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Factors associated with faculty readiness to adopt emerging technologies in higher education: an exploratory TAM-based study

Factores asociados a la disposición docente hacia tecnologías emergentes en educación superior: estudio exploratorio desde el TAM

Fatores associados à disposição docente para tecnologias emergentes no ensino superior: estudo exploratório a partir do TAM

Abstract

Introduction: the integration of emerging technologies in higher education largely depends on faculty attitudes; however, quantitative evidence regarding the factors associated with their willingness to adopt such technologies remains limited in Peru. **Objective:** to analyze the factors associated with higher education faculty's willingness to incorporate emerging technologies through an exploratory approach guided by the Technology Acceptance Model (TAM). **Method:** a quantitative, non-experimental, cross-sectional, and correlational study was conducted with 52 Peruvian faculty members selected through convenience sampling. Participants completed a digital questionnaire composed of single-item measures. Spearman correlations with Holm correction, nonparametric tests, and logistic regression analyses were performed. **Results:** a total of 63.5% (n = 33) reported the highest level of willingness to adopt emerging technologies. Willingness was associated with expectations regarding educational impact (ρ = .63) and with positive perceptions of educational innovation (ρ = .50), but not with methodological knowledge or previous use of virtual learning environments. Lack of training (63.5%) and insufficient technological resources (57.7%) were the most frequently reported barriers. **Conclusion:** in higher education, willingness to adopt educational technologies appears to be more strongly associated with expectations of educational benefits than with prior experience, highlighting faculty training and institutional support as key priorities.

Keywords: faculty attitude, higher education, educational innovation, educational technology

Resumen

Introducción: la incorporación de tecnología emergente en la universidad depende en buena medida de la actitud del docente; sin embargo, en el Perú la evidencia cuantitativa sobre los factores asociados a su disposición es escasa.

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Objetivo: analizar los factores asociados a la disposición del profesorado de educación superior para incorporar tecnologías emergentes, desde una aproximación exploratoria orientada por el Modelo de Aceptación Tecnológica (TAM). **Método:** estudio cuantitativo, no experimental, transversal y correlacional, con 52 docentes peruanos seleccionados por conveniencia que respondieron un cuestionario digital de ítems únicos; se aplicaron correlaciones de Spearman con corrección de Holm, pruebas no paramétricas y regresión logística. **Resultados:** el 63.5 % (33) manifestó disposición máxima; esta se asoció con la expectativa de impacto formativo (ρ = .63) y con la valoración de la innovación educacional (ρ = .50), pero no con el conocimiento metodológico ni con el uso previo de entornos virtuales; la falta de capacitación (63.5 %) y de recursos tecnológicos (57.7 %) fueron las barreras más reportadas. **Conclusión:** la disposición hacia la tecnología educacional en educación superior se vincula más con expectativas de beneficio formativo que con la experiencia de uso, lo que sitúa la capacitación y el apoyo institucional como prioridades.

Palabras clave: actitud del docente, educación superior, innovación educacional, tecnología educacional

Resumo

Introdução: a incorporação de tecnologias emergentes no ensino superior depende, em grande medida, da atitude dos docentes; entretanto, no Peru, as evidências quantitativas sobre os fatores associados à sua disposição para adotá-las ainda são escassas. **Objetivo:** analisar os fatores associados à disposição dos docentes do ensino superior para incorporar tecnologias emergentes, a partir de uma abordagem exploratória orientada pelo Modelo de Aceitação de Tecnologia (TAM). **Método:** estudo quantitativo, não experimental, transversal e correlacional, realizado com 52 docentes peruanos selecionados por conveniência, os quais responderam a um questionário digital composto por itens únicos. Foram aplicadas correlações de Spearman com correção de Holm, testes não paramétricos e regressão logística. **Resultados:** observou-se que 63,5% (n = 33) dos participantes apresentaram disposição máxima para adotar tecnologias emergentes. Essa disposição esteve associada à expectativa de impacto formativo (ρ = 0,63) e à valorização da inovação educacional (ρ = 0,50), mas não ao conhecimento metodológico nem ao uso prévio de ambientes virtuais de aprendizagem. A falta de capacitação (63,5%) e de recursos tecnológicos (57,7%) foram as barreiras mais frequentemente relatadas. **Conclusão:** no ensino superior, a disposição para adotar tecnologias educacionais está mais relacionada às expectativas de benefícios formativos do que à experiência prévia de uso, o que destaca a capacitação docente e o apoio institucional como prioridades.

