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THE COMPETENCE-TECHNOLOGY GAP IN TEACHING: EMPIRICAL EVIDENCE FROM AN AI-TPACK STUDY IN PORTUGUESE SCHOOLS

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Generative Artificial Intelligence (GenAI) is being rapidly adopted in schools, raising urgent questions about teachers' readiness to integrate it pedagogically. This study examines the levels and structure of Portuguese primary and secondary teachers' self-perceived knowledge of GenAI, using the AI-TPACK framework. A structured online questionnaire was administered to 203 teachers across disciplinary areas. Descriptive and inferential analyses examined overall knowledge, dimensional differences, and the role of personal and professional variables. Results show a moderate overall score (M = 3.58, SD = 0.64), with significantly higher means in traditional dimensions (CK: M = 4.40; PK: M = 4.26; PCK: M = 4.13) than in AI-specific ones (AI-TK: M = 3.06; AI-TCK: M = 3.03; AI-TPK: M = 3.01). Neither disciplinary area nor age predicted AI-TPACK scores. Prior AI-specific training, however, was associated with large differences across all AI dimensions (Cohen's d = 0.95–1.19). Findings reveal a structurally asymmetric competence profile that cuts across disciplines and age cohorts, and that responds robustly to structured training. Implications for teacher education, professional development policy, and the Portuguese digital competence framework are discussed.

***Keywords**: AI-TPACK, Generative Artificial Intelligence, Teacher Knowledge, Teacher Education, Digital Competence, Professional Development*

INTRODUCTION

The rapid proliferation of Generative Artificial Intelligence tools in educational settings has foregrounded a critical, yet insufficiently examined, question: to what degree are teachers prepared to engage with these technologies in ways that are purposeful, contextually appropriate, and ethically grounded? The extant literature, while rich in theoretical elaboration of the affordances and risks of GenAI in education (Bender *et al.* 2021; Holmes *et al.* 2019; UNESCO 2023), has

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hitherto devoted comparatively limited empirical attention to the specific professional knowledge profiles of practising teachers, a lacuna that this study seeks to address. Accordingly, the overarching aim is to map the levels and structure of primary and secondary school teachers' knowledge across the multidimensional construct operationalised through the AI-TPACK framework. This question is particularly salient in the Portuguese context, where the Plano de Ação para a Transição Digital (Resolution of the Council of Ministers No. 30/2020) has established national policy frameworks for digital competence development that are now being tested against the unprecedented pace of GenAI adoption in schools.

Five interrelated research questions, derived from and aligned with the theoretical architecture of the AI-TPACK model, structured the empirical inquiry:

RQ1: What is the overall level of GenAI knowledge among Portuguese primary and secondary teachers as measured by the AI-TPACK scale?

RQ2: How is this knowledge distributed across the seven dimensions of the AI-TPACK model?

RQ3: Do significant differences in AI-TPACK knowledge exist between teachers of different disciplinary areas (STEM vs. non-STEM and between recruitment groups)?

RQ4: Does AI-TPACK knowledge level vary significantly as a function of teacher age?

RQ5: What is the role of prior GenAI-specific training in predicting AI-TPACK knowledge levels?

Three directional hypotheses, derived from the theoretical framework and from prior empirical findings, were advanced to guide the inferential analyses:

H1: (Disciplinary Differences): Grounded in the disciplinary proximity argument − which holds that epistemic familiarity with formal and computational reasoning confers an advantage in the acquisition of AI-related competencies − it is hypothesised that statistically significant differences in AI-TPACK scores will be observed between STEM and non-STEM teachers, with the former demonstrating markedly higher performance particularly on AI-TK and AI-TCK dimensions (Yue, Jong, and Ng 2024).

H2: (Age Effects): Drawing on theoretical perspectives on digital nativity and generational technology socialisation, it is hypothesised that AI-TPACK knowledge levels will exhibit significant inter-group variation as a function of teacher age, albeit with a directionally ambiguous pattern: whilst older teachers may present stronger scores in conventional knowledge domains (CK, PK) by virtue of accumulated professional experience, younger cohorts may demonstrate comparative advantage in AI-specific dimensions, consistent with differential trajectories of technology exposure and adoption (Parreira, Lehmann, and Oliveira 2021; Yue, Jong, and Ng 2024).

