Generative Artificial Intelligence as Technological Innovation in Higher Education: Literacy, Technopedagogical Knowledge, and Faculty Integration

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ABSTRACT

Generative artificial intelligence (GenAI) represents a technological innovation with potential to support planning, material production, feedback, and activity design in higher education. However, pedagogical integration requires more than access to tools: it involves literacy to understand and evaluate their outputs, knowledge to connect technology with content and pedagogy, and criteria for deciding when their use adds educational value. This study aimed to describe GenAI literacy, artificial intelligence-related technological pedagogical content knowledge (AI-TPACK), and the pedagogical integration of these tools among faculty in the Department of Economic and Administrative Sciences at Instituto Tecnológico de Pachuca, and to explore their associations with age and the modality through which faculty learned to use GenAI. A quantitative, nonexperimental, cross-sectional study with an intended census approach was conducted. The 35 faculty members identified as the study population participated. A 34-item questionnaire comprising Likert-type scales and profile and experience questions was administered. The instrument was reviewed by three experts, and an external pilot test was conducted with 22 faculty members; internal consistency in the main study sample was high for all three scales. The results showed mean scores of 3.41 for GenAI literacy, 3.25 for AI-TPACK, and 2.85 for pedagogical integration. Literacy was associated with AI-TPACK (rho = .740), and both variables were related to pedagogical integration. The group aged 56 years or older had descriptively lower mean scores, particularly for literacy and integration. Institutional training was associated with higher AI-TPACK and integration scores, although causality cannot be inferred. The study concludes that situated and continuous faculty development is a priority.

Keywords: Generative Artificial Intelligence, Higher Education, Artificial Intelligence Literacy, AI-TPACK, Pedagogical Integration.

INTRODUCTION

The expansion of generative artificial intelligence (GenAI) tools has opened up new possibilities for producing texts, images, presentations, explanations, exercises, and other resources that can be incorporated into academic activities. In higher education, these capabilities can support both faculty preparation tasks and learning experiences, provided their use is accompanied by critical evaluation, pedagogical guidance, and ethical responsibility. In its UNESCO guidance, Miao and Holmes (2023) warn that GenAI integration should be grounded in a human-centered approach that attends to privacy, equity, output validation, and human agency.

The presence of these tools does not, by itself, guarantee educational innovation. The value of their integration depends on users' competencies, the instructional decisions guiding their use, and their ability to verify generated content. A faculty member may use GenAI frequently to streamline tasks while maintaining conventional teaching practices; another may use it occasionally to redesign activities, promote analysis, or provide feedback. It is therefore important to distinguish among GenAI literacy, technopedagogical knowledge, and specific integration practices.

This study addresses this issue in the Department of Economic and Administrative Sciences at Instituto Tecnológico de Pachuca, which serves students in the Bachelor's Degree in Administration and the Bachelor's Degree in Business Management Engineering programs. The study focuses on describing faculty-reported competencies and practices and exploring whether patterns differ by age group and GenAI learning modality. Age is analyzed as a contextual variable, not as a causal explanation for differences.

The general objective was to describe GenAI literacy, AI-TPACK knowledge, and the pedagogical integration of GenAI among faculty in the department, and to explore associations between these dimensions and the contextual variables considered. The specific objectives were to: (1) characterize faculty profiles and experience with GenAI; (2) estimate reported levels of literacy, AI-TPACK, and pedagogical integration; (3) examine relationships among the three dimensions; and (4) describe exploratory differences by age group and learning modality. The study contributes a local diagnostic that can inform professional development initiatives and proposes an integrative analytical model for future research.

LITERATURE REVIEW

Generative artificial intelligence literacy

GenAI literacy involves more than knowing how to enter prompts into an application. It includes understanding, at a functional level, what these tools can and cannot do; using them for appropriate purposes; evaluating the accuracy, relevance, and bias of their responses; designing interactions; and considering ethical, privacy, and authorship implications. Assessing these competencies is challenging because self-perception does not necessarily correspond to demonstrated performance. The Generative AI Literacy Assessment Test (GLAT) is a 20-item performance test developed and validated with higher education students; its authors report that it predicts performance on GenAI-supported tasks better than some self-perception measures (Jin et al., 2025). Although its participants were not faculty members, the study is relevant because it distinguishes demonstrated competence from self-perceived competence.

