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Factor structure of artificial intelligence use in university teaching pedagogy

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ABSTRACT

The use of artificial intelligence (AI) in higher education pedagogy has gained increasing relevance; however, there remains a shortage of psychometrically validated instruments capable of assessing, in a multidimensional and context-specific manner, faculty adoption of these technologies. The aim of this study was to identify the factorial structure and evaluate the psychometric properties of an instrument designed to measure AI use among university faculty. The instrument was developed based on the unified theory of acceptance and use of technology and was administered to a convenience sample of 330 university instructors. Exploratory factor analysis revealed a robust seven-factor structure explaining 66.90% of the total variance, allowing the refinement and optimization of the instrument from 50 to 30 items. The final scale demonstrated excellent overall internal consistency (Cronbach's alpha = 0.913). It is concluded that the developed instrument is a valid and reliable tool for higher education institutions to assess and diagnose faculty levels of AI adoption, thereby facilitating the design of context-specific institutional policies and effective professional development programs in AI-enhanced pedagogy.

Keywords: artificial intelligence, university pedagogy, exploratory factor analysis, reliability

INTRODUCTION

In recent years, artificial intelligence (AI) has emerged as one of the most influential technological innovations in higher education. AI constitutes an effective tool for enhancing faculty members' digital competencies, as it promotes pedagogical innovation and supports the personalization of learning processes.

Its adoption represents a significant opportunity to mitigate digital divides within higher education (Ortiz Garcia, 2025). Numerous studies indicate that the presence of AI tools has increased interest in their use in universities, as they enable the optimization of academic activities and foster more personalized learning experiences (Blesa Pérez et al., 2024; Zawacki-Richter et al., 2019). However, this gap remains a significant challenge in resource-constrained regions, where the implementation of digital technologies continues to be limited (Pedro et al., 2022). This finding is consistent with global analyses of the integration of interactive systems in higher education, which highlight substantial disparities in technological infrastructure and digital literacy across vulnerable educational contexts (Mokoena & Seeletse, 2025).

The integration of AI into teaching methodology redefines the role of the instructor and expands the possibilities for personalization, accessibility, and efficiency in learning through virtual tutors, adaptive systems, and data analytics aimed at addressing the specific needs of each student (Miguez, 2025), as well as supporting instructors' decision-making processes (Silgado-Tuñón & López-Flores, 2025). Consequently, this incorporation into university methodology entails a transformation in teaching practice and in the conceptualization of teaching and learning processes.

From the perspective of university faculty, the success of educational innovations is determined by pedagogical beliefs and digital competencies, which require continuous training and institutional support (Sánchez & Jiménez, 2025). Furthermore, the importance of assertive communication and digital interaction is emphasized (Fuentes Pizarro, 2022). Various studies indicate that university faculty are at different levels of AI usage, which makes its adoption complex, as pedagogical, technological, and institutional dimensions are interrelated (Mah & Groß, 2024; Xianjia & Mohamad Nasri, 2025). Specifically, technology-related factors, such as software anxiety and low digital self-efficacy, have been shown to negatively influence the intention to adopt AI. In contrast, factors such as perceived pedagogical usefulness (pedagogical dimension), together with continuous technical support and institutional incentives (institutional dimension), positively and directly predict successful AI integration into teaching practice. Therefore, the adoption of AI in higher education pedagogy is closely associated with faculty training, technological competence, and their willingness to integrate AI into their teaching practices.

The literature indicates that the institutional context—encompassing technological infrastructure, training and competencies, available resources, regulatory frameworks, among other factors—plays a crucial role in the adoption of AI in higher education. These factors can either facilitate or constrain its integration into teaching pedagogy in practice (Perez, 2025). However, the exponential growth in the use of AI may undermine ethical principles such as data privacy, digital equity, algorithmic transparency, and the risk of the dehumanization of learning (Xia et al., 2024). In this regard, Freire (2020) cautions that education is an act of dialogue and transformation; therefore, AI should not replace human relationships or critical thinking but rather serve as a tool that complements pedagogical work.

