (Lee, 2024). Learning among university students is more effective in areas such as entertainment, knowledge and skills updating, unexpected learning, and efficient learning (Rof et al., 2024). The virtual teaching modality enhances learning, precision, fluency, and academic passion (Li & Hu, 2024). The massive transition to teaching with the use of artificial intelligence (AI) has amplified the impact of technology on the daily lives of universities (Photopoulos et al., 2022). Online evaluation practices and support systems contribute significantly to the quality of higher education (Abdullah et al., 2024).

In this context, the concept of AI literacy becomes increasingly relevant. AI literacy refers to the knowledge, skills, and attitudes necessary to effectively understand, use, and evaluate AI technologies in various domains, including education. It encompasses technical competencies, such as understanding AI principles, and broader dimensions, such as ethical considerations and critical thinking about AI's societal impact. As AI in education (AIED) continues to reshape the educational landscape (Lérias et al., 2024). AI literacy plays a pivotal role in equipping students and educators to navigate this transformation. Students are no longer required to travel to campus or attend lectures in crowded auditoriums, allowing them to integrate academic tasks into their schedules alongside personal interests VanLeeuwen et al. (2021), with effective classes being delivered (Choi et al., 2023). In this new environment, the capacity to critically engage with AI-driven tools enhances learning outcomes and fosters a deeper integration of technology in academic and personal development.

While AI literacy is a critical skill for navigating AI-integrated educational environments, existing studies lack a comprehensive framework to evaluate its dimensions in university students (Kayal, 2024; Yang et al., 2024). Current research primarily focuses on technical competencies, often neglecting ethical reasoning, critical thinking, and motivational factors essential for a holistic understanding of AI literacy. Furthermore, there is limited evidence on how different educational modalities (in-person vs. virtual) influence the acquisition and application of AI literacy (Cilliers et al., 2022). This gap underscores the need for a validated instrument to measure

AI literacy and understand its role in improving learning outcomes.

This investigation is essential for bridging the identified gaps and providing actionable insights into how AI literacy can be fostered within diverse educational settings (Yuwono et al., 2024). By exploring the intersection of AI technologies and educational practices, the study aims to offer evidence-based recommendations for integrating AI literacy into curriculum design (Yue Yim, 2024). Understanding these dynamics will not only improve students' ability to use AI effectively but also prepare them to address its broader societal implications, fostering a generation of critically engaged and ethically responsible AI users.

Therefore, it becomes necessary to pose the following question: How does artificial intelligence literacy influence in-person and virtual study modalities among university students? To address this question, the study aims to analyze the influence of artificial intelligence literacy on in-person and virtual study modalities among university students.

METHODOLOGY

The methodology of this research adopted a quantitative approach with multivariate modeling based on multigroup confirmatory factor analysis (MCFA) using structural equations in a cross-sectional design. The sample consisted of 432 students from various higher education institutions, distributed as 56% in the virtual modality and 44% in the in-person modality, with a mean age of 23.82 years and a standard deviation of ±6.77 years.

The Artificial Intelligence Literacy Questionnaire (Kit Ng et al., 2023) was employed, encompassing dimensions of behavioral learning (intention, commitment, and collaboration), cognitive learning (knowing, understanding, applying, evaluating, and creating), and ethical learning (AI ethics). This instrument, previously validated in educational contexts, ensured robust evaluations.

Data analysis was performed using SPSS (Statistical Package for the Social Sciences) version 25 and AMOS (Analysis of Moment Structures) version 24. Internal consistency of the instrument was assessed using Cronbach's alpha and McDonald's omega, confirming high reliability.

Exploratory principal component analyses were conducted with Kaiser-Meyer-Olkin (KMO) tests for sampling adequacy and Bartlett's test of sphericity, ensuring data suitability for factor analysis. Varimax rotations and scree plots were applied to identify underlying patterns. Confirmatory analyses utilized Partial Least Squares (PLS) techniques to establish structural validity, evaluating discriminant validity with the Heterotrait-Monotrait (HTMT) ratio, ensuring acceptable thresholds below 0.85. Model fit indices, including RMSEA, CFI, TLI, and SRMR, adhered to stringent criteria to ensure the quality of the structural model.

The multigroup analysis focused on factorial invariance, comparing structural weights, intercepts, covariances, and residuals across groups using global tests such as Chi-square and Akaike Information Criterion (AIC). Specific AMOS plugins were employed to calculate fit measures and categorical thresholds, incorporating both standardized and unstandardized coefficients alongside significance levels. This comprehensive methodological framework validated the proposed hypothesis and ensured the rigor needed to assess differences in artificial intelligence literacy between virtual and in-person educational modalities.

