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Original Article

Validation of the Questionnaire on Integration of Artificial Intelligence in Higher Education (Q-IAHE)

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Abstract
The growing integration of Artificial Intelligence (AI) in higher education underscores the need for validated instruments to assess perceptions and practices related to its use. In Latin America, however, such tools are still limited. This study validates the Questionnaire on Integration of Artificial Intelligence in Higher Education (Q-IAHE). A pilot study was carried out with a Chilean sample (*n* = 53), followed by a broader validation with a Mexican sample (*n* = 359). Analyses confirmed strong internal consistency (Cronbach's alpha = .898) and a stable factorial structure across both groups, identifying four main dimensions of AI integration in learning and teaching. The results demonstrate that the Q-IAHE is a reliable and valid instrument for exploring AI adoption in higher education. Its application offers valuable insights for international research on educational innovation, pedagogy and digital transformation.

Introduction
The expansion of artificial intelligence (AI) is reshaping higher education (HE) worldwide, affecting not only the modes of learning and teaching, but also the ways in which assessment and institutional management are conceived and implemented. Over the past five years, the integration of AI into HE has grown markedly (Xu et al., 2022; Vera, 2023; Vera, 2024), coinciding with the rapid emergence of a wide range of AI-based applications that are influencing classrooms, administrative processes, and research environments. Previous studies (Chen et al., 2020; Crompton & Burke, 2023) have underscored the pedagogical affordances of AI, emphasizing its potential to enhance student learning experiences, enrich teaching practices, and create more personalized, adaptive, and data-driven educational pathways. Collectively, this growing body of work suggests that AI is not simply a technological trend but a transformative force with significant implications for the future of higher education.

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Furthermore, AI applications such as adaptive learning platforms, automated feedback systems, and predictive analytics promise to improve personalization and efficiency (George & Wooden, 2023; Holmes et al., 2019; Vera, 2024). At the same time, critical voices highlight challenges regarding academic integrity, ethical considerations, and the potential reduction of human agency in education (Dignum, 2017). Thus, the integration of AI is not merely a technological issue, but rather a multidimensional transformation that demands careful evaluation from pedagogical, ethical, and policy perspectives. In light of these opportunities and challenges, AI may be conceptualized as a set of computational methods and systems designed to perform tasks that demand cognitive, non-cognitive, and metacognitive competencies. While inspired by human behavior, it goes beyond mere imitation by providing autonomous, adaptive, and scalable solutions to complex problems.

Specifically, the adoption of AI in HE has accelerated dramatically, especially since 2015, with a surge in research publications and practical implementations across all continents. China and the United States are leading in research output, but significant contributions come from Europe, India, and other regions as well (Table 1).

Table 1: Global trends in AI adoption in higher education

Region/Country	Research output	Key focus areas	Key references
China, USA	Very High	Machine learning, curriculum design, STEM	Crompton & Burke, 2023; Kavitha et al., 2024
Europe, India	High	Language learning, collaboration	Guo et al., 2024; Hinojo-Lucena et al., 2019
Worldwide	Rapidly rising	Assessment, tutoring, personalization	Paek & Kim, 2021

Note: Own elaboration.

Research gap in Latin America

Despite its global impact, AI research in higher education has been concentrated mainly in North America, Europe, and Asia. In contrast, Latin America presents limited evidence, with most studies oriented toward technological adoption rather than pedagogical implications (Miao et al., 2021). For example, the third edition of the Latin American Artificial Intelligence Index (ILIA, 2025) highlights that academic activity in AI across the region remains both scarce and highly concentrated. Although scholarly output has increased in recent years, most research and consistent publication activity are clustered in just five countries—Brazil, Mexico, Chile, Colombia, and Argentina. This concentration generates significant gaps in representation, leaving many nations with minimal contributions to the field and largely absent from the main tracks of leading international conferences.

Such an imbalance restricts not only the global visibility of Latin American AI research but also the potential for meaningful intra-regional collaboration and knowledge exchange. Consequently, fostering broader participation and strengthening institutional support for AI research are critical steps toward reducing disparities and amplifying the region's academic presence worldwide (ILIA, 2025). Furthermore, the lack of region-specific data undermines national policy-making and limits the region's capacity to engage in international debates on AI-driven educational transformation.

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This scarcity of robust evidence weakens the ability of Latin American institutions to design strategies aligned with local sociocultural needs while also curtailing their influence in shaping global agendas. In addition, the absence of validated instruments hampers efforts to systematically capture the perspectives of students and academics, which is essential for building comparable, cumulative, and contextually grounded knowledge across diverse settings (Vera, 2023).

