International Journal of Learning, Teaching and Educational Research
Vol. 25, No. 5, pp. 779-799, May 2026
https://doi.org/10.26803/ijlter.25.5.34
Received Feb 23, 2026; Revised Apr 21, 2026; Accepted Apr 27, 2026

Psychometric Evidence and Associative Analysis of Dimensions of Familiarity, Frequency of Use and Satisfaction with AI Tools in University Research Training

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Abstract. The study examined the psychometric properties of the instrument and the associations between the dimensions of familiarity, frequency of use, and perceived satisfaction regarding the use of artificial intelligence (AI) tools in university research training. A quantitative approach was adopted, with a non-experimental, cross-sectional, and descriptive-correlational design, involving a final sample of 105 students. Data were collected using a 30-item questionnaire, and the analysis included exploratory factor analysis to assess construct validity, internal consistency estimation (Cronbach's α and McDonald's ω), and bivariate association analysis through Spearman correlations and chi-square tests. The results showed a predominance of low levels across the three dimensions, indicating a limited integration of these technological tools in university research training processes. The factor analysis confirmed a three-dimensional structure consistent with the theoretical model, explaining 72.8% of the variance, with high reliability ($\alpha = .974$; $\omega = .974$). Likewise, positive and statistically significant associations were found between the dimensions, with a particularly strong relationship between frequency of use and satisfaction ($\rho = .925$; $p < .001$). Overall, the findings suggest that the adoption of AI is still at an early stage, which highlights the need to strengthen AI literacy strategies that integrate technical, ethical, and methodological dimensions in higher education contexts.

Keywords: AI; AI literacy; higher education; psychometric validation; research training

Citation:
Casimiro Urcos, W. H., Casimiro Urcos, C. N., Casimiro Urcos, J. F., & Quinteros Osorio, R. O. (2026). Psychometric Evidence and Associative Analysis of Dimensions of Familiarity, Frequency of Use and Satisfaction with AI Tools in University Research Training. *International Journal of Learning, Teaching and Educational Research*, 25(5), 779–799. https://doi.org/10.26803/ijlter.25.5.34

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1. Introduction

Artificial intelligence (AI) has been consolidating itself as a structural element in the transformation of the main processes of higher education: teaching, learning and academic production. Specifically, the emergence of generative AI and large-scale language models has given rise to widespread international interest in their educational potential and the consequent ethical risks, because of their role in reconfiguring the dialogue with information and in the production of academic content (Kasneci et al., 2023).

In this regard, several studies confirm the potential of these tools to streamline academic tasks, such creating drafts, ordering ideas and synthesizing bibliographic sources, with results favoring greater efficiency in certain cognitive processes (Lo, 2023; Tlili et al., 2023). However, recent studies also point to possible negative impacts associated with dependence on technology and depreciations in students' ability to engage in deep critical thinking, without denying the contribution of AI as a cognitive support (Cotton et al., 2024). However, despite the increase in publications related to the topic of AI in the context of higher education, a large number of these studies have a fundamentally theoretical or exploratory nature, with little systematization of the empirical evidence associated with the incorporation of AI in standard processes of research training (Bond et al., 2024; Zawacki-Richter et al., 2019).

Consequently, we lack knowledge of the configuration of specific factors such as familiarity, frequency of use and level of student satisfaction with these tools. This insufficient precision—both conceptual and empirical—not only limits our actual understanding of the phenomenon but also slows down the development of more robust explanatory models. A gap has been identified in the specialized literature on the subject; this gap demonstrates the need for structured and psychometrically grounded studies, especially in educational settings where the adoption of these tools is still perceived to be in the consolidation phase.

Given this context, it is essential to delve into the repercussions of using AI for the development of research skills in students. Although AI can act as cognitive support for organizing knowledge and improving the productivity of academic tasks (Celik et al., 2022), it also poses risks linked to the possible delegation of fundamental analytical processes in university education. In the specific field of research training, the aim is to foster learning processes that enhance students' critical evaluation of sources, the construction of well-founded theoretical frameworks, and the development of their own arguments. Contrary to these objectives, students' increasing reliance on AI-generated content could limit active cognitive participation, thus reducing the development of critical thinking and autonomy in academic reflection.

Taking into account this perspective on the balanced and critical use of AI in research training, it is essential to ensure that AI is used as instrumental support, and that the cognitive construction that students must develop on their own is not eroded, especially during their training processes as researchers. Thus, in this context, the adoption of generative tools demands careful reflection to find the necessary balance between technological support and the autonomy of the student intellect (Kasneci et al., 2023). Research training should involve the development of complex skills, including the identification of significant problems, the critical analysis of sources, the development of coherent theoretical frameworks, solid methodological design, and rigorous argumentative writing. These competencies demand the activation of metacognitive processes and the constant exercise of critical thinking—actions that go beyond simple procedural execution (Zawacki-Richter et al., 2019).