RESULTS AND DISCUSSION

This section presents the results of the multigroup multivariate statistical analyses (MCFA) applied to the collected data, aimed at evaluating the validity of the AI literacy instrument within a sample of university students from various undergraduate programs.

Figure 1 presents the factor loadings of the multigroup multivariate model (MCFA) of artificial

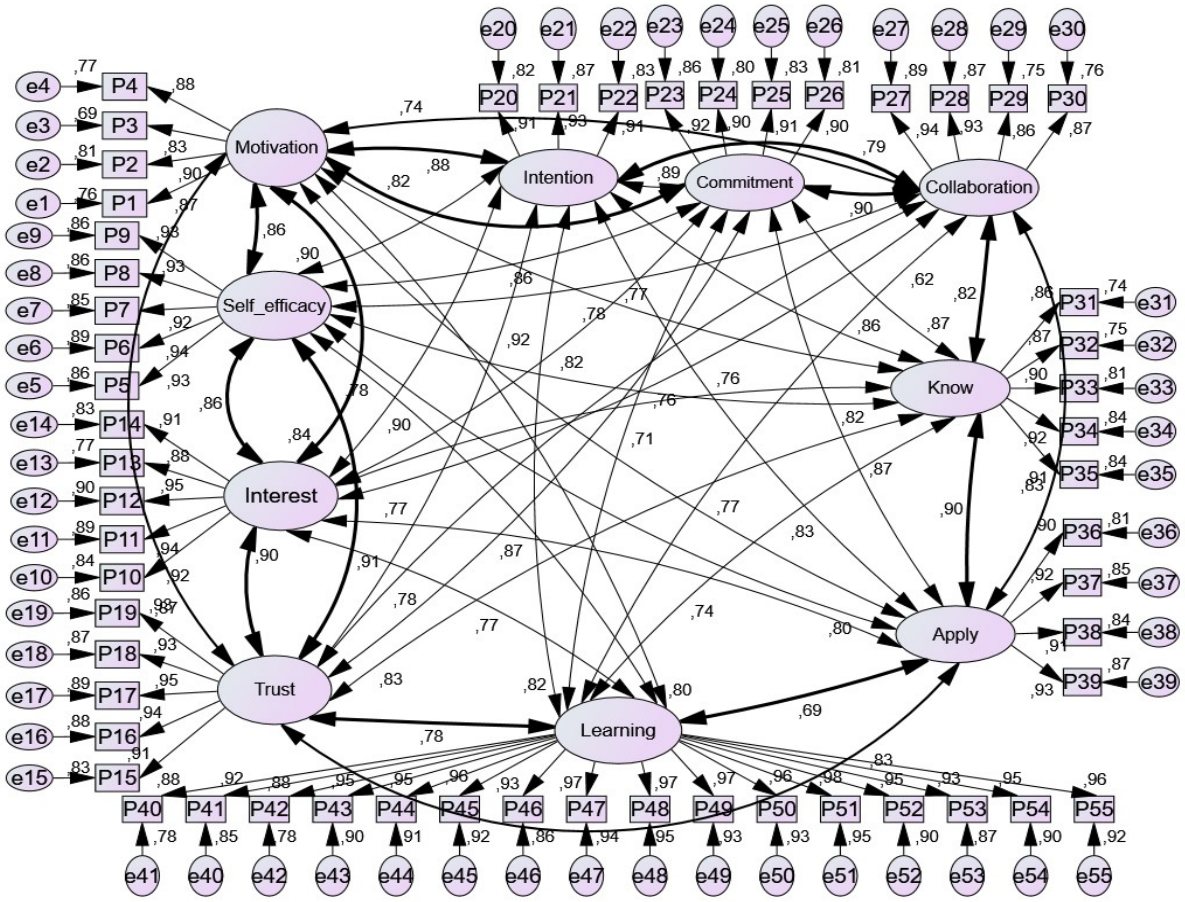

Figure 1. Factor loadings for the multigroup multivariate model (MCFA) of AI

intelligence, highlighting the relationships between latent dimensions and their respective observed indicators. The latent variables, such as Motivation, Self-Efficacy, Interest, Trust, Learning, Knowledge, Application, Intention, Commitment, and Collaboration, are represented by ellipses, while the observed variables are represented by rectangles.

Figure 1 illustrates the observed factor loadings for the items related to intrinsic motivation, which range from 0.828 to 0.886. Notably, the behavior of the items remained consistent across all subdimensions of the AI literacy questionnaire, indicating a strong contribution of the observed variables to the latent variable.