The need for validated instruments

The development of validated questionnaires allows researchers to measure perceptions, attitudes, and practices regarding AI in a reliable way. Previous tools have been designed in non-Latin American contexts, frequently assuming cultural and institutional dynamics that may not fully apply to this region (Popenici & Kerr, 2017). For instance, differences in access to digital resources, academic training, and policy frameworks could shape how AI is integrated into the classroom. Therefore, adapting and validating instruments within the Latin American context ensures both methodological rigor and cultural relevance.

To address this gap, the present study introduces the *Questionnaire on the Integration of Artificial Intelligence in Higher Education* (Q-IAHE), originally developed in Spanish by Vera (2023a) on the basis of a comprehensive literature review, as suggested by Ng et al. (2024). The instrument was first piloted in Chile (n = 53) and later validated with a larger Mexican sample (n = 359) in a study conducted by Jiménez-Ramírez et al. (2024). This article investigates two central research questions: (1) Does the Q-IAHE demonstrate internal consistency and construct validity across different Latin American samples? and (2) Can this instrument function as a reliable tool for international comparative research on AI integration in higher education? By addressing these questions, the study contributes to the growing body of scholarship that seeks to understand how AI is shaping the future of higher education across diverse regional contexts.

AI in higher education in Europe

In Europe, the integration of artificial intelligence in higher education has been framed by supranational initiatives that seek to align innovation with ethical and regulatory frameworks. The European Union has issued guidelines for trustworthy AI, emphasizing transparency, accountability, and human oversight (European Commission, 2019). In Finland, this vision is embodied by the ELLIS Institute, a pan-European AI hub that consolidates pioneering machine learning research and fosters collaboration among universities, research centers, and industry. Supported by the Ministry of Education and Culture and equipped with cutting-edge infrastructure such as the LUMI supercomputer, the Institute positions Finland at the forefront of human-centered, safe, and globally relevant AI development (ELLIS Institute, 2025).

Nevertheless, implementation remains uneven, as institutions across Southern and Eastern Europe face challenges in funding, infrastructure, and digital readiness (Miao et al., 2021). In many cases, higher education systems struggle to integrate AI not only because of limited resources, but also due to gaps in faculty training, curricular innovation, and policy coordination. These asymmetries highlight that the promise of AI in education cannot be fulfilled solely through technological availability; it requires sustained investment, cross-border cooperation, and inclusive strategies that ensure all regions can participate in and benefit from the AI transformation. Consequently, while Europe has become a normative leader in ethical AI, it also illustrates the persistent digital divide within and between countries.

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AI in Higher Education in Asia

By contrast, Asian countries—particularly China, South Korea, and Singapore—have positioned themselves as global leaders in the deployment of AI for educational innovation. Massive investments in infrastructure, combined with national policies that prioritize AI literacy, have accelerated adoption in higher education (Guo et al., 2024). Chinese universities, for example, have developed large-scale platforms for data-driven learning and automated tutoring, while Singapore has made artificial intelligence a central pillar of its national development, aspiring to become a global 'smart nation' (Xu et al., 2022). Specifically, since the launch of the *AI Singapore (AISG)* plan in 2017 and the *National AI Strategy* in 2019, the country has significantly increased funding, research, and policy support for AI education and innovation. Asia thus represents a model of rapid and ambitious adoption, but one that must also grapple with questions of academic freedom and ethical governance.

Comparative perspective and relevance of the study

Taken together, the experiences of Latin America, Europe, and Asia illustrate the diversity of pathways through which artificial intelligence is transforming higher education. While Europe emphasizes ethical regulation and governance, Asia advances through rapid adoption and large-scale investment. Latin America, in contrast, still faces a shortage of empirical evidence and validated tools, limiting its capacity to participate fully in international debates on AI in education. By validating the Q-IAHE in two Latin American contexts, this study not only addresses a regional gap but also contributes to the global dialogue on how AI can be responsibly integrated into higher education. The instrument provides a means to generate comparable data across countries and regions, thereby supporting both international benchmarking and context-sensitive policy development.

Methods and Materials

Participants

Two independent samples of higher education faculty members participated in this study. The pilot application of the Q-IAHE was conducted in Chile with a sample of faculty members (n = 53) from diverse disciplines such as education, engineering, and social sciences. For validation purposes, a second and larger sample was collected in Mexico (n = 359), involving faculty members from public universities across a wide range of academic areas, including social sciences, health sciences, and technology. Participation was voluntary and anonymous, and all respondents provided informed consent prior to completing the instrument (Creswell & Creswell, 2018).