H3: (Inter-dimensional Variation): Consistent with the convergent empirical finding, variously described in the literature as a "competence-technology gap" or "technological knowledge asymmetry," it is hypothesised that statistically significant differences will emerge across the seven AI-TPACK dimensions, with teachers demonstrating systematically higher mean scores in foundational knowledge domains (CK, PK) relative to the AI-specific and integrative dimensions (AI-TK, AI-TPK, AI-TCK, AI-TPACK), reflecting the structurally uneven distribution of competencies that characterises early-stage integration of disruptive technologies in professional practice.

THEORETICAL BACKGROUND

Generative Artificial Intelligence in Education

The accelerating integration of Generative Artificial Intelligence into educational contexts instantiates what Holmes *et al.* (2019) characterised as a structurally transformative inflection point − one that simultaneously expands the epistemic and pedagogical horizon of schooling and introduces a constellation of ethical, epistemological, and institutional challenges that existing frameworks are only partially equipped to address. The ability of these systems to generate content, such as text or images, is transforming the ways in which information is created, accessed, and used in educational settings. This epistemic disruption, as UNESCO (2023) underscores, necessitates not merely the adoption of new tools but a substantive reconfiguration of the pedagogical rationalities that govern their use − a reconfiguration that places heightened demands on teachers' capacity for critical, contextually sensitive, and ethically informed judgment.

Binhammad and Shaalan (2024) situate this adaptability within a broader personalisation paradigm, arguing that the ability to modulate content, pacing, and feedback in response to individual learner profiles can substantively enhance both cognitive engagement and meaningful knowledge construction. Complementary to this, Dickey and Bejarano (2024) demonstrate that GenAI tools can serve as instrumental resources for teachers in the design of instructional materials, task scaffolding, and formative feedback provision − functions that may free teachers' time for higher-order pedagogical mediation and relational engagement with learners.

These affordances, however, must be held in productive tension with a substantive body of critical scholarship that interrogates the epistemological and socio-political risks attending the uncritical deployment of GenAI systems. Bender *et al.* (2021), in their foundational critique of large language models, draw attention to what they term the "stochastic parrot" problem — the tendency of these systems to produce statistically plausible yet factually unreliable or ideologically skewed outputs that may, under conditions of insufficient critical literacy, be uncritically

assimilated by both teachers and students. This concern intersects with Garcia's (2020) analysis of algorithmic reproduction of structural inequalities: insofar as AI systems are trained on historically and socially situated corpora, their outputs inevitably reflect and may amplify the epistemic and representational asymmetries embedded within those data, raising profound questions of educational equity.

It is against this backdrop of competing affordances and risks that the ethical dimensions of GenAI integration in education assume their full salience. UNESCO (2024) positions data protection, algorithmic transparency, and the principle of human oversight not as peripheral compliance requirements but as constitutive features of any educationally defensible framework for AI use. The particular vulnerability of children and young people as both data subjects and as epistemically developing agents renders these provisions especially urgent, and implies that teacher competence in navigating the ethical landscape of GenAI is not optional but foundational.

From a pedagogical standpoint, the discourse of replacement — the proposition that AI tools might displace or render redundant the professional role of the teacher — is both empirically unsupported and theoretically misleading. On the contrary, as Soares*et al.* (2024) argue, the effective integration of GenAI into instructional practice demands forms of professional agency, critical reflexivity, and pedagogical intentionality that are constitutively irreducible to technical proficiency: the teacher's role is not diminished but reconstituted, requiring a more sophisticated and deliberate exercise of judgment precisely because the technological mediation of learning becomes more complex.

Notwithstanding the theoretical elaboration of these affordances and risks, the empirical literature on how practising teachers actually integrate — or fail to integrate — GenAI into their situated professional practice remains comparatively sparse, fragmented across disciplinary contexts, and methodologically heterogeneous. This lacuna not only constrains the evidence base available to inform policy and practice, but also points to the need for theoretically grounded, empirically rigorous investigations capable of mapping the specific knowledge configurations and competency gaps that characterise teachers' current relationship with GenAI.