Palavras-chave: atitude docente, ensino superior, inovação educacional, tecnologia educacional



Introduction

Higher education has undergone rapid digital transformation in recent years, changing how instruction is designed, mediated, and assessed. Kharchenko et al. (2024) showed that digital technologies have become a driving force in university learning, propelled by the mass adoption that the COVID-19 pandemic set off, and cautioned that successful integration requires strategic planning, sound regulatory frameworks, and sustained investment in infrastructure and professional development. Along similar lines, Tang et al. (2025) put forward a logical framework for universities' digital transformation and identified practical dilemmas, both psychological and objective in nature, that affect faculty and students alike. Mexhuani (2025), in turn, noted that the opportunities offered by digital tools coexist with persistent barriers, among them the digital divide, faculty resistance, and concerns about data privacy.

Emerging technologies, including artificial intelligence (AI), immersive virtual environments, simulations, virtual laboratories, and digital fabrication, have taken on growing prominence in this process. Aparicio-Gómez et al. (2024) describe how these technologies are converging with active methodologies such as problem-based learning, collaborative learning, and the flipped classroom, a shift that is reshaping university teaching. Romero Oliva et al. (2024) observe that emerging methodologies place students in an active role and add that instructors need continuing training that combines pedagogical, didactic, and technological components. Research on these tools has also expanded quickly. Crompton and Burke (2023) reviewed 138 studies of AI in higher education and found that publications in 2021 and 2022 had doubled or tripled relative to earlier years, and Bond et al. (2024), in a review of reviews, call for greater attention to ethical, methodological, and contextual questions and for extending the research to developing countries.

The literature agrees that faculty are a decisive actor in turning these technologies into real pedagogical change. Chugh et al. (2023) characterized the implementation of educational technology in higher education institutions as a complex, multifaceted process that must bring together the perspectives of different stakeholders. In a study of 527 instructors at four universities, Mercader and Gairín (2020) found that professional barriers were the most prevalent and that perceptions varied by disciplinary area; they concluded that stronger faculty professional development and greater institutional involvement through strategic plans were needed. Bond et al. (2018) had already observed that instructors and students used a limited number of digital tools, mostly for assimilative tasks. Drawing on the experience of emergency remote teaching, Mondragon-Estrada et al. (2023) documented that faculty valued information and communication technologies for sustaining students' interest and confidence, and recommended approaches such as the flipped classroom, problem-based learning, and game-based learning. Other studies have linked innovative educational technologies to the development of professional competencies (Sapargaliyeva et al., 2023) and, through thematic analysis, have examined the views of university health sciences faculty on digital transformation (Prosen & Ličen, 2025).

To understand why instructors accept or reject a technology, the Technology Acceptance Model (TAM) has become one of the most widely used frameworks. Davis

(1989) developed and validated scales for two fundamental beliefs, perceived usefulness and perceived ease of use, and his analyses suggested that ease of use operated as an antecedent of usefulness rather than as a direct, parallel determinant of use. Venkatesh and Davis (2000) extended the model as TAM2, which explained perceived usefulness and usage intentions through social influence processes and instrumental cognitive processes and accounted for between 34% and 52% of the variance in intentions. Venkatesh et al. (2003) subsequently integrated eight earlier models into the Unified Theory of Acceptance and Use of Technology (UTAUT), which rests on four core determinants: performance expectancy, effort expectancy, social influence, and facilitating conditions.

In educational settings, the TAM has shown consistent but uneven explanatory power. Teo (2009), working with 475 preservice teachers, found that perceived usefulness was the strongest determinant of behavioral intention, while ease of use and facilitating conditions operated indirectly. The meta-analysis by Scherer et al. (2019), which synthesized 114 studies involving 34,357 teachers, confirmed that the model adequately explains technology acceptance, although the role of some constructs and external variables ran counter to widespread beliefs about the TAM. Scherer and Teo (2019) estimated that the model's variables explained on average 39.2% of the variance in teachers' intention and that the relationships were moderated by teaching experience and by how the variables were represented. In higher education, Xue et al. (2024) reviewed 162 UTAUT-based articles and noted a predominance of student samples from Asia and North America, with performance expectancy emerging as the most influential predictor of intention, while Feng et al. (2025), in a systematic review of 39 studies, organized adoption factors around the four UTAUT dimensions.