Research on GenAI literacy among faculty is also developing dedicated instruments. Wang et al. (2025) developed and validated a GenAI literacy scale for teachers of English as a foreign language in China, covering knowledge, use, evaluation, design, and ethics. Their findings provide a useful precedent, although the disciplinary and national context differs from that of the present study. These dimensions support the importance of addressing both instrumental use and critical judgment and responsibility. In this study, literacy is treated as a self-reported dimension measured by ten items; therefore, the results describe perceptions and reported practices, not an objective test of competence. Xia et al. (2026) also developed a generative artificial intelligence competency self-efficacy scale for higher education teachers and researchers. This work is relevant as a precedent concerning perceived competencies, although it is not equivalent to an objective performance test.

Technological pedagogical knowledge and AI-TPACK

The TPACK framework proposes that technology-supported teaching requires the integration of content knowledge, pedagogical knowledge, and technological knowledge rather than treating each component in isolation (Mishra & Koehler, 2006). Recent AI-TPACK approaches adapt this logic to faculty work with artificial intelligence and recognize that AI integration requires specific decisions about tool selection, instructional design, disciplinary fit, evaluation of outputs, and learning mediation. Çelik (2023) proposes the Intelligent-TPACK framework, which includes the knowledge needed to integrate AI tools while considering ethical issues; Eyal (2025) develops and validates an AI-TPACK assessment framework based on authentic pedagogical artifacts produced by teacher educators. Both studies support treating AI-related technopedagogical knowledge as a dimension that cannot be reduced to instrumental tool use.

In this article, AI-TPACK is used as a dimension distinct from literacy. Literacy refers to understanding, using, and evaluating GenAI; AI-TPACK refers to perceived ability to connect it with subject content, teaching strategies, and pedagogical decisions. This distinction makes it possible to explore whether knowing and operating the tools is associated with feeling capable of integrating them instructionally.

Pedagogical integration and educational innovation

Here, pedagogical integration refers to the frequency with which faculty report using GenAI in teaching tasks. The SAMR framework—Substitution, Augmentation, Modification, and Redefinition—can help describe different forms of technology integration. However, its application requires consideration of context, the pedagogical process, and learning objectives; a critical review cautions against interpreting its levels as a universal hierarchy of quality (Hamilton et al., 2016). Analysis should take purpose, context, discipline, and active student participation into account.

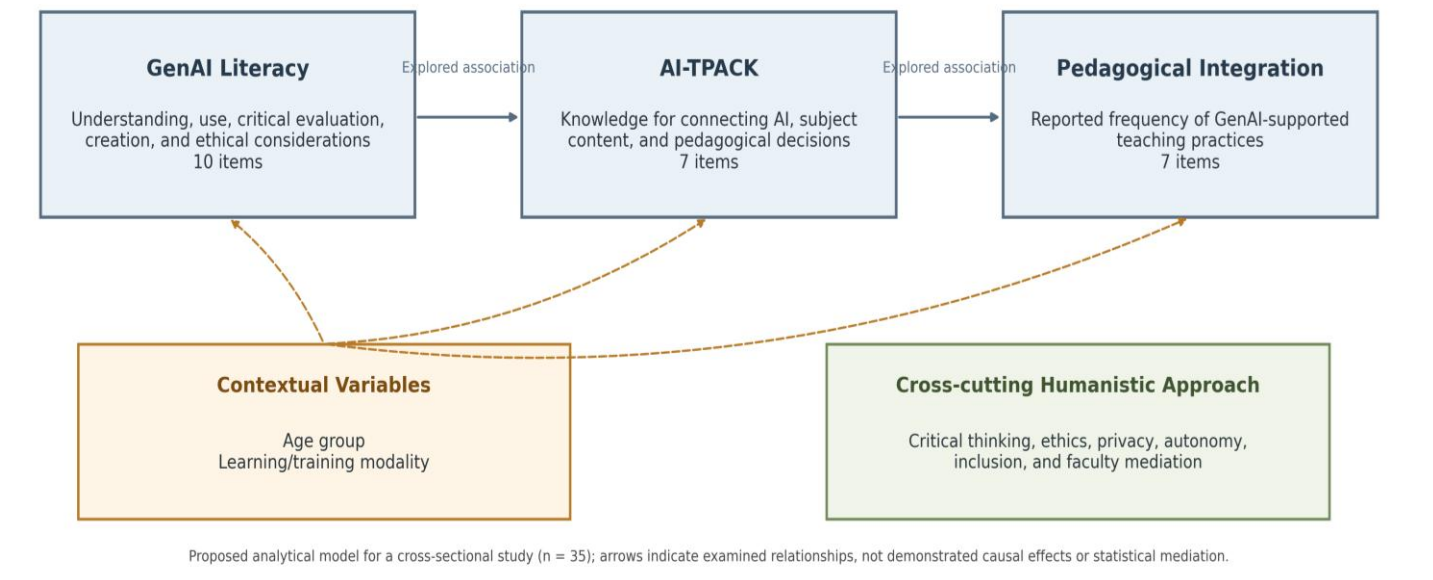
A humanistic perspective cuts across these dimensions. Miao and Holmes (2023) emphasize the need to preserve human agency, data protection, equity, and responsibility in GenAI integration. Accordingly, technological innovation is understood as intentional and critical integration, not adoption for the sake of novelty or replacement of professional teaching judgment. This orientation is consistent with Martínez Rodríguez et al. (2025), who discuss smart education and the transformation of pedagogical strategies from a lifelong-learning perspective. Their contribution is used here as contextual framing for educational transformation, not as empirical evidence specifically about faculty GenAI literacy.