In the development of the AI literacy questionnaire, prior studies significantly influenced its structure and content. For instance, methodologies employed by Wilson (2023) and Goetz et al. (2013) in similar instruments guided the selection of items and subdimensions. These studies emphasized the importance of measuring intrinsic motivation, perceived self-efficacy, and understanding of AI principles, which were foundational to the conceptual framework of this research.

Comparing the present study with previous research, our findings align with those of Marsh et al. (2018), who observed similar factor loadings within motivational constructs. However, this study extends the scope by focusing on a multigroup analysis across diverse undergraduate programs, which was not addressed in prior works. Moreover, while earlier studies often concentrated on technical literacy or coding skills, this research incorporates a broader perspective, including ethical considerations and critical thinking about AI technologies.

The following Table 1 summarizes the results of the goodness-of-fit tests for artificial intelligence models applied in in-person and virtual modalities.

The table includes key metrics such as the total model fit, modality-specific fit, and accepted limits based on established standards. The evaluated indicators include CMIN, the CMIN/DF ratio, and the Normed Fit Index (NFI), providing a detailed analysis of parsimonious fit and the mean error associated with the compared models.

TABLE 1. GOODNESS-OF-FIT TESTS FOR AI MODELS IN IN-PERSON AND VIRTUAL MODALITIES

Summary of Model Fit	Reference Comparisons	Parsimonious Fit	Mean Error
Models	CMIN	CMIN/DF	NFI
Total Model	3640.388	2.628	0.904
In-Person Model	3254.359	2.350	0.884
Virtual Model	3665.617	2.647	0.727
Accepted Limit	4181.727	2.5-3.0	0.923

The goodness-of-fit test for the AI literacy questionnaire among university students is summarized in Table 1. The results indicate an excellent chi-square value, with reference comparison indices and parsimonious fit indices categorized as acceptable. These goodness-of-fit coefficients confirm that the items and constructs are appropriate for assessing the use of AI among university students.

The development of the AI literacy questionnaire was informed by foundational research and existing frameworks in the field. For instance, the theoretical underpinnings established by Ellikkal and Rajamohan (2024) emphasized the need to include dimensions such as intrinsic motivation, ethical considerations, and practical applications of AI. Similarly, Celik (2023) highlighted the importance of capturing both cognitive and behavioral aspects of AI literacy, which directly influenced the inclusion of specific subdimensions in this study. These studies provided a critical reference for defining the constructs and operationalizing them through measurable items.

When comparing the results of this study with prior research, several parallels and distinctions emerge. Consistent with findings by McNeish (2020), the chi-square and fit indices in this study indicate a robust model structure. However, this study advances the field by incorporating a multigroup analysis that evaluates the applicability of the questionnaire across different undergraduate disciplines. Unlike earlier works that focused primarily on technical literacy, such as coding or algorithmic understanding, this research adopts a more holistic perspective, integrating ethical reasoning, critical thinking, and motivational factors into the assessment of AI literacy.

Table 2 is presented below, detailing the fit coefficients for the evaluation of configurational, metric, scalar, and strict invariance of the multigroup multivariate model (MCFA). The fit indices include CMIN, the CMIN/DF ratio, the Comparative Fit Index (CFI), and the Root Mean Square Error of Approximation (RMSEA) with its 90% confidence interval.

Table 2 summarizes the fit coefficients for configurational, metric, scalar, and strict invariance models from the multigroup confirmatory factor analysis (MCFA). The configurational invariance model (M1) tested the unifactorial structure of the AI literacy questionnaire, allowing free estimation of factor loadings, intercepts, and error variances. The results (CFI = 0.892; RMSEA = 0.062; $X^2/df = 2.503$) indicated adequate fit, confirming the structural validity of the instrument.

Subsequent analyses restricted various parameters across in-person and virtual study modalities. The metric invariance model (M2) showed consistent factor loadings between groups ($\Delta CFI < 0.000$; $\Delta RMSEA < 0.000$), while the scalar invariance model (M3) demonstrated minor changes in fit indices ($\Delta CFI = -0.001$; $\Delta RMSEA = -0.001$). Finally, the strict invariance model (M4) revealed acceptable fit, affirming the questionnaire's robustness across modalities.