The emergence of generative AI has renewed interest in these models. Kong et al. (2024), studying 367 Hong Kong teachers, found that self-efficacy, perceived usefulness, and attitude were essential to the intention to use generative AI tools, and that subjective norms also had an influence. Al-Abdullatif (2024), in a sample of 237 university instructors, identified AI literacy and perceived ease of use as the most influential factors in acceptance. Wang (2026) examined, with 615 university teachers, the relationship among perceived generative AI competence, TAM beliefs, and continuance intention, and Liu et al. (2025) applied an extended TAM to study preservice teachers' intention to adopt these tools. In Ibero-America, Cabero-Almenara, Palacios-Rodríguez, Loaiza-Aguirre, and Andrade-Abarca (2024) analyzed generative AI adoption among 425 university teachers using UTAUT2 and partial least squares models, and Cabero-Almenara, Palacios-Rodríguez, Loaiza-Aguirre, and De Rivas-Manzano (2024) related the acceptance of educational AI to teacher characteristics and pedagogical beliefs. García-Murillo et al. (2023), with 538 Ecuadorian teachers, found high levels of Moodle acceptance, higher still among those with more advanced training and prior experience with online learning systems, and counted facilitating conditions among its determinants. Still other studies have explored university teachers' beliefs about and uses of generative AI (Cabellos et al., 2024; Perezchica-Vega et al., 2024).

In Peru, by contrast, the evidence has been predominantly qualitative. Bernilla Rodríguez (2024), for example, worked with faculty at a public university in

the north of the country and found that instructors saw some advantages in using AI to generate texts and develop activities but doubted the accuracy of the output; they proposed addressing these limitations through training, for which the author called for institutional development. Even so, very little quantitative evidence examines, jointly, the readiness of Peruvian university faculty, their perceptions of innovation, and the conditions that could foster implementation. A common methodological limitation compounds this gap: many studies describe favorable attitudes without distinguishing intention from actual use or making explicit the theoretical framework that guides the selection of variables.

In response to this gap, the present study aimed to analyze the factors that influence higher education faculty's readiness to use emerging technologies in Peru, drawing on an exploratory approach based on the TAM. The following expectations were formulated as relationships between variables: (E1) expected educational impact, which comes closest to perceived usefulness, is related to readiness; (E2) the perceived importance of educational innovation is also related to readiness; (E3) knowledge of innovative methodologies is related to readiness; (E4) readiness is linked to actual use of virtual environments; and (E5) reporting difficulties in implementing these technologies is associated with lower readiness. Because the instrument did not measure perceived ease of use and showed no variability in perceived usefulness, the TAM served as a framework for organizing and interpreting the results rather than as a complete model put to an empirical test.

Methods and materials

Design

The study followed a quantitative, nonexperimental, cross-sectional design with an exploratory-correlational scope. Data were collected at a single point in time for each participant, and no variable was manipulated, so the observed relationships were interpreted as associations rather than causal effects.

Participants

The sample comprised 52 responses from higher education faculty in Peru, obtained through nonprobability convenience sampling with voluntary participation. Responses were collected between February and September 2026, depending on respondents' availability: 24 in February, 23 in May, and 5 in September. The questionnaire did not ask whether respondents were actively teaching during that period or what type of institution they worked at, so eligibility rested on self-identification as a higher education teacher.

Instrument and variables

The study used a digital questionnaire (https://forms.gle/N1QTNCpTXpqqmipq9) that included five sociodemographic questions (age, academic degree, area of specialization, and years of experience in higher education), four items rated on a 1–5 scale, one question on the usefulness of emerging technologies, one dichotomous question on prior experience with virtual environments or metaverse platforms together with a conditional frequency question

(1–5 scale), and a pair of true/false questions on barriers, observed benefits, problems encountered, and need for support. Each construct was measured with a single item (no evidence of the instrument's validity was available), and the verbal anchors of the frequency scale were not documented. Table 1 shows the correspondence between the instrument's variables and the TAM constructs, and Figure 1 depicts the exploratory conceptual model.