Teacher Knowledge and Technology Integration

The conceptualisation of teacher professional knowledge as a multi-componential, domain-specific, and pedagogically constituted construct has occupied a central position in educational research since Shulman's (1986, 1987) landmark reconceptualisation of teaching as a knowledge-intensive profession. Shulman's foundational distinction between content knowledge, pedagogical knowledge, and Pedagogical Content Knowledge (PCK) − the latter understood as the capacity to transform disciplinary knowledge into forms that are epistemically accessible and developmentally appropriate for specific learners in specific

contexts − established a productive analytical grammar for examining the cognitive architecture of teaching, one that has since been extended, contested, and refined across multiple theoretical traditions.

The emergence of digital technologies as structurally consequential features of educational practice prompted a significant reconceptualisation of this framework. Mishra and Koehler's (2006) Technological Pedagogical Content Knowledge (TPACK) model extended Shulman's tripartite structure by introducing technology as a third constitutive domain, theorising the interactions between technological, pedagogical, and content knowledge not as additive but as dynamically interdependent and mutually transformative. The epistemological contribution of TPACK lies precisely in its insistence that technological proficiency, abstracted from its pedagogical and disciplinary context, is insufficient as a basis for effective teaching: what matters is the quality of the integrative judgments that teachers make at the intersections of these knowledge domains.

The advent of Generative Artificial Intelligence has introduced a further and arguably more radical reconfiguration of this theoretical landscape. Mishra *et al.*'s (2023) AI-TPACK model extends the TPACK architecture to encompass the distinctive epistemic and operational demands posed by AI systems — demands that include not only the technical understanding of how these tools function, but also the capacity to critically interrogate the outputs they generate, to assess their pedagogical and ethical appropriateness across different disciplinary and learner contexts, and to exercise situated judgment about when, how, and with what objectives they ought to be deployed. This extension is not merely additive: it implies a qualitatively different order of professional knowledge, one that requires teachers to engage simultaneously with rapid technological change, disciplinary specificity, and normative educational values.

Within this reconstituted theoretical landscape, teacher knowledge assumes an explicitly multidimensional and relational character. The operative question is no longer simply whether a teacher can use a given tool, but whether they possess the epistemic resources to interrogate its design assumptions, assess its outputs critically, align its use with specific curricular and pedagogical objectives, and navigate its ethical implications in ways that are responsive to the particular vulnerabilities and capacities of their students (Mishra *et al.* 2023). This demands a form of professional knowledge that is simultaneously technical, hermeneutic, and normative − a constellation of competencies that existing pre-service and in-service training programmes are, by most accounts, inadequately prepared to cultivate.

The analytical purchase of the AI-TPACK model, in this regard, derives from its capacity to render legible precisely those integrative competencies that are most consequential for the responsible and effective use of GenAI in educational practice, yet most difficult to capture through unidimensional measures of technical literacy or general digital competence. As UNESCO (2023) makes explicit, what is required is not the sequential acquisition of separate competency domains − first

technical, then pedagogical, then ethical − but their simultaneous and mutually constitutive development within the professional cultures and institutional structures of schools.

In the present study, the AI-TPACK model fulfils a dual function: it provides the conceptual scaffolding through which the construct of teacher knowledge of GenAI is theorised and operationalised, and it supplies the analytical grammar through which empirically observed knowledge profiles can be interpreted in relation to their practical and policy implications.

METHODS

Research Design

This study is positioned within a post-positivist epistemological framework (Creswell 2010; Fortin 2009), adopting a quantitative, descriptive-correlational, cross-sectional design as its primary methodological configuration. The post-positivist orientation is epistemologically appropriate insofar as it treats AI-TPACK knowledge as an empirically accessible, structurally stable, and statistically characterisable construct − whilst simultaneously acknowledging that measurement instruments inevitably provide partial and fallible approximations of the underlying latent variable, and that the findings generated must therefore be interpreted with appropriate epistemic humility (Coutinho 2011). The hypothetico-deductive logic structuring the study − whereby formal propositions derived from the AI-TPACK theoretical framework are subjected to empirical falsification through inferential analysis − enables the articulation of theory-driven research questions with systematic empirical inquiry, thereby enhancing both the interpretive depth and the transferable value of the findings.