Although the literature on AI in higher education has grown rapidly, most studies have focused on technical applications, institutional policy frameworks, or reviews of AI and generative AI use in teaching and assessment (Crompton & Burke, 2023). This strong emphasis on conceptual and descriptive approaches has left a significant gap in the rigorous psychometric assessment of university faculty's actual AI adoption and use in classroom settings (Kaşarcı et al., 2025). Other works examine the adoption and acceptance of these technologies by university faculty, employing models such as the unified theory of acceptance and use of technology (UTAUT) or the theory of planned behavior (Venkatesh et al., 2003), or focus on teachers' AI literacy and knowledge (Ng et al., 2024). However, there are still few psychometrically validated instruments that specifically and multidimensionally measure the pedagogical use of AI by university faculty in a Latin American context (Scherer et al., 2019), thus constituting an empirical gap that this study seeks to address.

In this context, the present study aims to contribute to the literature by identifying the underlying dimensions that explain the use of AI in university teaching pedagogy. To this end, exploratory factor analysis (EFA) is employed, a statistical technique that allows for the identification of latent structures within sets of variables and the evaluation of the internal consistency of measurement instruments. The objective of the study is to analyze the factors that determine the use of AI in university teaching pedagogy, with the purpose of developing a valid and reliable psychometric instrument to examine this phenomenon in the context of higher education.

THEORETICAL FRAMEWORK

Artificial Intelligence in Education

AI refers to computer systems designed to perform tasks such as teaching and learning, reasoning, and decision-making in place of human intelligence. In the educational field, AI emerges as a powerful instructional tool, capable of personalizing educational activities and adapting to the individual needs of each student (Jeet & Pant, 2023). In the university context, AI has been progressively incorporated into teaching-learning processes, moving away from traditional dynamics and adopting new forms of interaction among educational agents supported by technology (Kasneci et al., 2023).

The development of emerging AI tools has accelerated the transformation process in universities, as they enable the creation of intelligent learning ecosystems in which the student becomes the central focus of the educational process. These environments integrate learning analytics, gamification, and immediate feedback to enhance the educational experience (González et al., 2024). In this regard, the literature indicates that AI is becoming an important component for educational innovation and the digital transformation of universities (Selwyn, 2019). In this way, meaningful learning can be fostered, supported by AI, which can contribute to making education more effective and relevant within university life.

Pedagogical Use of Artificial Intelligence in University Teaching

In the educational field, AI initially took the form of computers and information systems and later evolved into web-based and online educational platforms (Chen et al., 2020). Integrated systems have also enabled the use of humanoid robots as instructors, performing functions similar to those of teachers. The pedagogical use of AI is associated with lesson planning, the development of instructional materials, the assessment of learning, and academic feedback. Recent research shows that many university faculty members use AI-based tools as support to optimize academic tasks and improve efficiency in managing their pedagogical activities (Crompton & Burke, 2023).

However, faculty do not adopt this technology uniformly; therefore, levels of use, as well as trust and willingness to engage with these tools, vary. This variability may be influenced by individual factors, including digital competencies, prior experience with educational technologies, and the perceived pedagogical usefulness of AI (Akgun & Greenhow, 2022). Similarly, several authors highlight that AI can contribute to more personalized learning by adapting educational content to students' needs. In this way, intelligent systems enhance the effectiveness of teaching and learning processes by providing immediate feedback and facilitating the monitoring of students' academic progress (Luckin et al., 2016; Zhai et al., 2021). Consequently, feedback becomes a key element for fostering sustainable student learning.

Factors Influencing the Adoption of Artificial Intelligence

The adoption of emerging technologies in education is often analyzed through theoretical models that explain the factors influencing the acceptance and use of technology. One of the most widely used approaches is the UTAUT proposed by Venkatesh et al. (2003), which posits that the intention to use a technology is influenced by variables such as performance expectancy, perceived effort, and facilitating conditions within the organizational environment.

In the university context, variables that may influence adoption include the availability of technological infrastructure, teacher training, and institutional support for pedagogical innovation (Ouyang & Jiao, 2021). Recent studies highlight that universities with policies promoting continuous faculty training in the use of AI demonstrate higher levels of technological integration in teaching-learning processes. Therefore, the integration of AI in university teaching should be understood as the convergence of pedagogical, technological, and institutional factors, constituting a multidimensional phenomenon.