THEORETICAL FRAMEWORK

Based on the literature, an analytical model is proposed that brings together three dimensions: GenAI literacy, AI-TPACK, and pedagogical integration. The theoretical expectation is that greater literacy may be associated with stronger technopedagogical knowledge and that both may be related to integration practices. The model also includes two contextual variables—age group and learning/training modality—to explore descriptive patterns and associations. In the institutional context, Orán-Muñoz et al. (2026) document the relevance of technological and artificial intelligence competencies for updating professional profiles and making curricular decisions. This precedent complements the rationale for technological innovation at ITP, although it addresses competencies and curriculum design rather than the faculty dimensions measured in the present study.

Figure 1 presents the proposed model. The arrows represent examined or hypothesized relationships, not demonstrated causal relationships. Because of the cross-sectional design and the size of the population, the study cannot confirm statistical mediation or claim that age or training directly produces changes in competencies or practices. The humanistic perspective is represented as a cross-cutting principle guiding the interpretation of all three dimensions.

Figure 1. Proposed analytical model of GenAI literacy, AI-TPACK, and pedagogical integration among higher education faculty.



METHODOLOGY

Research Design

A quantitative, nonexperimental, cross-sectional study was conducted with a descriptive and exploratory correlational scope. Data were collected at a single time point, without manipulating variables or implementing a training intervention. The analysis aimed to describe responses from the identified population and explore associations among dimensions.

Population and Participants

The target population consisted of 35 faculty members in the Department of Economic and Administrative Sciences at Instituto Tecnológico de Pachuca. Thirty-five questionnaires were obtained, representing 100% of the population identified by the academic unit; therefore, this was a census of the defined population rather than a probability sample. The results describe this population at the time of data collection and should not automatically be generalized to other departments or institutions. The analytical dataset was prepared without the institutional email column. All 35 records were retained because they corresponded to distinct participants; a complete match between two records was not considered sufficient grounds to remove a response.

Instrument and procedure

A 34-item questionnaire entitled "Generative Artificial Intelligence and Pedagogical Integration in Higher Education" was used. It included profile and experience questions, ten GenAI literacy items, seven AI-TPACK items, and seven pedagogical integration items. The literacy and AI-TPACK items used a five-point agreement scale; the integration items used a five-point frequency scale. Because the scales have different response anchors, their means are interpreted separately and not as directly equivalent magnitudes. The questionnaire defined GenAI as tools capable of generating content—such as text, images, presentations, or code—in response to user instructions, with ChatGPT, Gemini, and Copilot as examples. The instrument was reviewed by three experts. In the second review, Aiken's V for clarity was 1.000 for 33 items and 0.889 for item 2; relevance and coherence received values of 1.000 for all 34 items. Item 2 was revised based on the feedback. An external pilot test was conducted with 22 faculty members from another institution, who were not included in the main dataset. The pilot assessed comprehensibility and administration, and participants reported an approximate completion time of 12 minutes. Feedback indicated that the GenAI concept required clarification and that some statements could be simplified; accordingly, a GenAI definition was included in the questionnaire instructions and item wording was reviewed. A suggestion to include age was also incorporated into the final instrument. Individual pilot responses were not retained for statistical analysis, so the pilot is reported as a usability and wording review rather than as a psychometric evaluation.