The survey design was selected on both pragmatic and methodological grounds: it enables the collection of standardised, comparable data from a geographically dispersed and professionally heterogeneous teacher population, whilst the psychometric properties of the adapted AI-TPACK instrument − established through the validation procedures detailed in the section "**Instrument Adaptation and Statistical Validation**" − provide adequate justification for its use as a self-report measure of knowledge and confidence constructs (DeVellis 2017). The cross-sectional configuration, whilst appropriate for the descriptive and correlational objectives of the present enquiry, carries inherent limitations with respect to causal inference and the detection of developmental trajectories in knowledge acquisition; these are addressed in the limitations section.

Participants

The target population comprised all teachers working in Portuguese primary and secondary education (Grades 1–12), including basic education (1st, 2nd, and

3rd cycles) and secondary education, as well as professional and adult education programmes. No restrictions were applied regarding subject area, teaching experience, or type of school (public or private).

The non-probabilistic purposive-convenience sampling strategy was selected as appropriate for exploratory research contexts characterised by population heterogeneity and the absence of accessible sampling frames (Taherdoost 2016; Coutinho 2011). The potential for self-selection bias, which may systematically overrepresent teachers with pre-existing interest in or exposure to digital technologies, is recognised as a constraint on the external validity of the findings.

The final sample included 203 teachers. The gender distribution reflected the national profile (CNE 2023) with 75.4% female (n = 153) and 24.6% male (n = 50). The sample was predominantly composed of mid-career and senior teachers: 47.8% were aged 46–55 (n = 97), 27.6% aged 36–45 (n = 56), 15.3% over 55 (n = 31), 7.4% aged 26–35 (n = 15), and 2.0% under 26 (n = 4). Consistent with this distribution, 47.3% reported more than 20 years of teaching experience (n = 96). Academic qualifications were mainly undergraduate degrees (44.8%, n = 91) and master's degrees (36.5%, n = 74), followed by postgraduate diplomas (14.8%, n = 30) and doctorates (3.0%, n = 6).

All Portuguese teaching groups/areas were represented, and for analysis, groups were classified as STEM (n = 84, 41.4%) and non-STEM (n = 119, 58.6%).

Instrument

Data were collected through a structured online questionnaire administered via EUSurvey, the European Commission's secure platform, which ensures GDPR compliance and prevents post-submission data access by participants. Data collection took place between 14 April and 13 May 2025. Participation was voluntary and anonymous, and informed consent was obtained from all respondents.

The online questionnaire comprised three sections, totalling 86 items (Q1.1–Q3.7.6):

Section 1 - Socio-professional characteristics (Q1.1–Q1.8): closed-ended items covering gender, age, academic qualifications, recruitment group, teaching level, years of service, and professional status.

Section 2 - Technology and AI use and training (Q2.1–Q2.36): 36 items examining training in digital technologies and AI, perceived impact of training, use of digital and GenAI tools in teaching, familiarity with specific GenAI platforms (e.g., ChatGPT, Gemini, Copilot, DALL·E), confidence in AI integration, training needs, and perceived barriers.

Section 3 - AI-TPACK scale (Q3.1.1–Q3.7.6): 42 items assessing AI-TPACK knowledge across seven dimensions, rated on a five-point Likert scale (1 = strongly disagree; 5 = strongly agree).

The AI-TPACK scale used in Section 3 is a Portuguese adaptation of the instrument developed by Ning *et al.* (2024), based on the theoretical framework of Mishra *et al.* (2023). Specifically, whilst Mishra *et al.* (2023) proposed the AI-TPACK model as a theoretical extension of the original TPACK framework (Mishra and Koehler 2006), Ning *et al.* (2024) operationalised this model as a validated psychometric instrument, enabling its application in empirical survey research. The present study extends this line of inquiry by adapting and validating the Ning *et al.* (2024) instrument for the Portuguese educational context, thereby contributing to the cross-cultural portability of AI-TPACK measurement. Each of the seven dimensions is measured by six items, as detailed in *Table no. 1*.