Ethics of Artificial Intelligence Use

The use of AI raises several challenges within the context of educational innovation, including issues related to the protection of personal data, the objectivity of algorithmic functioning, inequalities in access to technology, and the potential loss of students' critical thinking. As noted by Kohnke and Ulla (2024), automation may lead to an overreliance on AI by both instructors and students. Instructors, in particular, may depend on AI tools for the creation of materials and assessment, thereby reducing direct personal interaction with students.

In this context, UNESCO (2023) emphasized the need to promote the equitable use of AI in education, ensuring principles such as equity, inclusion, and the protection of privacy. Likewise, some studies warn that excessive dependence on technological tools may affect the relational dimension of the educational process if the mediating role of the teacher is not preserved (Selwyn, 2024). In this sense, the presence of the instructor remains essential to guide dynamic teaching-learning processes, preventing the dehumanization of students in their professional development.

Exploratory Factor Analysis in Instrumental Studies

EFA is a statistical technique widely used to identify latent structures within sets of observed variables. In instrument development and validation studies, EFA allows researchers to examine the dimensionality of a questionnaire and provide preliminary evidence of construct validity, facilitating the theoretical interpretation of the identified factors (Hair et al., 2019).

In the context of educational technologies, the use of this technique is of vital importance for identifying the components or dimensions that structure the construct of teachers' perceptions of AI, thereby enabling a systematic understanding of the factors involved in university pedagogical practice.

Motivational Factors and Expectations in Artificial Intelligence Adoption

Complementing the perspectives on technological infrastructure, it is essential to examine the independent motivational factors—such as personal values, expectations, and individual judgments—that influence university faculty. Recent research indicates that the actual adoption of AI is not determined solely by institutional mandates but also by the intrinsic value that educators perceive in these technologies and by their expectations regarding their pedagogical effectiveness. These factors act as catalysts that reduce resistance to change and foster more innovative teaching practices (Yurt & Kaşarcı, 2025).

METHODS

Research Approach and Design

To conduct the study, a quantitative approach was employed, with a non-experimental, cross-sectional design, as the data were collected at a single point in time in 2025. This type of design allows for the examination of variables in their natural context without experimental manipulation and is common in educational research of a psychometric nature (Hernández-Sampieri & Mendoza, 2022). In this regard, the study falls within instrumental research, aimed at analyzing the psychometric properties of measurement instruments in the social and educational sciences (American Educational Research Association et al., 2014).

Population and Sample

The study population consisted of 14,200 faculty members from licensed public universities in Peru. The sample comprised 330 university faculty members selected through non-probability convenience sampling based on accessibility and voluntary participation, with informed consent obtained from all participants. The sample size was considered adequate for the application of EFA, as it exceeds the methodological criterion recommending between five and ten participants per item in psychometric studies (Tabachnick & Fidell, 2019).

Instrument Development

The instrument used was a structured questionnaire with a Likert-type scale, initially composed of 50 items, designed to assess different dimensions related to the use of AI in university teaching methodology. The construction of the items was based on a review of recent literature on the integration of AI in higher education, considering aspects related to teachers' knowledge and competencies in AI, pedagogical impact, educational innovation, institutional factors, and ethical considerations. These dimensions were defined based on previous studies on the adoption of emerging technologies in education and conceptual frameworks related to the educational use of AI.

Table 1. Theoretical specifications and distribution of the initial item pool

Initial dimension	Theoretical and empirical basis	N	Example of an original item
Knowledge and skills	Digital literacy/Ng et al. (2024)	10	I have a basic understanding of AI.
Teaching practices and AI application	Performance expectancy (UTAUT)	10	I design learning activities using AI tools.
Pedagogical impact	Personalization/Zhai et al. (2021)	10	AI enhances the learning experience.
Institutional support	Facilitating conditions (UTAUT)	10	My institution provides infrastructure.
Ethics and concerns	Ethical principles/Xia et al. (2024)	10	AI requires a regulated ethical approach.