With this analytical framework, the controversy about using AI in the context of higher education involves the dilemma presented by its potential advantages as a resource for academic support and the dangers it represents for academic integrity and educational legitimacy. Cotton et al. (2024) stress that accessibility to generative systems requires institutions to rethink evaluation policies and to be more precise about the ethically acceptable delimitation of their use. Barrett and Pack (2023) identified differences in criteria between students and teachers regarding the stages of the writing process in which the use of AI could be considered legitimate. In the context of higher education, the use of AI for generating ideas or conducting preliminary organization is generally perceived as acceptable, while greater controversy arises regarding its application in the final versions of academic work submitted for formal evaluation.

Kasneci et al. (2023) argue that the emergence of tools such as ChatGPT challenges traditional conceptions of authorship and academic performance, raising important questions about the validity of conventional assessment models in higher education. Tensions are also perceived among teaching staff regarding the balance between innovation and prudence. Mamo et al. (2024) reports that teachers are manifestly interested in the pedagogical potential of these tools; however, teachers also express concerns about their impact on the authenticity of academic work. Likewise, case studies that investigated AI-based conversational assistants in educational settings suggest that their effectiveness is contingent on well-defined institutional frameworks and structured pedagogical strategies (Tlili et al., 2023). These findings highlight that the integration of AI goes beyond purely technological aspects and requires coordinated institutional support and intentional pedagogical design.

According to these reflections, an examination of the use of AI in research training must necessarily be connected to the development of digital skills. The European Framework for Digital Competence of Educators incorporates pedagogical, professional, and ethical dimensions of technology use, which go beyond merely instrumental skills (Redecker & Punie, 2017). Understood from this perspective, adopting AI demands from users the critical capacity to select, adapt, and evaluate tools according to educational purposes, which goes beyond the technical domain alone. Recent studies confirm the heterogeneity in the levels of digital competence achieved in higher education, which are influenced by contextual and institutional factors (Inamorato dos Santos et al., 2023). This heterogeneity is particularly relevant in the context of the increasing complexity of generative AI systems.

Long and Magerko (2020) define the concept of AI literacy as a notion of increasing relevance, which they describe as a set of competencies needed to understand the functioning of AI-based systems, recognize their limitations, and critically evaluate their results. Ng et al. (2021) expand this definition beyond functional understanding and incorporate competencies aimed at teaching and assessing AI literacy in educational settings. In the university context, this literacy involves the critical interpretation of generated content, the detection of potential biases, and making informed decisions about its academic use, thus establishing AI literacy as a transversal competence in the research training process (Ng et al., 2021; UNESCO, 2023).

Despite these advances, there is still a structural gap in empirical research: the propensity to define the use of AI as a unitary and uniform construct. It is common for general conceptualizations to be examined without distinguishing between different, specific degrees of interaction factor that hinders the distinction between conceptual familiarity, frequency of use in academic work, and the degree of satisfaction derived from experience (Bond et al., 2024; Zawacki-Richter et al., 2019). This absence of psychometric differentiation limits the full understanding of the internal architecture of the interrelationship between the student and the AI and restricts the design of instruments based on solid empirical foundations (Hair et al., 2019).

Accordingly, the conduct of solid empirical studies on the use of AI in research training requires instruments supported by robust evidence of validity and reliability. From a psychometric perspective, exploratory factor analysis is an essential tool for examining the internal structure of these instruments and assessing whether item organization aligns with the proposed conceptual framework. In this regard, Fabrigar et al. (1999) emphasize that the application of exploratory factor analysis requires method-based decisions regarding extraction procedures, rotation methods, and factor retention criteria in order to avoid artificial solutions or misleading interpretations.

Costello and Osborne (2005) argue that the interpretation of the factor structure must be supported by solid criteria, such as minimum levels of factor load, absence of problematic crossloads, and theoretical coherence between the items and the emerging factors. Though assessment through coefficients such as Cronbach's alpha for internal consistency is a widely used procedure for estimating the reliability of the scales, its interpretation must, similarly, be carried out with caution, because it does not establish sufficient evidence of psychometric quality by itself, even though it makes it possible to assess the internal homogeneity of the items (Tavakol & Dennick, 2011). These reasonings, together, corroborate the necessary rigorous methodological approach in research examining the use of AI in educational environments.

In non-experimental approaches of cross-sectional design, bivariate associative analysis is considered methodologically coherent in exploratory purposes of relationships between dimensions, without the establishment of inferences associated with causality. This perspective favors the identification of preliminary guiding patterns for subsequent research of explanatory or predictive nature (Schober et al., 2018). If applied to the use of AI in research training, the examination of the associations between familiarity, frequency of use and level of satisfaction can provide significant information on how these dimensions interact in university environments, thereby providing a more structured understanding of the phenomenon.

Taking into account the interests of this research, the three dimensions were conceptually defined in a differentiated way: Familiarity refers to the level of knowledge and previous experience with AI tools; use refers to the frequency and intensity of the application of AI in academic research work; and satisfaction refers to the subjective evaluation of the usefulness and efficiency of AI. Although the relationship between the different dimensions is recognized, they are neither equivalent nor interchangeable; therefore, its independent examination makes possible a greater precision in the structural evidence obtained on the phenomenon. As for the full operational definitions, these are detailed in the Methodology section.