Table 1

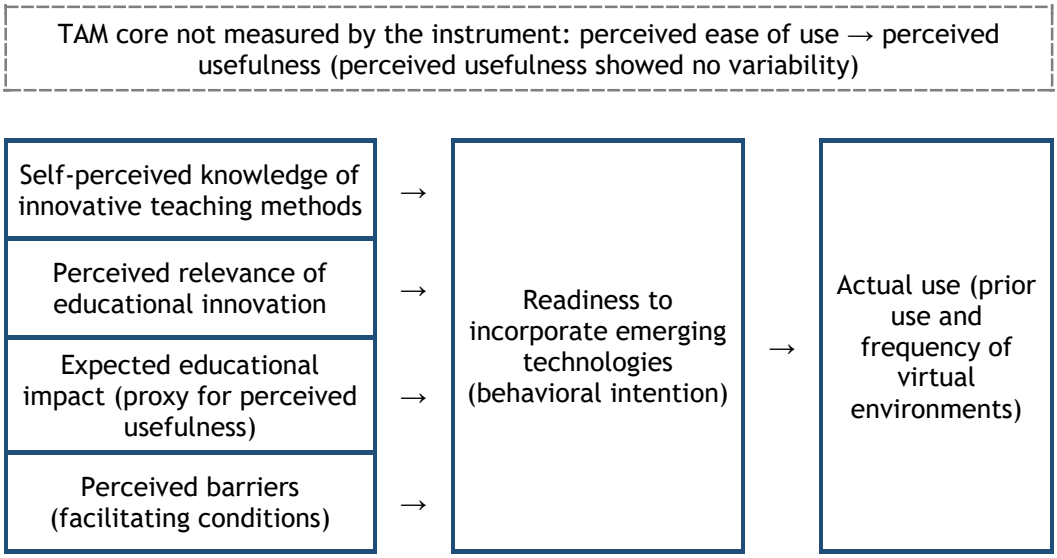
Correspondence between instrument variables and TAM constructs

Instrument variable	Scale	Theoretical correspondence	Use in the analysis
Readiness to incorporate emerging technologies in the next 12 months	Ordinal 1–5	Behavioral intention (TAM core)	Main dependent variable
Is adopting emerging technologies useful in your teaching?	Categorical (Essential / Not at all useful)	Perceived usefulness (TAM core) Perceived ease of use (TAM core)	Descriptive only: 98.1% (51) chose "Essential"
Expected impact of innovation on student education	Ordinal 1–5	Outcome expectancy; approximation of perceived usefulness	Predictor
Relevance of educational innovation for university learning	Ordinal 1–5	External variable: perceived value of innovation	Predictor
Knowledge of innovative teaching methods	Ordinal 1–5	External variable: self-perceived knowledge	Predictor
Prior use of virtual environments or metaverse and frequency	Dichotomous; ordinal 1–5 (users only)	Actual use (restricted to one technology)	Behavioral outcome
Barriers and required supports	Multiple choice	Perceived facilitating conditions (UTAUT)	Descriptive and comparisons
Age, degree, experience, and area	Continuous and categorical	Sociodemographic variables	Descriptive and comparisons

Source: Authors' own elaboration based on Davis (1989) and Venkatesh et al. (2003).

Figure 1

Exploratory conceptual model guided by the TAM



Source: Authors' own elaboration based on Davis (1989) and Venkatesh et al. (2003).

Note. Solid-bordered boxes represent measured variables, and arrows represent associations examined in a cross-sectional design, without implying causality. The dashed box represents TAM constructs that the instrument could not measure.

Procedure and ethical considerations

The form was distributed digitally, and the responses were exported to a spreadsheet. For comparisons by degree, the bachelor's (n = 2) and professional degree categories were combined; likewise, the 27 free-text responses on area of specialization were recoded into six disciplinary categories.

Data analysis

Because the variables ranged from 1 to 5, they were treated as ordinal, and the descriptive analysis relied on medians, interquartile ranges, means, standard deviations, percentile bootstrap 95% confidence intervals for the mean, and the percentage of responses at the top of the scale. Proportions were reported with Wilson intervals. For multiple-response questions, the denominator was all participants in the case of barriers and supports, and users only in the case of benefits and difficulties.

Associations were estimated with Spearman correlations, using bootstrap intervals and Holm correction for the ten comparisons. Differences in readiness by prior use and by each barrier were assessed with the Mann-Whitney U test and the rank-biserial correlation (rrb), and differences by academic degree, experience, and disciplinary area with the Kruskal-Wallis test and the ε^2 statistic. Given the ceiling effect in readiness, a binary logistic regression was fitted for maximum readiness (5

vs. ≤ 4) with two predictors chosen for their theoretical role: expected impact and perceived relevance of innovation. With only 19 cases in the less frequent category, the number of predictors was kept small to limit the risk of overfitting. As sensitivity analyses, methodological knowledge was added to the model, an ordinal logistic model (≤ 3, 4, and 5) was estimated, and the main correlations were recalculated using the first 43 responses and excluding cases with atypical or incoherent answers. Because the expectations were formulated after an exploratory inspection of the data, p values are interpreted as exploratory. Analyses were run in Python 3 with pandas, SciPy, and statsmodels at a significance level of .05; the reproducible analysis notebook is available from the author upon request.