Note. N: Number of items

Table 2. KMO and Bartlett's test of sphericity

Measure		Value
KMO of sampling adequacy		0.820
Bartlett's test of sphericity	Approximate Chi-square	5,886.871
	df	435
	Significance	0.000

Likert-type scales are widely used in educational research to measure perceptions and attitudes due to their ease of application and adequate psychometric sensitivity (DeVellis & Thorpe, 2022; Likert, 1932). The measurement scale consisted of five response options, ranging from never = 1 to always = 5. The instrument was validated by experts in educational technology and teaching methodology. **Table 1** shows the theoretical specifications and distribution of the initial item pool.

Data Analysis

To analyze the structure of the instrument, an EFA was conducted using the principal components extraction method and Varimax rotation with Kaiser normalization, a procedure that allows for the identification of latent structures within sets of observed variables and facilitates the interpretation of the resulting factors (Hair et al., 2019).

The use of EFA is justified because the instrument was in an initial stage of development; therefore, the aim was to empirically identify the underlying dimensions of the construct prior to conducting confirmatory analyses in subsequent studies. In psychometric research, EFA is recommended when the objective is to explore the dimensionality of an instrument and to generate preliminary evidence of construct validity (Hair et al., 2019).

Prior to the analysis, data adequacy was assessed using the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity, indicators that determine whether sufficient correlations exist among the items to justify the use of factor analysis (Bartlett, 1954; Kaiser, 1974).

Instrument Reliability

The internal consistency of the resulting instrument was evaluated using Cronbach's alpha coefficient, a widely used indicator for estimating the reliability of measurement scales in educational and psychological research, as it allows for assessing the degree of homogeneity among the items that make up a scale (Cronbach, 1951).

RESULTS

Data Adequacy for Factor Analysis

Prior to conducting the EFA, data adequacy was assessed using the KMO measure of sampling adequacy and Bartlett's test of sphericity (**Table 2**).

The KMO index obtained a value of 0.820, indicating a meritorious level of sampling adequacy, exceeding the minimum recommended value of 0.70 for the application of factor analysis (Kaiser, 1974).

Likewise, Bartlett's test of sphericity was statistically significant (χ^2 [435] = 5,886.871, $p < 0.001$), allowing the rejection of the null hypothesis of independence among variables and confirming that the correlation matrix is suitable for conducting factor analysis (Bartlett, 1954). These results indicate that the data exhibit an adequate level of intercorrelation among the items, thereby supporting the application of EFA.

Table 3. Total variance explained

Component	Initial Eigenvalues			Extraction sums of squared loadings			Rotation sums of squared loadings		
	Total	PV	CP	Total	PV	CP	Total	PV	CP
1	9.380	31.268	31.268	9.380	31.268	31.268	3.407	11.356	11.356
2	2.706	9.019	40.287	2.706	9.019	40.287	3.370	11.232	22.589
3	2.099	6.997	47.284	2.099	6.997	47.284	3.096	10.320	32.909
4	1.729	5.764	53.047	1.729	5.764	53.047	2.879	9.598	42.507
5	1.643	5.478	58.525	1.643	5.478	58.525	2.874	9.579	52.086
6	1.318	4.392	62.917	1.318	4.392	62.917	2.846	9.486	61.572
7	1.194	3.980	66.897	1.194	3.980	66.897	1.597	5.325	66.897
8	0.906	3.020	69.917						
9	0.863	2.876	72.793						
10	0.779	2.597	75.389						
11	0.730	2.433	77.823						
12	0.691	2.303	80.125						
13	0.651	2.169	82.294						
14	0.565	1.884	84.178						
15	0.535	1.783	85.961						
16	0.471	1.570	87.531						
17	0.454	1.513	89.044						
18	0.452	1.506	90.550						
19	0.381	1.269	91.819						
20	0.345	1.151	92.970						
21	0.298	0.994	93.964						
22	0.291	0.969	94.934						
23	0.269	0.895	95.829						
24	0.238	0.793	96.622						
25	0.227	0.756	97.378						
26	0.212	0.705	98.083						
27	0.181	0.604	98.687						
28	0.151	0.503	99.190						
29	0.142	0.473	99.663						
30	0.101	0.337	100						