Internal consistency estimated from the main dataset was high: Cronbach's alpha was .977 for GenAI literacy, .979 for AI-TPACK, and .943 for pedagogical integration. These coefficients indicate internal consistency but do not establish construct validity. Their particularly high values also make potential item redundancy worth considering. Since the questionnaire had already been administered to a small population, no items were retrospectively removed and no factor analysis was conducted.

Data analysis

Frequencies, percentages, and item and dimension means were calculated. Internal consistency was estimated using Cronbach's alpha. Spearman's rho correlations were used to explore monotonic relationships, and Kruskal–Wallis tests were used for group comparisons. Age comparisons were supplemented with pairwise Mann–Whitney tests and Holm adjustment. To control multiplicity in the global comparisons by age and learning modality, Holm adjustment was applied to a family of six tests (three dimensions × two contextual variables). Kruskal–Wallis effect sizes (epsilon squared, ε^2) are reported with 95% confidence intervals obtained from 10,000 stratified bootstrap resamples by group. Spearman correlations were also accompanied by 95% confidence intervals based on 10,000 paired bootstrap resamples. The association between grouped age and learning modality was explored using a Monte Carlo permutation test based on the chi-square statistic, due to

low expected frequencies in several cells; Cramér's V was calculated as the effect size. An exploratory linear regression was also estimated, with pedagogical integration as the dependent variable and GenAI literacy and AI-TPACK as predictors, using HC3 robust standard errors. Analyses were conducted in Python 3.14, using pandas for data organization, Pingouin for Cronbach's alpha, SciPy for statistical tests, and statsmodels for regression.

RESULTS AND DISCUSSION

Faculty profile and experience

The participating population included faculty members of different ages, employment arrangements, workloads, and educational attainment levels. By program, 18 participants reported teaching in both degree programs, 15 in Administration, and 2 in Business Management Engineering. Regarding employment arrangement, 19 reported a permanent appointment, 11 reported fee-based contracts, and 5 reported both arrangements. In terms of workload, 18 reported teaching by course, 15 reported full-time employment, and 2 reported part-time employment. The most common academic degree was a master's degree (n = 15), followed by a bachelor's degree (n = 11), doctorate (n = 5), specialty qualification (n = 2), and postdoctoral qualification (n = 2).

Table 1. Self-perceived knowledge, frequency of use, and GenAI learning modality (n = 35).

Indicator	Category	n	%
Self-perceived GenAI knowledge	Basic	18	51.4
Self-perceived GenAI knowledge	Very basic	7	20.0
Self-perceived GenAI knowledge	Intermediate	10	28.6
Frequency of use	Sometimes	17	48.6
Frequency of use	Frequently	9	25.7
Frequency of use	Very frequently	5	14.3
Frequency of use	Rarely	4	11.4
GenAI learning modality	Self-directed	12	34.3
GenAI learning modality	Combination of training and self-directed learning	11	31.4
GenAI learning modality	Institutional training	9	25.7
GenAI learning modality	External training	3	8.6

The most frequent response regarding self-perceived knowledge was "basic" (51.4%), while 20.0% reported a "very basic" level and 28.6% an "intermediate" level. Nearly half reported using GenAI sometimes (48.6%); 40.0% reported frequent or very frequent use, and 11.4% reported rarely using it. The most common learning modality was self-directed learning (34.3%), followed by a combination of training and self-directed learning (31.4%). In response to the question about difficulties, the most frequent answers were a need for training (n = 10), no current difficulty (n = 8), and insufficient knowledge (n = 7). This pattern suggests heterogeneous needs: some faculty identify training barriers, while others report no difficulties.

Table 2. Overall means for the three dimensions. The response scales have different anchors.

Dimension	Items	Overall mean
GenAI literacy	10	3.41
AI-TPACK	7	3.25
Pedagogical integration	7	2.85

GenAI literacy had the highest mean (3.41), followed by AI-TPACK (3.25). Pedagogical integration had a mean of 2.85 on a frequency scale. These figures should not be compared as though they were measured on the same scale: the first two reflect agreement with competency statements, whereas the third reflects the frequency of practices. Nevertheless, the integration mean suggests that reported practices are not performed as frequently as knowledge and ability are perceived. Within the literacy scale, the highest means were observed for items related to understanding and basic use (3.71–3.69), whereas some items related to critical evaluation and application had lower means, around 3.11–3.20. AI-TPACK means ranged from 3.00 to 3.43. For pedagogical integration, item means ranged from 2.66 to 3.31, with lower values for practices involving the transformation or redesign

of activities.