These decisions followed from the characteristics of the data rather than from a search for significance. Spearman correlations were preferred over Pearson's because the variables were ordinal, had few categories, and showed marked negative skew. Readiness was modeled as a binary variable because 63.5% of participants chose the maximum value, which left too few cases in the lower categories for a stable ordinal model; the ordinal model was therefore reserved for sensitivity analysis. Bootstrap intervals were used because they do not require normality assumptions and are well suited to small samples. Finally, effect sizes and confidence intervals were reported alongside p values to separate statistical significance from the practical relevance of the associations.

Results and discussion

Sample characteristics

Participants' mean age was 47.77 years (SD = 13.00; Mdn = 48; range, 26–72). Most held a master's or doctoral degree, had more than 11 years of experience in higher education, and worked in education or in engineering, architecture, and design (Table 2). Overall, 67.3% (35) reported having used virtual environments or metaverse platforms in their teaching (Wilson 95% CI: 53.8%–78.5%).

Table 2

Sample characteristics (n = 52)

Variable	Category	% (n)
Academic degree	Master's	46.2% (24)
	Doctorate	34.6% (18)
	Professional degree	15.4% (8)
	Bachelor's	3.8% (2)
Experience in higher education	0–5 years	19.2% (10)
	6–10 years	15.4% (8)
	11 years or more	65.4% (34)

Variable	Category	% (n)
Disciplinary area	Education	30.8% (16)
	Engineering, architecture, and design	26.9% (14)
	Economics, administration, and management	17.3% (9)
	Humanities and social sciences	13.5% (7)
	Health sciences	9.6% (5)
	Unclassifiable	1.9% (1)
Prior use of virtual environments or metaverse	Yes	67.3% (35)
	No	32.7% (17)

Source: Authors' own elaboration from the study data.

Note. Age: M = 47.77; SD = 13.00; Mdn = 48; range, 26–72. Disciplinary area was recoded from open-ended responses.

Perceptions, readiness, and use

Perceived relevance of educational innovation, expected educational impact, and readiness to incorporate emerging technologies clustered at the top of the scale, with 65.4%, 75.0%, and 63.5% of responses at 5, respectively (Table 3). Self-perceived knowledge of innovative teaching methods was lower and concentrated at 4. A total of 98.1% (51) rated the usefulness of emerging technologies as essential, so this variable was left out of the inferential analyses. Among users, the frequency of use of virtual environments fell at intermediate values.

Table 3

Descriptive statistics for the ordinal variables (1-5 Scale)

Variable	n	Mdn (IQR)	M (SD)	95% CI for M	Min-Max	% at 5 (n)
Knowledge of innovative teaching methods	52	4 (3–4)	3.79 (0.87)	[3.54, 4.02]	1–5	17.3% (9)
Relevance of educational innovation	52	5 (4–5)	4.54 (0.80)	[4.31, 4.73]	1–5	65.4% (34)
Expected impact on student education	52	5 (5–5)	4.73 (0.49)	[4.60, 4.85]	3–5	75.0% (39)
Readiness to incorporate emerging technologies	52	5 (4–5)	4.52 (0.75)	[4.31, 4.71]	2–5	63.5% (33)

Variable	n	Mdn (IQR)	M (SD)	95% CI for M	Min-Max	% at 5 (n)
Frequency of use of virtual environments (users)	35	3 (3–4)	3.34 (1.19)	[2.94, 3.71]	1–5	17.1% (6)

Source: Authors' own elaboration from the study data.

Note. IQR = interquartile range. 95% CI obtained by percentile bootstrap.

Implementation conditions

Lack of faculty training and lack of technological resources were the most frequently reported barriers, followed by institutional resistance (Table 4). Consistent with this, continuing faculty training and technological infrastructure were the supports most in demand. Among users, the most commonly observed benefits were greater student participation and motivation, whereas technical problems were the most frequent difficulty.