There is still a lack of empirical literature related to the dimensional distinction of the use of AI in university research training context, especially in Latin American contexts, even though previous research has investigated the integration of AI in these contexts from general or descriptive perspectives (Bond et al., 2024; Zawacki-Richter et al., 2019), as well as the development of digital skills in university environments (Inamorato dos Santos et al., 2023). Despite these investigations, there is still limited empirical evidence that differentiates specific dimensions, such as familiarity, frequency of use and satisfaction, linked to AI tools in research training processes.

Consequently, the present research aimed to examine the psychometric evidence and the associations between the dimensions of familiarity, frequency of use, and perceived satisfaction in the university environment. To this end, a quantitative, non-experimental, and descriptive-correlational design was adopted, incorporating exploratory factor analysis, the estimation of internal consistency (α and ω), and bivariate association analysis through non-parametric coefficients and independence tests. In this way, the study aimed to contribute structural empirical evidence that informs the current debate on the critical incorporation of AI in higher education.

2. Methodology

2.1 Study Design

The study was carried out from a non-experimental quantitative and cross-sectional paradigm, with a descriptive-correlational scope and a bivariate associative analysis. The conception was considered appropriate for its ability to describe, at a specific time point, the corresponding levels of familiarity with, frequency of use of, and satisfaction with the use of AI tools for activities associated with research training, as well as to examine the relationships between these dimensions without intervening in the manipulation of the variables. This quantitative approach allowed the structured measurement of the phenomenon and its corresponding analysis, through statistical procedures. In turn, the non-experimental and cross-sectional nature of the paradigm contributed to the interest in observing it in its natural environment and at a single, specific time.

In the same way, the coherence of the descriptive-correlational scope was conceived to satisfy the purpose of describing the dimensions analyzed, and to explore their relationships without the establishment of causal inferences (Setia, 2016). Consequently, and to ensure analytical transparency, it is declared that the present research did not assume an explanatory or predictive scope, therefore, no regression models were performed, and the relationships were examined in their statistical associations, not in their causal effects.

2.2 Participants and Sampling

To carry out the study, a population of approximately 450 university students was formed. They were enrolled between the sixth and eighth academic cycles of the Faculty of Technology of the Enrique Guzmán y Valle National University of Education, Peru, and were involved with research training. The sample size was calculated from the formula for finite populations (Hernández-Sampieri et al., 2014), considering a confidence level of 95% (Z = 1.96), maximum variability (p = q = 0.5) and a margin of error of 8%, the result of which estimated a sample of 115 students. On the basis of this calculation, an invitation to participate was extended to this initial number of participants; however, 10 of them did not complete the questionnaire or did not ratify their interest in participation. Thus, the response rate is 91.3%, which is considered appropriate for cross-sectional educational studies; the final sample, which comprised 105 participants, was considered valid.

The sampling was non-probabilistic for convenience and defined according to accessibility and availability criteria. This approach was considered relevant for a descriptive study in which access to the entire population was not possible and the objective was to analyze the relationships between variables, not to make generalizable inferences (Hernández-Sampieri et al., 2014). Accordingly, the definition of the sample size was indicative and considered only complete questionnaires that were accompanied by the informed consent of each participant.

2.3 Instrument

A structured questionnaire was developed as an instrument for the study; it is based on specialized literature on the use of AI and digital skills in the context of higher education (Inamorato dos Santos et al., 2023; Ng et al., 2021; Zawacki-Richter et al., 2019). This instrument consists of 30 items, distributed in three dimensions: (1) Familiarity with AI tools (10 items), (2) Frequency of use of AI tools in activities related to research training (10 items) and (3) Perceived satisfaction with academic use of AI tools (10 items). The answers were recorded using a four-point Likert scale (1 = never/nothing; 4 = always/a lot) and without inverted items; the highest values showed higher levels in the dimension evaluated.

For the descriptive interpretation, the values of each dimension were recoded as one of three levels (low, medium and high). Taking into account that each dimension was made up of 10 items with values from 1 to 4 (range 10–40), the following intervals were defined: low (10–20), medium (21–30) and high (31–40). This classification was considered only for descriptive purposes and to help the interpretation of the results, as well as their associative examination with categorical variables. This practice is common in the study of data derived from Likert-type scales (Sullivan & Artino, 2013).

2.4 Validity and Reliability

The determination of the validity of the instrument was considered from its integrality, encompassing both content validity and construct validity. First, content validity was established through expert judgment (n = 5), involving academics specializing in research methodology and educational technology, who evaluated the items according to the criteria of clarity, relevance, and coherence. Based on these evaluations, the experts' observations were incorporated into the final version of the questionnaire, and care was taken to ensure the conceptual and semantic adequacy of the questionnaire.

Subsequently, based on the defined purpose of identifying underlying constructs rather than a reduction in data, construct validity was examined by exploratory factor analysis, by using the principal axis factoring method. Oblique rotation (Oblimin) was used, taking into account the expected theoretical correlation between the study dimensions (familiarity, use, and satisfaction). The adequacy of the data for factor analysis was corroborated by the Kaiser–Meyer–Olkin index (KMO = 0.947) and the Bartlett sphericity test (χ^2 = 3034.494; df = 435; p < .001), which confirmed the relevance of the correlation matrix for factor extraction (Table 1).