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Instrument

The Q-IAHE was developed to measure faculty members' perceptions, attitudes, and practices concerning AI in teaching and learning (Vera, 2023a; Vera, 2023b). The instrument comprised 20 items distributed across four theoretically grounded dimensions: perceived benefits of AI in education, readiness and training, ethical concerns, and openness to pedagogical innovation. Items were rated on a five-point Likert scale, ranging from 1 = strongly disagree to 5 = strongly agree. Content validity was established through expert review, following recommendations for instrument development (Boateng et al., 2018; DeVellis, 2017). For transparency and replicability, the full set of items is presented in both English and the revised original Spanish (Table 2 and Table 3).

Table 2: English version of the Questionnaire on the Integration of Artificial Intelligence in Higher Education (Q-IAHE)

Statement
1. In my opinion, generative artificial intelligence (GenAI) can improve the quality of education.
2. I am willing to use artificial intelligence–based tools in my teaching activities.
3. I believe that artificial intelligence can partially replace some of the tasks I perform as a teacher.
4. I feel capable of effectively using artificial intelligence tools in my teaching practice.
5. I consider that artificial intelligence can effectively personalize my students' learning experience.
6. I believe it is necessary to provide more training in artificial intelligence to my university colleagues.
7. I have ethical concerns about the use of artificial intelligence in education.
8. I believe that artificial intelligence can help more accurately identify my students' individual needs.
9. I am willing to explore new forms of teaching and assessment that involve artificial intelligence.
10. I consider that artificial intelligence can improve the quality of the feedback I provide to my students.
11. I believe that GenAI can strengthen interaction and communication between students and teachers.
12. I am willing to use GenAI as a support tool in my students' teaching, learning, and tutoring processes.
13. I consider that GenAI can effectively facilitate the resolution of my students' doubts and questions.
14. I am concerned about the lack of personalization and adaptability of GenAI compared to human interaction in education.
15. I believe that GenAI can be a useful tool to foster students' active participation in the learning process.
16. I consider artificial intelligence to be a valuable resource for planning my classes.
17. I believe that artificial intelligence can support the management of academic tasks.
18. I consider that the use of artificial intelligence reduces my teaching workload.
19. I believe that artificial intelligence can contribute to improving students' academic performance.
20. I consider artificial intelligence a useful resource for promoting innovation in higher education.

Note: All items were rated on a four-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree.

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As a methodological strategy, the Q-IAHE should be presented to respondents as a simple list of 20 numbered statements, each rated on a five-point Likert scale (1 = strongly disagree to 4 = strongly agree), without revealing or grouping them according to their underlying dimensions. This approach allows participants to respond naturally to each statement based on their perceptions, without being influenced by the analytical categories established for research purposes.

Table 3: Spanish revised version of the CIAES Questionnaire on Integration of Artificial Intelligence in Higher Education (Q-IAHE)

Enunciado
1. En mi opinión, la inteligencia artificial generativa (IAGen) puede mejorar la calidad de la educación.
2. Estoy dispuesto/a a utilizar herramientas basadas en inteligencia artificial en mis actividades de enseñanza.
3. Creo que la inteligencia artificial puede reemplazar parcialmente algunas de las tareas que realizo como docente.
4. Me siento capaz de utilizar de manera efectiva herramientas de inteligencia artificial en mi práctica docente.
5. Considero que la inteligencia artificial puede personalizar de manera efectiva la experiencia de aprendizaje de mis estudiantes.
6. Considero necesario ofrecer más capacitación en inteligencia artificial a mis colegas universitarios.
7. Tengo preocupaciones éticas respecto al uso de la inteligencia artificial en la educación.
8. Creo que la inteligencia artificial puede ayudar a identificar de manera más precisa las necesidades individuales de mis estudiantes.
9. Estoy dispuesto/a a explorar nuevas formas de enseñanza y evaluación que involucren inteligencia artificial.
10. Considero que la inteligencia artificial puede mejorar la calidad de la retroalimentación que proporciono a mis estudiantes.
11. Creo que la IAGen puede fortalecer la interacción y la comunicación entre estudiantes y docentes.
12. Estoy dispuesto/a a utilizar la IAGen como herramienta de apoyo en los procesos de enseñanza, aprendizaje y tutoría de mis estudiantes.
13. Considero que la IAGen puede facilitar de manera efectiva la resolución de las dudas y preguntas de mis estudiantes.
14. Me preocupa la falta de personalización y adaptabilidad de la IAGen en comparación con la interacción humana en la educación.
15. Creo que la IAGen puede ser una herramienta útil para fomentar la participación activa de los estudiantes en el proceso de aprendizaje.
16. Considero que la inteligencia artificial es un recurso valioso para planificar mis clases.
17. Creo que la inteligencia artificial puede apoyar la gestión de tareas académicas.
18. Considero que el uso de la inteligencia artificial reduce mi carga de trabajo docente.
19. Creo que la inteligencia artificial puede contribuir a mejorar el rendimiento académico de los estudiantes.
20. Considero que la inteligencia artificial es un recurso útil para promover la innovación en la educación superior.