Table 4

Reported barriers, supports, benefits, and difficulties (Multiple response)

Question (base)	Option	% (n)
Barriers to implementing innovation (*n* = 52)	Lack of faculty training	63.5% (33)
	Lack of technological resources	57.7% (30)
	Institutional resistance	44.2% (23)
	Student resistance	25.0% (13)
	Other	5.8% (3)
	None	1.9% (1)
Support considered necessary (*n* = 52)	Continuing faculty training	73.1% (38)
	Technological infrastructure	67.3% (35)
	Institutional support and clear policies	59.6% (31)
	Adequate educational materials	46.2% (24)
Observed benefits (users, *n* = 35)	Greater participation	65.7% (23)
	Greater motivation	65.7% (23)
	Improved understanding of concepts	40.0% (14)

Question (base)	Option	% (n)
	Inclusion of students with diverse needs	34.3% (12)
Difficulties experienced (users, *n* = 35)	Technical problems	71.4% (25)
	Lack of preparation time	40.0% (14)
	Lack of institutional support	37.1% (13)
	Student resistance	11.4% (4)
	Other	8.6% (3)

Source: Authors' own elaboration from the study data.

Note. Percentages do not sum to 100 because multiple responses were allowed. Benefits and difficulties were calculated only for respondents who reported prior use.

Factors associated with readiness

After Holm correction, readiness was positively associated with expected educational impact (ρ = .63; 95% CI [.39, .82]) and with perceived relevance of innovation (ρ = .50; 95% CI [.22, .73]), consistent with E1 and E2 (Table 5). The association with methodological knowledge was weak and its interval included zero, so E3 received no support. Among users, frequency of use showed no appreciable association with any variable; with 35 cases, however, the power to detect weak associations was low.

Table 5

Spearman correlations among study variables

Variable pair	n	ρ	95% CI	p	Holm p
Expected impact – Readiness	52	.63	[.39, .82]	< .001	< .001
Relevance – Readiness	52	.50	[.22, .73]	< .001	.002
Relevance – Expected impact	52	.44	[.15, .68]	.001	.008
Knowledge – Relevance	52	.30	[.06, .51]	.032	.223
Knowledge – Readiness	52	.23	[−.02, .48]	.095	.573
Knowledge – Expected impact	52	.17	[−.10, .43]	.231	.743
Frequency of use – Expected impact	35	.25	[−.07, .52]	.147	.737
Frequency of use – Knowledge	35	.23	[−.19, .60]	.186	.743
Frequency of use – Relevance	35	.17	[−.14, .47]	.322	.743
Frequency of use – Readiness	35	.15	[−.18, .45]	.406	.743

Source: Authors' own elaboration from the study data.

Note. 95% CI by bootstrap. Holm correction was applied to the ten comparisons.

Frequency of use was recorded only for users.

Readiness did not differ between respondents who had used virtual environments and those who had not (Table 6), so E4 received no support. No differences emerged by academic degree, years of experience, or disciplinary area either. Among the barriers, only student resistance was associated with lower readiness, with a moderate effect size, but the association did not hold after Holm correction; support for E5 was therefore partial and inconclusive.

Table 6

Comparison of readiness by participant characteristics

Comparison	Groups: n; Mdn; M	Statistic	p	Effect size
Prior use	Yes: 35; 5; 4.57 / No: 17; 5; 4.41	U = 323.0	.566	r_{rb} = .09
Academic degree	Doctorate: 18; 5; 4.72 / Master's: 24; 5; 4.50 / Bachelor's or professional degree: 10; 4; 4.20	$H(2)$ = 4.98	.083	ε^2 = .06
Experience	0–5 years: 10; 4; 4.50 / 6–10 years: 8; 4; 4.12 / 11 or more: 34; 5; 4.62	$H(2)$ = 4.50	.105	ε^2 = .05
Disciplinary area	Six categories (n from 1 to 16)	$H(5)$ = 7.38	.194	ε^2 = .05
Barrier: lack of training	Reported: 33; M = 4.52 / Not reported: 19; M = 4.53	U = 311.5	.973	r_{rb} = −.01
Barrier: lack of resources	Reported: 30; M = 4.50 / Not reported: 22; M = 4.55	U = 323.5	.896	r_{rb} = −.02
Barrier: institutional resistance	Reported: 23; M = 4.48 / Not reported: 29; M = 4.55	U = 354.5	.656	r_{rb} = .06
Barrier: student resistance	Reported: 13; M = 4.08 / Not reported: 39; M = 4.67	U = 157.5	.017	r_{rb} = −.38

Source: Authors' own elaboration from the study data.

Note. U = Mann-Whitney test; H = Kruskal-Wallis test; rrb = rank-biserial correlation. With Holm correction for the four barriers, student resistance yielded p = .070.