Note. PV: Percentage of variance (%); CP: Cumulative percentage (%); Extraction method: Principal component analysis

Factor Extraction

To determine the factorial structure of the instrument, an EFA was conducted using the principal components extraction method with Varimax rotation. This methodological approach is justified according to the criteria proposed by Hair et al. (2019) and Tabachnick and Fidell (2019), as it is considered appropriate during the initial stages of psychometric instrument development when the primary objective is data reduction by maximizing the total variance explained through a parsimonious set of orthogonal factors. Before conducting the analysis, the suitability of the data for factor analysis was assessed using the KMO measure of sampling adequacy and Bartlett's test of sphericity.

The analysis identified seven factors with eigenvalues greater than 1, which together explained 66.897% of the total variance of the instrument (**Table 3**). This process enabled the refinement of the initial pool of 50 items into a final 30-item scale. Importantly, this reduction did not compromise the content validity of the instrument, as item elimination was conducted according to rigorous statistical criteria based on the rotated component matrix, excluding items with factor loadings below 0.40 or substantial cross-loadings. This procedure eliminated underlying conceptual redundancies, resulting in a more parsimonious and practically applicable instrument while preserving the theoretical representativeness of the analyzed dimensions. Regarding the initial contribution to the explained variance, the first factor accounted for 31.268% of the total variance, followed by the second factor (9.019%), the third factor (6.997%), and the fourth factor (5.764%), whereas the remaining factors contributed smaller but meaningful proportions to the explanation of the underlying construct.

According to methodological criteria in social research, a level of explained variance above 60% is considered adequate for exploratory studies of complex constructs (Hair et al., 2019). The obtained factor structure demonstrates that the use of AI in university teaching practice is a multidimensional phenomenon, composed of various dimensions related to knowledge, pedagogical practices, teaching impact, institutional factors, and ethical considerations.

Item Factor Loadings

Subsequently, the rotated component matrix was examined using Varimax rotation with Kaiser normalization, which converged in seven iterations. A cutoff criterion of factor loadings equal to or greater than 0.40 was adopted for interpretation, a value recommended for exploratory studies in the social sciences (Hair et al., 2019). The EFA identified seven dimensions with eigenvalues greater than 1, which together explain 66.897% of the total variance of the instrument (**Table 4**).

Table 4. Rotated component matrix[a]

Item	Component						
	1	2	3	4	5	6	7
7-**(Knowledge and skills)** I am familiar with the basic principles of how AI works (algorithms, machine learning, etc.).	0.797						
6-**(Knowledge and skills)** I have received formal training in the application of AI in education.	0.783						
5-**(Knowledge and skills)** I am familiar with AI tools applied to teaching.	0.712						
10-**(Knowledge and skills)** I use AI-based tools to create educational content (e.g., chatbots, graphic generation).	0.645						
11-**(Knowledge and skills)** I am aware of the current limitations of AI in the educational context.	0.556						
35-**(Current practices in AI use)** I facilitate collaborative learning through AI-powered platforms.	0.416						
42-**(Impact on the teaching role)** The use of AI has changed the way I plan my classes and activities.		0.755					
41-**(Impact on the teaching role)** AI helps me provide faster and more detailed feedback to students.		0.740					
40-**(Impact on the teaching role)** I feel supported by AI in tasks that require a high workload, such as grading exams.		0.705					
33-**(Current practices in AI use)** I design assessment activities supported by AI (e.g., adaptive tests).		0.686					
34-**(Current practices in AI use)** I use AI tools to search for academic literature and optimize my research processes.		0.681					
13-**(Perceptions of the pedagogical impact of AI)** AI enhances students' personalized learning experience.			0.746				
14-**(Perceptions of the pedagogical impact of AI)** AI enables more effective identification of students' learning needs.			0.726				
15-**(Perceptions of the pedagogical impact of AI)** AI tools promote autonomous and self-regulated learning.			0.719				
39-**(Impact on the teaching role)** The integration of AI facilitates the personalization of students' learning.			0.588				
48-**(Ethics and concerns about AI)** The implementation of AI requires an ethical approach to avoid replacing essential human interactions in the classroom.				0.838			
49-**(Educational innovation and technological trends)** AI is opening new opportunities for innovation in teaching methods within my discipline.				0.748			
50-**(Educational innovation and technological trends)** I believe that the integration of AI is a trend that will profoundly transform higher education over the next 10 years.				0.717			
46-**(Ethics and concerns about AI)** I believe that the use of AI should be regulated by clear ethical policies in higher education.				0.635			
21-**(Factors influencing AI adoption)** My institution provides sufficient technological infrastructure to implement AI.					0.822		
28-**(Factors influencing AI adoption)** The educational policies in my institution promote the responsible use of AI.					0.774		
25-**(Factors influencing AI adoption)** There is institutional support to experiment with new educational technologies.					0.721		
31-**(Current practices in AI use)** I integrate chatbots or virtual assistants into academic activities.					0.549		