Table no. 1

AI-TPACK Scale: Dimensions, Item Codes, and Construct Descriptions

Dimension	Items	Construct	Example item
CK	Q3.1.1–Q3.1.6	Content Knowledge	I have a solid understanding of the concepts and principles of the subjects I teach.
PK	Q3.2.1–Q3.2.6	Pedagogical Knowledge	I am able to use diverse teaching methodologies in the classroom.
AI-TK	Q3.3.1–Q3.3.6	AI Technological Knowledge	I am familiar with AI technologies in educational settings.
PCK	Q3.4.1–Q3.4.6	Pedagogical Content Knowledge	I am proficient in designing curriculum plans.
AI-TCK	Q3.5.1–Q3.5.6	AI Technological Content Knowledge	I can select AI tools appropriate to the content I am teaching.
AI-TPK	Q3.6.1–Q3.6.6	AI Technological Pedagogical Knowledge	I can use AI to optimise my pedagogical practices.
AI-TPACK	Q3.7.1–Q3.7.6	Integrated AI-TPACK	I have knowledge of how to use AI integrated with content and teaching methods to improve classroom effectiveness.

*Note:*Items translated and adapted from Ning *et al.* (2024). CK = Content Knowledge; PK = Pedagogical Knowledge; AI-TK = AI Technological Knowledge; PCK = Pedagogical Content Knowledge; AI-TCK = AI Technological Content Knowledge; AI-TPK = AI Technological Pedagogical Knowledge; AI-TPACK = integrative construct.

Instrument Adaptation and Statistical Validation

Translation and Cultural Adaptation

The absence of a psychometrically validated Portuguese-language version of the AI-TPACK questionnaire originally developed by Ning *et al.* (2024) necessitated a comprehensive process of cross-cultural adaptation, encompassing translation, cultural and curricular contextualisation, and systematic psychometric validation. This process was conducted in accordance with established international protocols for cross-cultural scale adaptation (e.g., Beaton *et al.* 2000), which prescribe iterative procedures designed to preserve conceptual equivalence across linguistic and cultural contexts whilst ensuring that the adapted instrument is sensitive to the specificities of the target educational system.

Following the formal authorisation of the original authors, a forward–backward translation procedure was conducted by a qualified professional translator with expertise in educational research terminology, ensuring the semantic and pragmatic equivalence of the adapted items. The resulting Portuguese version was subsequently subject to systematic review by a panel of educational researchers and practising teachers, whose evaluative judgments informed targeted revisions to items whose literal translation, whilst semantically accurate, carried connotations or presupposed institutional referents poorly suited to the Portuguese educational context. The iterative character of this adaptation process, moving between linguistic fidelity and contextual validity, were essential to the interpretive legitimacy of the findings.

Psychometric Validation

Psychometric evaluation of the adapted instrument was conducted within a classical test theory framework, addressing three inter-related dimensions of measurement quality: sensitivity, internal consistency reliability, and construct validity. Item-level sensitivity was assessed through distributional statistics (skewness, kurtosis, mean, and standard deviation), with thresholds of $|Sk| < 3$ and $|Ku| < 7$ − consistent with Marôco (2014) and Kline (2016) − adopted as indicative of acceptable univariate normality; all items met these criteria, confirming adequate discriminatory capacity. Internal consistency was evaluated via Cronbach's alpha (α), with item-total correlations ($r \geq 0.30$) and alpha-if-item-deleted statistics examined to identify and, where necessary, address items that attenuated subscale reliability; all seven AI-TPACK dimensions attained coefficients exceeding the conventional threshold of $\alpha \geq 0.70$ (Nunnally and Bernstein 1994). An overall Cronbach's alpha of 0.96 was obtained for the full scale, with values above 0.80 across all seven dimensions (CK, $\alpha = 0.81$; PK, $\alpha = 0.86$; AI-TK, $\alpha = 0.90$; PCK, $\alpha = 0.80$; AI-TCK, $\alpha = 0.94$; AI-TPK, $\alpha = 0.97$; AI-TPACK, $\alpha = 0.93$).