The logistic regression model improved fit relative to the null model (Table 7). Expected impact was associated with higher odds of readiness, whereas relevance showed no independent association. With relevance held at its median, the predicted probability of maximum readiness was .24 (95% CI [.06, .63]) at an expected impact of 4 and .83 (95% CI [.67, .92]) at an expected impact of 5. Adding methodological knowledge did not change these results. In the ordinal model, relevance reached significance, indicating that its independent role depended on model specification. The wide intervals call for caution in interpreting the magnitude of the odds ratios, since the model in practice contrasted instructors with an

expected impact of 4 against those with 5 (only one case scored 3). In the sensitivity analyses, the correlations of readiness with expected impact (ρ between .51 and .63) and with relevance (ρ between .38 and .55) held across all scenarios.

Table 7

Logistic regression of maximum readiness (5 vs. ≤ 4)

Model and predictor	B (SE)	OR	95% CI for OR	p
M1. Expected impact	2.72 (0.89)	15.14	[2.66, 86.05]	.002
M1. Relevance of innovation	0.67 (0.53)	1.95	[0.69, 5.52]	.210
M2. Expected impact	2.71 (0.89)	14.95	[2.61, 85.47]	.002
M2. Relevance of innovation	0.60 (0.54)	1.83	[0.63, 5.29]	.265
M2. Methodological knowledge	0.23 (0.43)	1.26	[0.55, 2.91]	.585
M3 (ordinal). Expected impact	2.99 (0.88)	19.78	[3.56, 109.83]	< .001
M3 (ordinal). Relevance of innovation	0.96 (0.48)	2.62	[1.03, 6.68]	.043

Source: Authors' own elaboration from the study data.

Note. n = 52 (33 with maximum readiness). M1: LR $x^2(2) = 19.54$, $p < .001$, Nagelkerke $R^2 = .43$, McFadden $R^2 = .29$. M2: LR $x^2(3) = 19.83$, $p < .001$, Nagelkerke $R^2 = .43$. M3: ordinal logistic model with categories ≤ 3, 4, and 5. OR = odds ratio.

The values from the earlier draft, calculated with the first 43 responses, were reproduced exactly (ρ = .51 for impact and readiness; ρ = .38 for relevance and readiness), which confirmed the traceability of the analysis. Adding the nine later responses did not change the direction of any association and slightly increased its magnitude. Likewise, excluding the one participant who rated emerging technologies as "not at all useful," and whose answer was at odds with a maximum readiness score, did not alter the conclusions.

The results portray faculty with very high readiness toward emerging technologies, in line with the high levels of acceptance that García-Murillo et al. (2023) documented among Ecuadorian teachers and with the advantages that Peruvian faculty attributed to artificial intelligence in the study by Bernilla Rodríguez (2024). Responses clustered mostly at the top of the scale, however, which suggests that the instrument discriminates poorly among high levels of readiness. This property attenuates correlations, and the measure should be used with caution; high readiness cannot be taken as a guarantee of adoption.

The strongest association linked readiness with anticipated educational impact. This pattern is compatible with the central status the TAM grants to perceived usefulness (Davis, 1989), with the finding of Teo (2009) that usefulness was the strongest determinant of teachers' intention, and with the evidence from Xue et al. (2024) that performance expectancy was the most influential predictor. The impact item, however, does not gauge the usefulness of a specific technology for teaching; it taps general expectations about educational innovation, so its equivalence with perceived usefulness is only approximate. Moreover, the two items share a generalized optimism, and their association may therefore reflect a broad

stance in favor of change rather than a relationship between distinct constructs.

Perceived relevance of innovation was associated with readiness in the bivariate analysis, but its independent contribution varied with model specification. This instability is consistent with the heterogeneity that Scherer and Teo (2019) attribute to how TAM variables are represented and with the caution that Scherer et al. (2019) express about the role of external variables. Knowledge of innovative methodologies, for its part, was not associated with readiness, in contrast to studies in which self-efficacy (Kong et al., 2024) or AI literacy (Al-Abdullatif, 2024) predicted acceptance. The difference may stem from operationalization: knowing about innovative methodologies is not the same as feeling capable of using a specific technology, which is what technological self-efficacy captures.