Table 1: Factorial adequacy indices (KMO and Bartlett)

Table of contents	Value
KMO	0.947
Bartlett's χ^2	3 034.494
df	435
p	< .001

Note. *The KMO value indicates excellent sampling adequacy, and the Bartlett test confirms that the correlation matrix is suitable for factor analysis*

The exploratory factor analysis made it possible to identify the consistency of a three-factor structure according to the theoretical model formulated, confirming 72.8% of the total variance. The factor loads revealed an appropriate grouping of the items in their corresponding dimensions, thereby checking the structural coherence of the instrument (Table 2). In line with the exploratory nature of factor analysis, the objective of which is to identify the underlying structure in the statistical relationships between the items, it is relevant to note that the empirical distribution of these items was not strictly limited to the initial organization of the instrument (Items 1–10, 11–20 and 21–30). Consequently, the grouping achieved manifests an empirically supported organization, thus strengthening the construct validity of the instrument.

Table 2: Exploratory factor analysis (pattern matrix)

Item	Familiarity	Use	Satisfaction
p18	0.905	–	–
p11	0.800	–	–
p14	0.771	–	–
p15	0.761	–	–
p16	0.738	–	–
p17	0.727	–	–
p29	0.711	–	–
p19	0.667	–	–
p24	0.614	–	–
p13	0.527	–	–
p30	0.522	–	–
p8	–	0.780	–
p9	–	0.778	–
p10	–	0.664	–
p4	–	0.649	–
p2	–	0.630	–
p1	–	0.620	–
p5	–	0.466	–
p3	–	0.455	–
p28	–	–	0.815
p20	–	–	0.748
p23	–	–	0.732
p22	–	–	0.681
p25	–	–	0.672
p26	–	–	0.571
p27	–	–	0.537

Note. *Only factor loads ≥ 0.40 are presented. Items with significant cross loads were excluded from the final interpretation*

The correlations between the factors fluctuated between moderate and high values (0.464 to 0.729), which supports the use of oblique rotation and confirms the theoretical interrelation between the evaluated constructs (Table 3).

Table 3: Matrix of correlations between factors

Factor	1	2	3
1	1.000	0.528	0.729
2	0.528	1.000	0.464
3	0.729	0.464	1.000

Note. *The values indicate moderate to high correlations between the dimensions evaluated*

Although, in traditional terms, the subject–item relationship can be considered moderate, the high value of the KMO and the clarity of the factorial solution achieved confirm the relevance of the sample size for exploratory purposes. Finally, Cronbach's alpha and McDonald's omega coefficients—with values of $\alpha = 0.974$ and $\omega = 0.974$—enabled us to evaluate the internal consistency of the instrument and indicated the excellent reliability and high internal homogeneity of the items (Table 4).

Table 4: Internal consistency of the instrument

Table of contents	Value
Cronbach's Alpha (α)	0.974
McDonald's Omega (ω)	0.974
Number of items	30

Note. *The values show the excellent internal consistency of the instrument*

2.5 Procedure

The data collection procedure was carried out between March 15 and April 30, 2024, and used a mixed modality administration (face to face and online). In the case of the face-to-face modality, its application was carried out in academic classrooms (with prior authorization from the teachers); the estimated duration was 20 to 25 minutes. In the online modality, administration was carried out from a digital form, preserving equivalent instructions, order of items and approximate response time, all with the purpose of guaranteeing procedural equivalence between both modalities.

Subsequently, for data purification, questionnaires with more than 10% empty or incomplete answers were excluded from analysis. For omissions below this threshold, the average value of the corresponding dimension was imputed. Finally, a total of 105 valid questionnaires were analyzed.

2.6 Data Analysis

For the corresponding processing and statistical analysis of the data obtained, SPSS software, Version 29, was used. During the first phase, descriptive analyses were carried out to characterize the behavior of the variables studied to produce frequencies, means, medians, and standard deviations for each of the dimensions of the instrument.

Subsequently, taking into account that the measurement of the items was carried out from a four-point Likert-type scale, the associations between dimensions were examined according to Spearman's rank correlation coefficient (ρ), which is considered appropriate for variables of an ordinal nature and when the assumption of strict normality is not met. A bilateral significance level of $\alpha = .05$ was determined.

Additionally, for the examination of associations between variables categorized into levels (low, medium and high), the chi-square test (χ^2) was used, after verifying the fulfillment of its assumptions; above all, that no more than 20% of the cells had expected frequencies of less than five. In addition, the effect size was calculated using Cramer's V coefficient, in order to complement the interpretation of statistical significance. Finally, according to the descriptive-correlational design of the study, the analysis was aimed exclusively at exploring bivariate associations, without the application of regression models or predictive inference.

2.7 Ethical Considerations

All phases of this study respected the principles of voluntariness, confidentiality and informed consent. Participants were informed of the purpose of the research and its academic nature, and that deciding to participate or not held no risk of academic repercussions. Participants remained anonymous and the resulting data was used only for the stated scientific purposes.