Table 3. Exploratory correlations among the dimensions (Holm-adjusted p values).

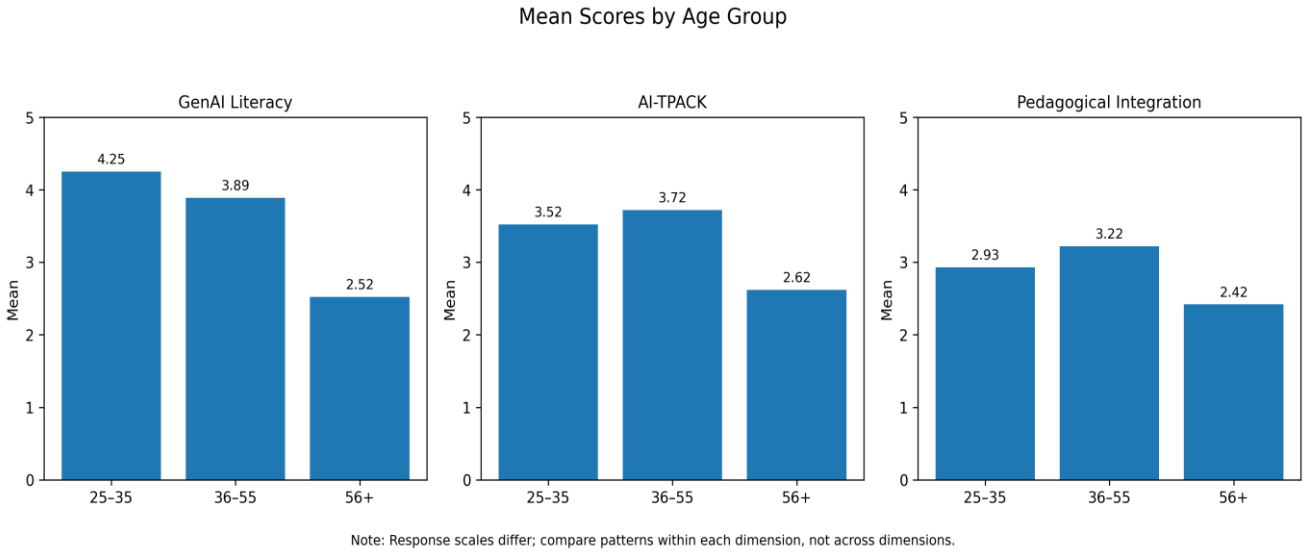
Relationship	Spearman's rho	Unadjusted p	Holm-adjusted p
GenAI literacy – AI-TPACK	0.740	< 0.001	< .001
GenAI literacy – pedagogical integration	0.484	0.003	.006
AI-TPACK – pedagogical integration	0.469	0.004	.006

The strongest association was observed between GenAI literacy and AI-TPACK (rho = .740; 95% bootstrap CI [.494, .899]), followed by literacy and pedagogical integration (rho = .484; 95% CI [.112, .752]) and AI-TPACK and integration (rho = .469; 95% CI [.105, .747]). All three associations were positive and statistically significant before and after Holm adjustment for the three correlations (adjusted p values approximately < .001, .006, and .006, respectively). The confidence intervals are wide, particularly for associations involving integration, and should be interpreted in light of the population size. The findings are consistent with the proposed analytical model but do not demonstrate a causal sequence or statistical mediation.

Table 4. Mean scores for the dimensions by regrouped age categories.

Age group	n	GenAI literacy	AI-TPACK	Integration
25–35	6	4.25	3.52	2.93
36–55	15	3.89	3.72	3.22
56 or older	14	2.52	2.62	2.42

Figure 2. Descriptive comparison of mean scores by age group.



The group aged 56 years or older had descriptively lower means across all three dimensions: 2.52 for literacy, 2.62 for AI-TPACK, and 2.42 for integration. The Kruskal–Wallis test showed a nominal overall difference for literacy ($H = 6.43$, $p = .040$, $\varepsilon^2 = .138$, 95% bootstrap CI [.000, .459]), whereas AI-TPACK ($H = 4.05$, $p = .132$, $\varepsilon^2 = .064$, 95% CI [.000, .373]) and integration ($H = 5.01$, $p = .082$, $\varepsilon^2 = .094$, 95% CI [.000, .452]) did not reach nominal significance. However, after Holm adjustment across the six exploratory global comparisons (age and learning modality for each dimension), the adjusted p value for age-related literacy was .161; no global comparison retained statistical significance. Pairwise age comparisons with Holm adjustment were also nonsignificant. Therefore, these differences are interpreted as descriptive and exploratory, without attributing them to age.