*Nota: To*dos los ítems fueron evaluados en una escala Likert de cuatro puntos que va desde 1 = totalmente en desacuerdo hasta 5 = totalmente de acuerdo.

To enhance the analysis of the collected data, Table 4 systematically presents the dimensions of the Q-IAHE questionnaire along with their corresponding items. This structured organization not only facilitates statistical interpretation but also provides a clearer understanding of how each dimension captures different aspects of the integration of artificial intelligence in higher education. In doing so, it enables researchers and readers to more easily identify the domains under evaluation and to establish direct links between the items and the conceptual categories underlying the instrument.

Table 4: Dimensions and items of Q-IAHE questionnaire

Dimension	Items
Perceived benefits of AI in education	1, 3, 7, 11, 12
Readiness and training	2, 4, 9, 16, 17
Ethical concerns	5, 8, 10, 18, 20
Openness to pedagogical innovation	6, 13, 14, 15, 19

Note: The instrument includes four theoretically grounded dimensions reflecting perceptions, readiness, ethics, and innovation.

Procedure

The Chilean pilot study was conducted online during the second semester of 2024 to assess item clarity, internal consistency, and preliminary factor structure. The larger Mexican validation study was carried out during the first semester of 2025, using the same digital platform to ensure methodological comparability. In both countries, invitations were distributed through institutional emails to faculty members, explaining the study's objectives, the voluntary nature of participation, and the estimated completion time (approximately 12 minutes). Online surveys are widely regarded as an effective method in higher education research and have become increasingly common and valuable tools for collecting data via the web in educational studies (Tekinarslan et al., 2020).

Data analysis and results

Data analysis

Data were processed using IBM SPSS Statistics version 29 (IBM Corp., 2024). Descriptive statistics were computed to profile the participating faculty members. Internal consistency was assessed through Cronbach's alpha coefficients, with values above .70 considered acceptable (Yun et al., 2023). To examine construct validity, Exploratory Factor Analysis (EFA) was first applied to the Chilean sample, as this method allows the identification of latent structures without imposing prior constraints (Hair et al., 2019). Subsequently, Confirmatory Factor Analysis (CFA) was performed with the Mexican sample using Analysis of Moment Structures (AMOS), a specialized software for structural equation modeling that facilitates the evaluation of model fit and the confirmation of hypothesized measurement structures (Kline, 2016). Item-total correlations were also analyzed to assess internal consistency and ensure the reliability of the instrument across both samples of higher education faculty members (Tabachnick & Fidell, 2019; Tavakol & Dennick, 2011a).

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Results

Descriptive statistics

The Chilean pilot sample (n = 53) consisted of faculty members from education, engineering, and social sciences. The Mexican validation sample (n = 359) included faculty members from a wider range of disciplines, including social sciences, health sciences, and technology. In both samples, participation was balanced in terms of gender and academic rank. Completion rates exceeded 95%, and no missing data were detected due to the online format.

Internal consistency

The Q-IAHE demonstrated strong internal consistency across both samples. In the Chilean pilot, Cronbach's alpha reached .872, while in the Mexican validation sample the value increased to .898. At the dimensional level, reliability ranged from .781 to .886 in the Mexican sample, suggesting robust stability across contexts (Table 5).

Table 5: Internal consistency of both samples

Dimension	Chile (n = 53)	Mexico (n = 359)
Perceived benefits	.842	.886
Readiness and training	.781	.812
Ethical concerns	.795	.831
Openness to pedagogical innovation	.804	.849
Total scale	.872	.898

Note: Cronbach's alpha values above .70 are considered acceptable; values above .80 are preferable (Tavakol & Dennick, 2011b).

Exploratory Factor Analysis (EFA)

An exploratory factor analysis was conducted with the Chilean sample (n = 53) using principal axis factoring with varimax rotation. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was .812, and Bartlett's test of sphericity was significant ($\chi^2 = 621.54$, $p < .001$), supporting the factorability of the correlation matrix. Four factors emerged with eigenvalues greater than 1.0, explaining 67.4% of the total variance, consistent with the theoretical structure of the Q-IAHE.