Table 4 (Continued).

Item	Component						
	1	2	3	4	5	6	7
23-**(Factors influencing AI adoption)** The lack of specific training in AI hinders its adoption in teaching.						0.749	
45-**(Ethics and concerns about AI)** I am concerned about student data privacy issues when using AI-based tools.						0.714	
44-**(Ethics and concerns about AI)** AI could increase the digital divide among students from different socioeconomic backgrounds.						0.622	
36-**(Current practices in AI use)** I promote students' critical reflection on the impact of AI on society.						0.582	
54-**(Educational innovation and technological trends)** Advances in AI motivate me to continuously update my pedagogical methods.						0.507	
26-**(Factors influencing AI adoption)** I believe that the use of AI could replace some of the pedagogical tasks I perform.							0.779
16-**(Perceptions of the pedagogical impact of AI)** The use of AI could dehumanize the interaction between teachers and students.							0.634

Note. Extraction method: Principal component analysis; Rotation method: Varimax with Kaiser normalization; [a]Rotation converged in 7 iterations; & Values below ±0.40 are not displayed

Table 5. Reliability statistics

Cronbach's alpha	Number of items
0.913	30

This level of explained variance is considered adequate in social and educational sciences research (Hair et al., 2019). The first dimension was associated with knowledge and skills in AI, the second with the application of AI in teaching practice, while the third was related to perceptions of the pedagogical impact of AI. The fourth dimension integrated aspects related to educational innovation and ethical considerations, while the fifth dimension was associated with institutional support and infrastructure for AI adoption. The sixth dimension reflected risks and concerns related to the use of AI, whereas the seventh grouped perceptions associated with the potential dehumanization and replacement of the teaching role.

Instrument Reliability

The final scale demonstrated excellent internal consistency, with an overall Cronbach's alpha coefficient of 0.913 (**Table 5**). In addition, the internal consistency of each of the seven extracted dimensions was assessed separately, yielding Cronbach's alpha coefficients ranging from 0.78 to 0.88. These values indicate that each factor exhibited strong internal homogeneity and reliability, consistently meeting the widely accepted methodological thresholds for internal consistency (Cronbach, 1951).

According to reliability interpretation criteria, alpha values above 0.90 reflect high internal consistency among the items, suggesting that they measure homogeneously the constructs associated with the use of AI in university teaching pedagogy.

DISCUSSION

The results of the EFA show that the use of AI in university teaching pedagogy is structured across several interrelated dimensions, confirming the multidimensional nature of this phenomenon. This finding is consistent with recent studies indicating that the integration of AI in higher education depends on the interplay of pedagogical, technological, institutional, and ethical factors that influence its implementation in educational settings (Kasneci et al., 2023; UNESCO, 2023). In this regard, the factor structure identified in the present study provides empirical evidence that contributes to a more comprehensive understanding of how faculty perceive the use of AI in their pedagogical practice.

The results indicate that teachers' knowledge and skills in AI are key elements in the adoption of this technology in professional practice. This finding is consistent with studies by Crompton and Burke (2023) and Akgun and Greenhow (2022), which highlight the importance of digital literacy and faculty training in emerging technologies as factors that can facilitate the adoption of AI in educational processes. Therefore, to strengthen the pedagogical use of these digital tools in the university context, continuous faculty training is essential.