Construct validity was examined through factorial analysis, with factor loadings ($\lambda \geq 0.40$), Kaiser–Meyer–Olkin sampling adequacy indices (KMO $\geq$ 0.60), and significant Bartlett's tests of sphericity ($p < 0.05$) confirming both the factorability of the correlation matrix and the structural alignment of the adapted instrument with the theoretical dimensionality of the AI-TPACK model. The confirmatory factor analysis revealed acceptable fit indices for the seven-factor model to the empirical sample data ($\chi^2(798) = 1644.17$, $p < 0.001$; Comparative Fit Index (CFI) = 0.90; Tucker–Lewis Index (TLI) = 0.89; Root Mean Square Error of Approximation (RMSEA) = 0.07, 90% CI [0.07, 0.08]; Standardized Root Mean Square Residual (SRMR) = 0.05; Akaike Information Criterion (AIC) = 15859.58; Bayesian Information Criterion (BIC) = 16346.62). Although the chi-square value is significant (which is common in large samples), the remaining indices suggest an overall acceptable fit of the model to the data (Hu and Bentler 1999). A CFI value of 0.90 and a TLI close to 0.90 indicate a good level of model fit. The RMSEA value of 0.07, with the upper limit of the confidence interval at 0.08, is considered marginally acceptable, while the SRMR value below 0.08 further supports the adequacy of the proposed model.

Data Collection Procedure

The online questionnaire was disseminated between 14 April and 13 May 2025 via EUSurvey, the European Commission's GDPR-compliant platform. Recruitment followed a non-probabilistic purposive-convenience and snowball strategy, operationalised through professional social networks (Facebook teacher communities, WhatsApp channels), institutional mailing lists, and collaborative teacher networks. The survey link was accompanied by a participant information sheet detailing the study's objectives, the voluntary and anonymous nature of participation, and the right to withdraw at any stage without prejudice. Informed consent was obtained from all participants prior to questionnaire completion. The estimated response rate cannot be precisely determined given the snowball design; however, the final sample (N = 203) was obtained from an estimated distribution to approximately 600–800 contacts, implying a provisional response rate in the range of 25–34%.

Data Analysis Procedure

All statistical analyses were conducted using Jamovi (version 2.6.26.0) within a structured, sequential analytical protocol. The initial phase comprised systematic data screening, encompassing verification of missing data patterns, detection and examination of potential univariate and multivariate outliers, and assessment of the distributional properties of all continuous variables. The subsequent descriptive phase characterised both the sample and the distribution of AI-TPACK scores across dimensions, providing the empirical foundation for the

inferential analyses that followed. The choice of inferential procedures was guided by the distributional properties of each variable analysed. Given evidence of non-normal distribution in several subscale scores, non-parametric procedures were used for the dimension-level analyses: Spearman's rho was employed to examine the inter-dimensional correlational structure, and the Friedman test for related samples, followed by Bonferroni-corrected pairwise comparisons, was used to compare scores across the seven AI-TPACK dimensions. By contrast, the global AI-TPACK score showed an approximately normal distribution (Sk = 0.07; Ku = −0.52; Shapiro–Wilk W = 0.99, p = 0.086), and group comparisons based on this score were therefore conducted with parametric procedures: an independent-samples Student's t-test was used to compare STEM and non-STEM teachers, and Welch's one-way ANOVA was used to compare the five age groups. Independent-samples t-tests with Welch's correction were applied to examine the effects of prior AI training across the AI-TPACK dimensions. Prior AI training was operationalised as a binary variable (yes/no) based on participants' self-report of having completed at least one formal or structured training activity specifically focused on Artificial Intelligence for educational purposes (including online courses, workshops, institutional professional development programmes, or equivalent). Informal or incidental exposure (e.g., self-directed use of AI tools without structured training) was explicitly excluded from this definition. The decision to apply parametric t-tests to this comparison, even though several AI-specific subscale scores departed from normality, was grounded in the established robustness of the t-test to violations of normality when group sizes are adequate (n_1 = 81 and n_2 = 122; Field 2018), with Welch's correction adopted given the unequal group sizes, and is consistent with precedent in comparable AI-TPACK survey studies (e.g., Ning *et al.* 2024). The alpha level was set at $p < 0.05$ for all tests, and effect sizes (Cohen's d, Kendall's W, ω^2) were systematically reported to enable substantive interpretation of statistically significant results, consistent with contemporary reporting standards for quantitative educational research.