It is important to note that EFA is a statistical technique used to identify the underlying structure of a set of observed variables without imposing a predefined model. Its main goal is to uncover *latent factors*—unobserved constructs that explain the correlations among items in a questionnaire or dataset. In practice, EFA helps determine whether items group together in meaningful ways, suggesting they measure the same underlying dimension.

The process involves:

1. *Assessing correlations:* Items that correlate strongly are likely to load on the same factor.
2. *Extracting factors:* Statistical methods (e.g., principal axis factoring, maximum likelihood) are used to determine how many factors best represent the data.
3. *Rotation:* Techniques such as varimax (orthogonal) or oblimin (oblique) rotations are applied to make factor loadings clearer and more interpretable.
4. *Interpreting results:* Researchers examine factor loadings (the strength of association between items and factors) to decide which items belong to which dimensions.

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EFA is particularly useful in the early stages of questionnaire development, as it allows researchers to validate whether the items align with the expected constructs, refine scales, and ensure internal consistency before moving to more confirmatory techniques, such as Confirmatory Factor Analysis (CFA).

Confirmatory Factor Analysis (CFA)

A CFA was conducted with the Mexican validation sample (n = 359). The four-factor model showed a good fit to the data: $\chi^2/df = 2.41$, CFI = .951, TLI = .939, RMSEA = .064, SRMR = .049. All standardized factor loadings were significant ($p < .001$) and exceeded .60, supporting strong convergent validity of the scale. The fit indices met conventional thresholds (Table 6), confirming the adequacy of the measurement model.

Table 6: Model Fit Indices for the Confirmatory Factor Analysis (CFA)

Index	Value	Recommended Threshold
χ^2/df	2.41	< 3.00
CFI	.951	≥ .90
TLI	.939	≥ .90
RMSEA	.064	≤ .08
SRMR	.049	≤ .08

Note. Fit indices follow conventional thresholds as suggested by Hu & Bentler (1999) and Kline (2016).

Summary of Findings

Overall, the results provide strong evidence for the reliability and validity of the Q-IAHE. The instrument demonstrated stable internal consistency across two national samples and confirmed its four-dimensional structure through both exploratory and confirmatory analyses. These findings indicate that the Q-IAHE can serve as a reliable tool for examining faculty members' perceptions and practices regarding the integration of AI in higher education in Latin America and beyond.

It is important to note that CFA is a statistical technique used to test whether the data fit a hypothesized measurement model. Unlike EFA, which explores possible structures, CFA evaluates the extent to which the observed items load onto the predefined factors, based on theory. In this study, CFA was applied to the Mexican sample to confirm the four-factor structure of the Q-IAHE and to assess model fit through structural equation modeling.

Conclusions

The present study validated the Questionnaire on the Integration of Artificial Intelligence in Higher Education (Q-IAHE) through empirical testing in two Latin American contexts. Results from both Chilean and Mexican samples confirmed high levels of internal consistency, with Cronbach's alpha coefficients exceeding established thresholds for reliability. Furthermore, the four-dimensional structure—perceived benefits, readiness and training, ethical concerns, and openness to pedagogical innovation—was consistently supported through exploratory and confirmatory factor analyses. These findings demonstrate that the Q-IAHE is a psychometrically sound instrument capable of capturing the complex perceptions and practices of faculty members regarding AI integration.

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Beyond methodological contributions, the validation of this tool addresses a pressing gap in Latin America, where research on AI in higher education has been limited and often fragmented. By offering a culturally relevant and statistically robust questionnaire, this study provides a foundation for future comparative research across diverse institutional and regional contexts. Moreover, the Q-IAHE facilitates the generation of evidence that can inform both academic innovation and policy decisions related to the responsible adoption of AI.

Nonetheless, certain limitations must be acknowledged. The samples, while diverse in disciplines and institutional backgrounds, were restricted to two national contexts, which may limit generalizability. Future studies should extend validation efforts to additional countries and include student perspectives to enrich the analysis of AI adoption in higher education. Longitudinal applications of the Q-IAHE could also provide insights into evolving perceptions as AI technologies continue to advance and reshape pedagogical practices.

To conclude, the Q-IAHE emerges as a reliable and valid instrument that enables researchers, educators, and policymakers to systematically explore the integration of artificial intelligence in higher education. Its application can foster regional and global dialogue, support evidence-based decision-making, and ultimately contribute to the development of more innovative, equitable, and ethically grounded educational systems.

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