TABLE 2. FIT COEFFICIENTS FOR CONFIGURATIONAL, METRIC, SCALAR, AND STRICT INVARIANCE OF THE MCFA

Models	CMIN	CMIN/ DF	CFI	RMSEA (90% CI)	Compari-son	ΔX² (p-value)	ΔCFI	ΔRM-SEA
M1. Configurational Invariance	6934.459 (2770)	2.503	0.892	0.062 (0.060 - 0.064)				
M2. Metric (Weak) Invariance (λ restricted)	6990.384 (2815)	2.483	0.892	0.062 (0.060 - 0.063)	M2 VS M1	55.925 (p=0.127)	0.000	0.000
M3. Scalar (Strong) Invariance (λ and θ restricted)	7072.155 (2870)	2.464	0.891	0.061 (0.059 - 0.063)	M3 VS M2	81.771 (p=0.011)	-0.001	-0.001
M4. Strict Invariance (λ, θ, and ω restricted)	7203.837 (2925)	2.463	0.889	0.061 (0.059 - 0.063)	M4 VS M3	131.682 (p=0.000)	-0.002	0.000

Note: ΔX^2: $p > 0.05$ indicates acceptable difference, ΔCFI: ≤ 0.01 indicates acceptable change and ΔRMSEA: ≤ 0.015 indicates acceptable change.

The development and validation of the AI literacy questionnaire were guided by prior research, including studies by Ma and Chen (2024) and Suthakorn et al. (2020), which informed the use of invariance testing and subdimension construction. Compared to earlier studies that primarily validated instruments in single settings, this research advances the field by addressing multigroup differences and including diverse dimensions such as ethics, technical literacy, and motivation. These contributions enhance the questionnaire's applicability and relevance, providing a reliable tool for assessing AI literacy across varied educational contexts.

Table 3 is presented below, showing the results of the global test for multigroup analysis of in-person and virtual modalities in the context of artificial intelligence literacy.

Table 3 presents the results of the global test for the multigroup analysis comparing in-person and virtual modalities among university students. The Pearson Chi-square (X^2) yielded a non-significant probabilistic value ($p > 0.05$), indicating no statistical differences between the groups. This result suggests that students in both in-person and virtual modalities exhibit similar patterns of artificial intelligence usage in the learning process, demonstrating the generalizability and applicability of the AI literacy questionnaire across diverse educational contexts. The consistency in responses underscores the instrument's reliability in capturing key dimensions of AI literacy independent of the mode of study.

TABLE 3. GLOBAL TEST OF AI FOR MULTIGROUP ANALYSIS: IN-PERSON AND VIRTUAL MODALITIES

	X^2	DF
No Restrictions	6934.000	459
Restricted	6934.000	459
Difference	0.000	0
P-Value	1.000	

Source: Self-elaboration

The development of the AI literacy questionnaire was informed by key studies in the field, which provided theoretical and methodological guidance. For instance, Brown et al. (2017) emphasized the importance of assessing consistency across diverse learning environments, influencing the

inclusion of multigroup invariance testing in this study. Additionally, Looney et al. (2018) highlighted the need for instruments that encompass both technical competencies and broader dimensions, such as ethical reasoning and motivation, which were integrated into the questionnaire.

CONCLUSIONS

The study successfully achieved its objective of analyzing the influence of artificial intelligence literacy on in-person and virtual study modalities among university students. The results demonstrate that the AI literacy instrument effectively evaluates key dimensions across both modalities, showcasing its validity and reliability. The findings further suggest that AI literacy contributes to a deeper understanding of technological integration in education, reinforcing its applicability in diverse learning environments. By addressing the equivalence of AI literacy across modalities, the study offers valuable insights into how technological competencies can be fostered in both in-person and virtual settings.

Nevertheless, some limitations must be acknowledged. The research design, based on self-reported data, may introduce subjectivity, and the exclusive focus on a specific population restricts the broader applicability of the conclusions. Future studies should consider longitudinal designs to explore the long-term impact of AI literacy on learning outcomes and employ mixed methods to capture the nuanced experiences of students and educators. Expanding research to include diverse educational and cultural contexts will further contribute to the development of comprehensive strategies for enhancing AI literacy and its role in shaping the future of education.

Author Contributions

Conceptualization, J.S.M.-C.; methodology, A.R.S.-G.; data collection, A.A.B.-L.; validation, A.R.S.-G.; formal analysis, J.S.M.-C.; investigation, A.B.B.-M.; resources, A.A.B.-L.; data management, A.B.B.-M.; writing of initial draft, A.R.S.-G.; writing, review and editing, J.S.M.-C.; visualization, A.B.B.-M.; supervision, A.A.B.-L.; project administration, A.R.S.-G.

Institutional Review Board Statement

This study was conducted following the principles set out in the Declaration of Helsinki and in compliance with the guidelines of the Institutional Review Board.

Informed consent statement

Informed consent was obtained from all participants who took part in this study.

Data Availability Statement

For ethical and privacy reasons, the data cannot be shared publicly, but are available upon request from the corresponding author.

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Conflict of Interests

No conflicts of interest are declared.

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