The study abided by the ethical guidelines established for research in social sciences and education, given the non-experimental nature of the study, the minimal risk it posed and its use of self-report measures. Similarly, for the application of the instrument, the necessary institutional authorization was obtained.

3. Results

3.1 Sample Features

Table 5 shows the sample distribution according to sex and age variables for the defined sample. Regarding sex, there is a relative balance in distribution, with 54.3% (n = 57) being women and 45.7% (n = 48) men.

In relation to age, 54.3% of the participants were between 17 and 21 years old (n = 57), 31.4% were between 22 and 25 years old (n = 33) and 14.3% between 26 and 30 years old (n = 15). Most participants were in the range of 17 to 21 years old, because of the predominance of young students in intermediate and advanced stages of their university academic training.

Table 5: Distribution of the sample according to sex and age

Category	Frequency	Percentage (%)
Women	57	54.3
Men	48	45.7
17–21 years	57	54.3
22–25 years	33	31.4
26–30 years	15	14.3

3.2 Descriptive Results by Dimension

3.2.1 Familiarity with AI Tools

Next, the descriptive results derived from the first dimension of the study are presented, which answers the following research question: What is the level of student familiarity with AI tools applied to academic research? Table 6 shows that familiarity of 61.9% (n = 65) of participants was at a low level, 24.8% (n = 26) at a medium level, and 13.3% (n = 14) at a high level. The average score of M = 1.96 (SD = 0.47) was determined, which is close to the lower limit of the scale. Overall, for this dimension, both the frequency distribution data and the central tendency values show a predominance of low levels of familiarity.

Table 6: Level of familiarity with AI tools

Level of familiarity	Frequency	Percentage (%)
Low	65	61.9
Medium	26	24.8
High	14	13.3

3.2.2 Frequency of Using AI Tools

The second dimension of the study was aimed at answering the following question: How often do students use AI tools in the development of their research projects? Table 7 presents the descriptive results for the distribution of the frequency of use of AI tools for the development of student research projects. A total of 70.5% of participants (n = 74) indicated a low level of use, 22.9% (n = 24) indicated a medium level of use, and only 6.7% (n = 7) reported a high level of use. The average score of this dimension is located in the lower range of the scale, generally indicating a low frequency of use of AI tools.

From the interpretative point of view, these results indicate limited integration of AI tools in research training tasks, despite their progressive access. These results could suggest the presence of barriers associated with a lack of knowledge of the potentialities of AI use, insufficient specific training about the potentialities, or an absence of educational strategies that favor the use of AI tools in academic contexts.

Table 7: Frequency of use of AI tools in research projects

Frequency of use	Frequency	Percentage (%)
Low	74	70.5
Medium	24	22.9
High	7	6.7

3.2.3 Perceived Satisfaction

The third dimension of the study was established in response to the question: What is the level of satisfaction perceived by students regarding the use of AI tools in their research projects? The descriptive results corresponding to this dimension (Table 8) indicate that a total of 68.6% (n = 72) of participants indicated low levels of satisfaction, 22.9% (n = 24) a medium level and 8.6% (n = 9) high levels of satisfaction. Furthermore, the average score of this dimension is positioned at the lower range of the scale, which confirms a generalized low level of perceived satisfaction.

From an interpretative perspective, these findings indicate that students have a low perception of the value or usefulness of using AI tools in their research processes. These results for satisfaction could be related to factors such as limitations in the mastery of these tools, experiencing that its use is not particularly effective or that students lacked pedagogical integration that could guide the application of AI tools in academic environments.

Table 8: Perceived satisfaction with the use of AI tools

Level of satisfaction	Frequency	Percentage (%)
Low	72	68.6
Medium	24	22.9
High	9	8.6

3.2.4 Global Level of Appropriation of AI Tools

The results in Table 9 indicate the integrated variable, to answer the following research question: What global level of appropriation of AI tools does university students show in the field of research training? The global level of appropriation was calculated with the average of the scores achieved on the three dimensions evaluated (familiarity, frequency of use, and perceived satisfaction), which were all measured with the same four-point Likert scale. This procedure made it possible to obtain a synthetic indicator of the level of appropriation of AI tools in the university academic context. The findings were interpreted according to the cut-off points consistent with those used for each dimension, specifying three levels: low, medium, and high. Equidistant intervals were used for categorization, considering that the scale varies between 1 and 4: low (1.00–2.00), medium (2.01–3.00) and high (3.01–4.00). This criterion is widely used in the analysis of variables derived from Likert-type scales.

The results of the distribution of the global level of appropriation are presented in Table 9, with values that confirm a predominance of low levels of appropriation: 66.7% (n = 70) at the low level, 25.7% (n = 27) at the medium level and 7.6% (n = 8) at the high level. From an interpretative point of view, this pattern indicates that the integration of AI tools in university research training is still incipient—a result consistent with the independent analysis of each dimension observed. Interpreted as a whole, these findings indicate a convergence of low levels of familiarity, limited use, and low satisfaction, resulting in a low overall appropriation of these technologies in the academic setting.