The lack of association between readiness and prior use deserves attention. In both the TAM and the UTAUT, intention is the immediate antecedent of use (Davis, 1989; Venkatesh et al., 2003). Here, however, intention referred to emerging technologies in general over the next 12 months, whereas use referred to a single technology in the past, so the two measures share neither an object nor a time frame. The result is better read as a gap between what is accepted and what is actually done, consistent with the limited, predominantly assimilative use of digital tools that Bond et al. (2018) found among university instructors and with the complexity of implementation described by Chugh et al. (2023).

The barriers reported agree with the literature. The lack of training and resources, together with institutional resistance, mirrors the predominance of professional and institutional barriers documented by Mercader and Gairín (2020) and the conditions that Kharchenko et al. (2024) and Mexhuani (2025) consider necessary for sustainable integration. The demand for training matches what Peruvian faculty expressed in the study by Bernilla Rodríguez (2024), and the most requested supports correspond to what the UTAUT calls facilitating conditions (Venkatesh et al., 2003). That these barriers were unrelated to readiness is compatible with the idea that facilitating conditions bear more on actual use than on intention, although these data cannot test that interpretation. Nor were differences by academic degree observed, unlike in García-Murillo et al. (2023), though the small groups limit the power of the comparison.

From a theoretical standpoint, the results illustrate both the usefulness of the TAM as an interpretive framework and the risks of applying it without an instrument that represents its constructs. The model makes it possible to organize the available variables around behavioral intention and to distinguish among beliefs, intention, and use, but the absence of perceived ease of use precludes examining the sequence that Davis (1989) proposed between ease of use and usefulness. Scherer and Teo (2019) showed that the way TAM variables are represented moderates the magnitude of their relationships, and studies with full psychometric evidence, such as Dou and Feng (2025), illustrate the kind of validation that a confirmatory application of the model requires. Accordingly, the findings of this study should be understood as a preliminary approximation that suggests hypotheses for future research, not as a confirmation of the TAM among Peruvian faculty.

In practical terms, the findings suggest that institutions do not need to

convince faculty of the value of innovation, since they are already favorably disposed. The task is rather to narrow the distance between readiness and practice through continuing training, infrastructure, and clear institutional provisions, in line with the integrated approach to teacher preparation described by Romero Oliva et al. (2024) and Aparicio-Gómez et al. (2024).

The study also has limitations that bear on the scope of its conclusions. The cross-sectional design precludes establishing the temporal order of the relationships, and convenience sampling, with 52 participants and possible self-selection of instructors interested in innovation, restricts generalizability. All constructs were measured with single items lacking prior validity evidence, the instrument did not measure perceived ease of use, and perceived usefulness lacked variability, so the core of the TAM could not be tested. The measures come from self-report on a single instrument, which exposes the associations to common-method bias, and the ceiling effect reduced the available variability. The form required respondents to answer questions that did not apply to them, which called for documented recoding, and the expectations were formulated after an exploratory inspection of the data. Future research should use validated multi-item scales for each construct, whose reliability in education has generally proved adequate (Açıkgül & Şad, 2026), provide evidence of construct validity (Dou & Feng, 2025), focus on a specific technology such as generative AI (Kong et al., 2024; Wang, 2026), calculate the sample size a priori, and incorporate longitudinal designs that measure actual use following intention.

Conclusions

The participating higher education faculty show a highly favorable readiness to incorporate emerging technologies, together with a strong appreciation of educational innovation and high expectations about its educational impact. This readiness is associated mainly with expected impact and, to a lesser extent, with the valuation of innovation, but not with methodological knowledge, prior use of virtual environments, or sociodemographic characteristics. From an exploratory standpoint, these results support the relevance the TAM attributes to expectations of benefit, although they do not allow the model to be tested in full.

The study's main contribution is to show that declared acceptance does not automatically translate into practice and that institutional conditions, above all training, technological resources, and supportive policies, are the obstacles that faculty most often point to. Institutional strategies should therefore aim less at promoting attitudes that are already favorable and more at the conditions that can convert that predisposition into sustained pedagogical use. Advancing this line of research will require studies with validated multi-item instruments, larger and more representative samples, and designs that assess intention and use of specific technologies together.

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Declaration of author responsibility

Jesús Leonardo Vivanco Enriquez 1: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Supervision, Validation/Verification, Visualization, Writing – original draft, and Writing.
Silvana Tabata Espinoza Gomez 2: Data curation, Visualization, Writing – original draft, and Writing.
Hayashi Rafael Mateo Nuñez 3: Methodology, Resources, Software, Supervision, Validation/Verification, Visualization, Writing – original.

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