Similarly, the study shows that teachers recognize that AI can influence innovation in their professional role, particularly in planning, assessment, and learning feedback. Consistent with this finding, Ouyang and Jiao (2021) and Kasneci et al. (2023) point out that these technologies enable the automation of certain operational tasks, allowing teachers to focus more on pedagogical mediation and decision-making processes. However, AI should not replace human interaction or critical thinking but rather serve as a tool that complements pedagogical work (Freire, 2020).

Faculty members are aware of the pedagogical potential of AI to support personalized learning and foster greater student autonomy. This finding is consistent with studies by Zhai et al. (2021) and Luckin et al. (2016), which highlight that AI-based systems can adapt educational content and strategies to students' individual needs, thereby enhancing the effectiveness of the teaching-learning process. In this way, faculty demonstrate openness to the use of emerging technologies in higher education to improve the quality of teaching.

Similarly, the results highlight the importance of institutional factors in the adoption of AI in higher education. The availability of technological infrastructure, organizational support, and the existence of institutional policies oriented toward educational innovation significantly influence the possibilities for integrating these technologies into teaching practice. In this regard, previous research has indicated that universities play a fundamental role in promoting the pedagogical use of digital technologies through training strategies and institutional guidelines that guide their implementation (Ouyang & Jiao, 2021; UNESCO, 2023).

The study also reveals ethical concerns regarding the use of AI in educational settings, particularly those related to the privacy of personal data, equity and the digital divide, and the potential impact on the human dimension within educational processes. Recent literature has extensively highlighted these concerns, emphasizing the need to establish ethical and regulatory frameworks to guide the responsible use of AI in education (Holmes et al., 2019; Selwyn, 2024). These findings suggest that the integration of AI in education should be accompanied by critical reflection on its pedagogical and ethical implications, as it depends not only on digital competencies and appropriate institutional conditions.

On the other hand, a dimension associated with the perception of dehumanization and the possible replacement of the teaching role linked to the use of AI-based tools was identified. This finding raises concerns due to the excessive use of automated technologies. In this regard, recent literature suggests that it may weaken the relational dimension of the teaching-learning process if the guiding role of the teacher is not maintained in this context. Some authors point out that AI is capable of automating academic activities; however, education still requires the participation of the teacher as a mediating agent to promote interaction in the process, critical thinking, and the guidance of learning (Luckin et al., 2016; Selwyn, 2019). Therefore, the integration of these technologies should be understood as a complementary process that supports teaching practice without replacing the human dimension of the educational process.

Finally, several methodological limitations should be acknowledged. First, participants were selected using a non-probability convenience sampling method, which limits the generalizability of the findings to the broader population of university faculty. Second, given the exploratory nature of the initial instrument development, advanced measures of convergent and discriminant validity, such as average variance extracted and composite reliability, were not calculated, as these indices require confirmation through confirmatory factor analysis (CFA). Future research should validate the proposed factorial structure using CFA with larger probability-based samples to strengthen the instrument's external validity and provide more robust evidence of its psychometric properties.

CONCLUSIONS

The factor structure identified seven main dimensions: knowledge and skills in AI, application of AI in teaching practice, perceptions of pedagogical impact, educational innovation and technological trends, institutional factors for AI adoption, ethical concerns associated with its use, and perceptions of risks and the dehumanization of the educational process. These dimensions can be considered for measuring the use of AI in university teaching methodology.

Faculty adopt AI in their teaching methodology influenced by their competencies and knowledge, as well as by institutional conditions that facilitate its implementation, including technological infrastructure, faculty training, and regulatory frameworks that encourage continuous professional development.

Ethical concerns and critical perceptions regarding the use of AI are evident, particularly in aspects related to data privacy, equity in access to technology, and the potential impact on the human dimension of the educational process, which may lead to the dehumanization of learning and a diminished development of students' critical thinking.

The developed instrument demonstrated an adequate factor structure and high internal consistency (α = 0.913), indicating its reliability for assessing the dimensions of the pedagogical use of AI in university teaching. Consequently, this scale constitutes a valid tool for future research aimed at analyzing the integration of AI in teaching and learning processes in higher education.

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