Table 9: General level of critical appropriation of AI tools

General level	Frequency	Percentage (%)
Low	70	66.7
Medium	27	25.7
High	8	7.6

Note. *The overall level of appropriation was calculated as the average of the dimensions of familiarity, use, and satisfaction. Categorization was performed using equidistant intervals: low (1.00–2.00), medium (2.01–3.00), and high (3.01–4.00)*

3.3 Inferential Results

3.3.1 Spearman Correlations

The data on Spearman's correlations presented in Table 10 show positive and statistically relevant associations between the three dimensions analyzed ($p < .001$). Above all, a strong relationship was found between familiarity and frequency of use ($\rho = .871$); this result reveals that students with greater understanding and experience of the use of AI tools tend to use the tools more frequently for activities associated with research.

In addition, the correlation between familiarity and satisfaction ($\rho = .689$; $p < .001$) was found to be positive and statistically significant, with an evaluated magnitude of moderate–high, which, although it is lower than that perceived between familiarity and frequency of use, continues to ratify a relevant relationship between technology knowledge and a subjectively positive experience. This finding suggests an association in which greater understanding and experience of the use of AI tools corresponds with more favorable evaluations of the academic advantage and efficiency of AI tools.

In the same way, the data points to a marked relationship between the dimensions of frequency of use and satisfaction, with a stronger correlation between these two dimensions ($\rho = .925$; $p < .001$). Based on this result, it can be inferred that greater use of AI tools is associated with higher levels of perceived satisfaction. Because the cross-sectional conception of this study is limited to the interpretation of statistical and not causal relationships, by using an inferential approach, these findings could reveal a positive feedback dynamic, where frequent experience of the use of these technologies improves the perception of the usefulness of the tools, or vice versa.

Overall, from a conceptual point of view, the results support the integration of these three dimensions into a global index of appropriation of AI tools in the context of university research training, because the correlation matrix confirms that the dimensions of familiarity, frequency of use, and perceived satisfaction form an interrelated but non-redundant system.

Table 10: Spearman's correlation between familiarity, use, and satisfaction with AI tools (n = 105)

Dimension	Familiarity	Use	Satisfaction
Familiarity	1	.871**	.689**
Use	.871**	1	.925**
Satisfaction	.689**	.925**	1

***Note. ρ = Spearman's correlation coefficient; p <.001 (bilateral)*

3.3.2 Categorical Associations (Cramer's χ^2 and V)

Results of the chi-square tests show statistically significant associations among the dimensions analyzed. The greatest association is between the dimensions of use and satisfaction (χ^2 (4) = 138,578, $p < .001$), with a high effect size (V = .81). The associations between familiarity and use (χ^2 (4) = 91.218, $p < .001$), with a large effect size (V = .66), and between familiarity and satisfaction (χ^2 (4) = 106.602, $p < .001$), with effect size V = .71, are lower.

According to the conventional interpretation criteria established by Cramer's V coefficient, the values calculated by this study reveal associations of high magnitude—results that reinforce the structural coherence between the dimensions examined. The evidence of perceived methodological convergence between the analyses carried out with continuous and categorized variables is remarkable, because results are consistent with the previously reported Spearman correlations between familiarity and use ($\rho = .871$), familiarity and satisfaction ($\rho = .689$), and use and satisfaction ($\rho = .925$). Associations in this study should be interpreted as statistical relationships and not as causal inferences, given the non-experimental cross-sectional design of the research.

Table 11: Association between categorized dimensions (χ^2 test and effect size)

Associated with	x^2	df	*p*-value	Cramer's V
Familiarity x Use	91.218	4	< .001	.66
Familiarity x Satisfaction	106.602	4	< .001	.71
Usage x Satisfaction	138.578	4	<.001	.81

4. Discussion

4.1 Integrated Interpretation of Dimensions

In general, the results of the study identify a convergent pattern characterized by a predominance of low to medium levels across the three dimensions of analysis. Regarding the integration of AI tools in the context of university research training, this convergence suggests that the implementation of AI tools remains at an early stage, because this implementation is perceived to be closer to exploratory phases than to a stage of consolidated pedagogical institutionalization, in accordance with the explanation of Zawacki-Richter et al. (2019).

The findings for the familiarity dimension are that a relevant proportion of students do not have high levels of understanding or mastery of the academic use of these tools. These results are consistent with other studies on AI literacy, which identify gaps in the development of competencies for use in educational settings (Long & Magerko, 2020; Ng et al., 2021). Recent studies point out that the availability of generative tools, such as ChatGPT, alone does not guarantee sufficient literacy to execute complex academic activities (Chan & Hu, 2023; Kasneci et al., 2023). Literature differentiates between technology accessibility and structured formative appropriation and emphasizes in the explicit pedagogical orientation a need for real curricular integration and clear institutional guidelines.

In relation to the frequency of use of AI tools for the development of research projects, the results of the study indicate that AI has not yet been incorporated in these tasks as a systematic praxis. Recent evidence corroborates a heterogeneous dependence on factors such as performance expectation, perceived ease of use, social influence, and favorable institutional scenarios for technology adoption (Feng et al., 2025; Venkatesh et al., 2012). In the absence of these components, as indicated by systematic reviews, there is a tendency for integration to be limited to experimental rather than structural levels (Celik et al., 2022; Zawacki-Richter et al., 2019).