Table 5. Mean scores by reported GenAI learning modality.

Modality	n	Literacy	AI-TPACK	Integration
Self-directed	12	2.69	2.49	2.21

Training + self-directed learning	11	3.30	3.14	3.01
Institutional training	9	4.19	4.10	3.44
External training	3	4.30	4.14	3.00

The highest descriptive means for AI-TPACK and integration were observed among those reporting institutional training (4.10 and 3.44, respectively), whereas the self-directed group had lower means (2.49 and 2.21). Kruskal–Wallis tests showed nominal differences by learning modality for AI-TPACK ($H = 8.93$, $p = .030$, $\varepsilon^2 = .191$, 95% bootstrap CI [.049, .494]) and integration ($H = 10.71$, $p = .013$, $\varepsilon^2 = .249$, 95% CI [.120, .551]), but not for literacy ($H = 6.03$, $p = .110$, $\varepsilon^2 = .098$, 95% CI [.000, .433]). After Holm adjustment across the six global tests, adjusted p values were .151 for AI-TPACK, .080 for integration, and .245 for literacy; none reached .05. The external-training group included only three participants, so its mean is presented for descriptive purposes only.

These findings support considering institutional training as a potential avenue for professional development, but they do not demonstrate that training caused the observed scores. Those with greater interest or experience may be more likely to seek training, or the groups may have differed beforehand. A subsequent evaluation should include measurements before and after a training intervention and, if possible, a comparison group.

Table 6. Distribution of GenAI learning modality by age group (n = 35).

Age group	Self-directed	Institutional training	External training	Training + self-directed
25–35 years	2	1	1	2
36–55 years	3	5	2	5
56 years or older	7	3	0	4
Total	12	9	3	11

Note. The Monte Carlo permutation test did not detect an association between grouped age and learning modality ($p = .619$; Cramér's $V = .258$). Given the low frequencies in several cells, this result is interpreted as exploratory.

Implications for technological innovation

Taken together, the findings suggest a descriptive gap between self-perceived competencies and the reported frequency of pedagogical integration. The proposed model may guide a faculty development strategy with three components: (1) GenAI literacy, focusing on verification, limitations, bias, privacy, and authorship; (2) AI-TPACK knowledge, through the design of activities aligned with subject content and learning outcomes; and (3) pedagogical integration, assessing whether GenAI serves the instructional purpose rather than merely automating a task.

Training should offer differentiated pathways based on experience and needs, avoiding the assumption that age determines digital competence. It is also advisable to promote communities of practice, contextualized examples for Administration and Business Management Engineering, institutional guidance on data and responsible use, and explicit criteria for declaring or documenting GenAI use. The goal is not to maximize tool use, but to develop intentional, critical, learning-centered integration.

CONCLUSION

This study provides a descriptive diagnostic of GenAI literacy, AI-TPACK, and pedagogical integration among the 35 faculty members in the Department of Economic and Administrative Sciences at Instituto Tecnológico de Pachuca. The means were 3.41, 3.25, and 2.85, respectively, bearing in mind that the response scales have different anchors. GenAI literacy was positively associated with AI-TPACK, and both dimensions were associated with pedagogical integration. The findings support the value of analyzing general GenAI literacy, technopedagogical knowledge, and teaching practices as distinct dimensions.

The group aged 56 or older had descriptively lower scores. The overall age-group difference was nominally

significant only for literacy, and pairwise comparisons with adjustment were not significant. By learning modality, nominal overall differences were observed for AI-TPACK and integration, with higher means in the institutional-training group; however, none of the six global comparisons remained significant after Holm adjustment. These findings suggest prioritizing structured, practical, and contextualized training opportunities without interpreting them as causal effects.