In turn, the pattern identified in the dimension of perceived satisfaction is consistent with models of technology acceptance that relate perceived satisfaction to perceived usefulness and ease of use (Venkatesh et al., 2012). The coexistence of indicators of low familiarity, limited use, and moderate satisfaction indicates an experience with these tools that depends on guided environments of use rather than on spontaneous practices, which have yet to achieve a consolidated level of integration.

It is necessary, however, to underline that technological resistance should not be assumed from the low familiarity with and limited use of AI tools, because recent research reveals a tendency among students to have favorable attitudes in this regard, even though they also declare a certain ambivalence in relation to the use of AI tools in formal academic environments, mainly because of ethical and quality concerns (Almassaad et al., 2024; Cotton et al., 2024). In general, the findings of this study corroborate the multidimensionality inherent in the process of appropriation of AI, because the appropriation of AI is constituted through the articulation of cognitive, behavioral, and attitudinal factors**.** These results are consistent with current models of adoption of technology (Venkatesh et al., 2012).

4.2 Structural Coherence and Psychometric Contributions

From an inferential approach and considering the positive and statistically significant associations found between the dimensions analyzed, a reinforcement of the structural coherence of the conceptual model is perceived. The high correlation between use and satisfaction hints, in particular, at a close link between practical experience with AI tools and the subjective appreciation of AI tools, which has been abundantly documented in the literature on technology acceptance (Venkatesh et al., 2012). However, taking into account that the exploratory factor analysis corroborated the empirical differentiation of the factors, it cannot be assumed that the magnitude of this association identified implies conceptual redundancy.

In psychometric terms, the three-dimensional factor structure indicates strong indicators of adequacy, including a high KMO index and a substantial proportion of explained variance. This finding is consistent with classic methodological observations in relation to exploratory factor analysis, which underscore theoretical coherence, clarity of factor loadings, and the absence of problematic cross-loadings (Costello & Osborne, 2005; Fabrigar et al., 1999). Likewise, high levels of reliability were identified in the internal consistency coefficients (α and ω), in accordance with widely accepted psychometric criteria (Tavakol & Dennick, 2011).

In the Latin American context, specifically, this contribution is of particular relevance, because the Latin American context is still characterized by a limited availability of instruments with specific structural validation for measuring the appropriation of AI tools in research training environments. Systematic reviews on the topic underscore the need to strengthen methodological rigor and to develop contextualized tools for AI research in higher education (Zawacki-Richter et al., 2019). In addition to merely descriptive findings, the present research also provides preliminary structural evidence that empirically supports the differentiation between the dimensions of familiarity, use, and perceived satisfaction.

However, the exploratory nature of the study requires moderation, because confirmatory validation by independent samples is part of an essential advance toward the consolidation of factor stability and the examination of possible refinements of the structural model, as highlighted by Hair et al. (2019). Therefore, the preliminary results should be understood as initial evidence of the transition to a line of research that is susceptible to further deepening through confirmatory analyses and structural models of greater complexity.

4.3 Implications for Education

The repercussions of the results of this study for education highlight the need to strengthen strategies aimed at promoting the consolidation of AI literacy in the context of university research training. Recent literature on the subject underlines that, in addition to technology accessibility, the responsible integration of AI requires the promotion of critical thinking, understanding of algorithmic biases, and ethical and conscious reflection on the use of AI tools in academic environments (Crawford, 2021; Kasneci et al., 2023). In this framework, AI literacy should be understood as a transversal competence that integrates multiple dimensions at the technical, ethical, and methodological levels.

In terms of concrete praxis, strengthening conceptual familiarity and promoting more systematic integration could be improved by incorporating specific modules on the academic use of AI in methodology courses. Similarly, the incorporation of defined institutional guidelines on the use of AI tools in assessed tasks could lead to the reduction of regulatory ambiguity while encouraging responsible appropriation, as pointed out by studies on academic authenticity in the era of generative AI (Cotton et al., 2024).

The present study, in summary, provides structured empirical evidence of contributing to the emerging field of research on the use of AI in the field of higher education, by underlining technology appropriation as a complex, gradual, and multidimensional process that integrates knowledge, praxis, and evaluation in a pedagogical framework still in development.

5. Conclusion

The objective of this research was to analyze the empirical and psychometric evidence of the internal structure and associations between the dimensions of familiarity, frequency of use of, and perceived satisfaction with the use of AI tools in the environment of university research training. The results identify the predominance of low levels for all three dimensions, which suggests that AI integration, in this context, is still emerging and in an incipient state that is mostly characterized by individual exploratory praxis, and not as a product of a solid pedagogical institutionalization.

The structural coherence evidenced in the exploratory factor analysis, together with the significant associations identified between the dimensions, ratify the conceptual validity of the model presented, and the assimilation of AI tools as a multidimensional process that could integrate cognitive, behavioral, and attitudinal components. However, the magnitude of the correlations identified—

especially between use and satisfaction—suggests the need for confirmatory research that delves into factor stability and underlying structural relationships.

From an education point of view, these results underscore the need to strengthen actions that promote critical, conscious, and responsible incorporation of AI use in university research training, with literacy strategies for AI that integrate dimensions at the technical, ethical, and methodological levels. By providing methodological foundations and empirical evidence for the orientation of future research and curricular decisions in university contexts, this research, in short, contributes to the emerging field of research on AI in the field of higher education.

6. Limitations and Future Lines of Research

Among the limitations identified by this study are, firstly, that the use of non-probabilistic sampling for convenience must be taken into account in the interpretation of its results, which limits its possible generalization to other institutional contexts. The sample size was appropriate for descriptive analyses, bivariate associations, and exploratory factor analysis; however, this feature restricts the application of confirmatory or structural models of greater complexity.

Secondly, cross-sectional design hinders the possibility of analyzing longitudinal changes, and of examining causal relationships between the variables studied (Setia, 2016). In the same way, although standardized procedures were drawn up, administration in mixed modalities (face-to-face and virtual) could lead to the introduction of biases associated with the mode of response. Likewise, although the subject–item relationship in the exploratory factor analysis was corroborated by a high KMO index and adequate structural clarity, a measured interpretation of the results in terms of model extrapolation is considered necessary.

In relation to future lines of research, the incorporation of confirmatory validation processes from independent samples is recommended, as is the use of longitudinal designs and multi-institutional samples that promote the strengthening of factorial stability and generalization of the results. Likewise, it would be appropriate to integrate variables such as previous digital competence (Inamorato dos Santos et al., 2023), institutional policies, and the disciplinary area, to encourage enrichment of the explanatory model and a deepening of understanding of the appropriation of AI in the context of university research training.

7. Statement on the Use of Artificial Intelligence Tools

The process of writing and reviewing the manuscript was mediated by the use of the ChatGPT tool (OpenAI), which was used as a support to optimize the academic style, organize the argument and conduct linguistic review. This tool was not used for data generation, statistical analysis or the formulation and interpretation of results. All methodological provisions, interpretations and conclusions are the sole responsibility of the authors. In addition, all the content generated was critically reviewed, validated, and contextualized by the authors before its definitive incorporation in the manuscript.

8. Conflict of Interest

The authors declare the absence of conflicts of interest of a financial, institutional or personal nature that could have influenced the design, execution, analysis or publication of this study.

9. Acknowledgments

The authors express their gratitude to the students who voluntarily participated in the study, whose collaboration made it possible to carry out this research.

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Appendix

Questionnaire on Familiarity, Frequency of Use of and Satisfaction with AI Tools in University Research Training

Purpose of the instrument

The purpose of this questionnaire is to assess familiarity, frequency of use and satisfaction with artificial intelligence (AI) tools in the context of university research training. Responses are anonymous and will be used exclusively for academic and scientific research purposes.

Instructions

Read each statement carefully and select the option that best describes your personal experience using the following scale: 1 = Never, 2 = Rarely; 3 = Frequently; 4 = Always

I.- General Data

1.- Sex:

2.- Age:

No.	Dimension 1: Familiarity with AI tools	S	F	BY	N
1	Do you know the basic functioning of AI tools applied to academic research?				
2	Have you received information or training on the use of AI tools in research projects?				
3	Do you identify different AI tools that can be used in the development of research?				
4	Do you understand the benefits that AI can offer in the research process?				
5	Do you recognize the limitations of AI tools in academic papers				
6	Do you know how to formulate proper instructions when using AI tools?				
7	Do you know the ethical aspects related to the use of AI in research?				
8	Are you informed about the institutional rules regarding the use of AI in academic papers?				
9	Do you feel ready to use AI tools in research activities?				
10	Do you critically evaluate the results generated by AI tools?				
	Dimension 2: Frequency of use of AI tools	**S**	**F**	**BY**	**N**
11	Do you use AI tools to search for academic information?				
12	Do you use AI tools to write parts of your research papers?				
13	Do you use AI tools several times a week in the development of research activities?				
14	Do you use AI tools to organize ideas in your projects?				
15	Do you use AI tools during the preparation of your research projects?				
16	Do you use AI tools to summarize academic texts?				
17	Do I spend a significant amount of time per session using AI tools in academic papers?				
18	Do you use AI tools to process or analyze information?				
19	Do you use AI tools to generate examples related to your research?				

20	Do you consider AI to be a regular part of your research process?				
	Dimension 3: Satisfaction with AI tools	**S**	**F**	**BY**	**N**
21	Are you satisfied with the support that AI tools provide in your academic work?				
22	Do you think that AI tools facilitate the development of your research?				
23	Do you perceive that AI tools improve the quality of your academic papers?				
24	Do AI tools help you better understand research topics?				
25	Do AI tools optimize the time you spend on your academic activities?				
26	Do you trust the information provided by AI tools when you use them?				
27	Do you find it easy to use AI tools in investigative activities?				
28	Do you think that the use of AI contributes positively to your research learning?				
29	Would you recommend the use of AI tools in academic projects?				
30	Are you generally satisfied with the integration of AI into your training process?				