Limitations include the cross-sectional design, the small and localized population, self-reported measures, the absence of objective performance assessment, and the lack of factor-validity evidence. High internal-consistency coefficients may reflect item overlap and should not be interpreted as proof of validity. The analytical model is a proposal and has not been validated as a causal or mediation model. Future research could include a larger population, performance-based assessments, observation of teaching practices or artifacts, and pre–post evaluations of interventions. The exploratory regression model was statistically significant overall ($R^2 = .380$; adjusted $R^2 = .342$; $F(2, 32) = 6.186$, $p = .005$), but neither predictor was individually significant (GenAI literacy: $B = .269$, $p = .174$, 95% CI [−.119, .658]; AI-TPACK: $B = .196$, $p = .259$, 95% CI [−.144, .537]). Therefore, it is not interpreted as evidence of independent or causal effects.

As a practical contribution, the model is proposed as a diagnostic guide for informing faculty training and designing future research, while maintaining a humanistic approach in which technology complements—rather than replaces—professional judgment, autonomy, and educational interaction.

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Ethical Approval

The questionnaire administration received institutional authorization from the Academic Subdirectorate and academic authorization from the Department of Economic and Administrative Sciences through its head and academic committee (Academia). The need for the diagnostic study was discussed in the department's Academia to identify faculty training needs. Participation was voluntary, and informed consent was obtained from participants in both the pilot and the main study. No approval from an institutional ethics committee or approval number is claimed.

Conflict Of Interest

The authors declare that they have no conflict of interest related to the conduct of this research, the analysis of the results, or publication of the article.

Data Availability

The questionnaire used in this study and the anonymized dataset supporting the results are available from the corresponding author upon reasonable request, subject to applicable institutional and ethical considerations. The tables presented in the manuscript summarize the main findings and describe the constructs and dimensions assessed.

REFERENCES

1. Çelik, I. (2023). Towards Intelligent-TPACK: An empirical study on teachers' professional knowledge to ethically integrate artificial intelligence (AI)-based tools into education. Computers in Human Behavior, 138, Article 107468. https://doi.org/10.1016/j.chb.2022.107468
2. Eyal, L. (2025). Developing and validating an AI-TPACK assessment framework: Enhancing teacher educators' professional practice through authentic artifacts. Education Sciences, 15(11), Article 1452. https://doi.org/10.3390/educsci15111452
3. Hamilton, E. R., Rosenberg, J. M., & Akcaoglu, M. (2016). The Substitution Augmentation Modification

Redefinition (SAMR) Model: A critical review and suggestions for its use. TechTrends, 60(5), 433–441. https://doi.org/10.1007/s11528-016-0091-y

4. Jin, Y., Martinez-Maldonado, R., Gašević, D., & Yan, L. (2025). GLAT: The generative AI literacy assessment test. Computers and Education: Artificial Intelligence, 9, Article 100436. https://doi.org/10.1016/j.caeai.2025.100436
5. Martínez Rodríguez, R. del C., Benítez Corona, L., Hernández Márquez, J., Guerrero Azpeitia, L. A., Muñoz Orán, M., & Robles Gutiérrez, M. P. (2025). The smart education contribution to lifelong learning. In J. A. Ruiz-Vanoye & O. Díaz-Parra (Eds.), Revolutionizing pedagogy through smart education (pp. 43–62). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3693-7793-2.ch003
6. Miao, F., & Holmes, W. (2023). Guidance for generative AI in education and research. UNESCO. https://doi.org/10.54675/EWZM9535
7. Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. Teachers College Record, 108(6), 1017–1054. https://doi.org/10.1111/j.1467-9620.2006.00684.x
8. Orán-Muñoz, M. G., González-Mosqueda, M. L., Martínez-Tapia, K., Ávila-Pérez Tagle, A., Mohedano-Torres, E. J., Chiapa-Téllez, F., & Marrón Ramos, D. N. (2026). Data pipeline architecture for the integration of technology and artificial intelligence in the competencies of the future manager. International Journal of Combinatorial Optimization Problems and Informatics, 18(1), 189–199. https://doi.org/10.61467/2007.1558.2027.v18i1.1509
9. Wang, Y., Derakhshan, A., & Ghiasvand, F. (2025). EFL teachers' generative artificial intelligence (GenAI) literacy: A scale development and validation study. System, 133, Article 103791. https://doi.org/10.1016/j.system.2025.103791
10. Xia, Q., Yang, Y., Weng, X., Cilsalar-Sagnak, H., Cheng, W. K., & Chiu, T. K. F. (2026). Generative artificial intelligence competency self-efficacy scale for teachers and researchers (GAICS-TR) in higher education. Journal of Computers in Education, 13, 769–793. https://doi.org/10.1007/s40692-025-00373-y