Ethical Considerations

The conduct of this study was governed by the ethical principles applicable to social science research involving human participants, in accordance with both institutional requirements and supranational regulatory frameworks. Prior to data collection, formal ethical approval was obtained from the institutional ethics committee, providing independent verification of the study's compliance with the core principles of voluntary participation, fully informed consent, and proportionate data protection. Participants were provided with comprehensive written information regarding the study's objectives, the nature and scope of their involvement, the procedures governing data handling, and their unconditional right to withdraw at any point without prejudice. The decision to administer the

questionnaire through the EUSurvey platform − an instrument developed and maintained by the European Commission specifically to ensure GDPR compliance − reflects a deliberate commitment to procedural rigour in data protection, encompassing anonymisation at point of collection, secure server-side storage, and the structural exclusion of post-submission data access by respondents.

RESULTS

Overall Level of Teachers' Knowledge of GenAI

The aggregate analysis of AI-TPACK scores across the full sample indicates a moderate overall level of self-perceived knowledge of Generative Artificial Intelligence, positioning the majority of participants at an intermediate stage of competence development. The global mean score was M = 3.58 (SD = 0.64), with a median of 3.57 and a mode of 3.48, positioning the central tendency of responses between "neutral" and "agree" on the Likert scale. The relatively constrained standard deviation suggests a moderate degree of distributional homogeneity, indicating that the sample does not bifurcate into clearly distinct subgroups of high and low competence, but rather clusters around a shared centrist position. The distributional properties support the assumption of approximate normality: skewness (Sk = 0.07) and kurtosis (Ku = −0.52) fall well within accepted thresholds, a finding corroborated by the non-significant Shapiro–Wilk test (W = 0.99, p = 0.086). The boxplot analysis further reveals that the central 50% of observations fall within the interval Q1 = 3.14 to Q3 = 4.02, with no extreme outliers, reinforcing the characterisation of the distribution as compact and approximately symmetric.

Table no. 2

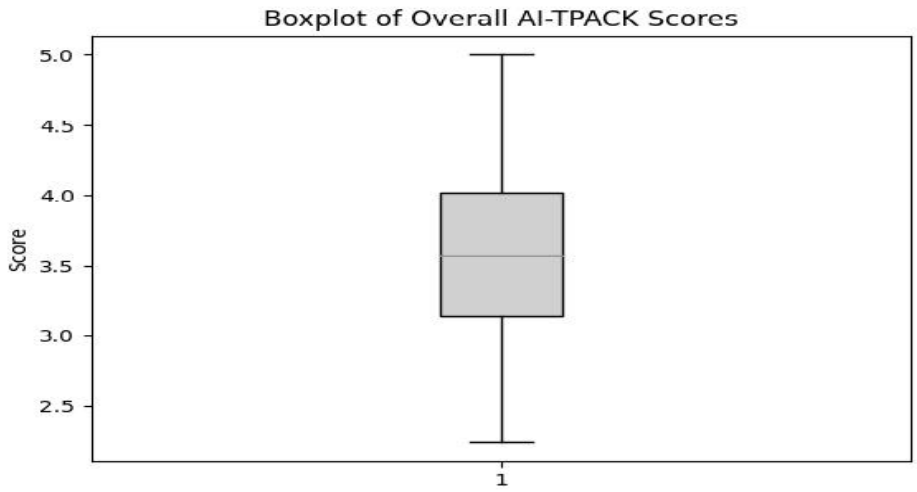
Descriptive Statistics of the Global AI-TPACK Score

M	*Mdn*	*Mo*	*SD*	*Var*	*Min*	*Max*	*Sk*	*Ku*	*W*	*p*	*Q1*	*Q3*
3.58	3.57	3.48	0.64	0.41	2.24	5.00	0.07	-0.52	0.99	0.08	3.14	4.02

Note: M = mean; Mdn = median; Mo = mode; SD = standard deviation; Var = variance; Sk = skewness; Ku = kurtosis; W = Shapiro–Wilk statistic; p = significance level.

Figure 1

Boxplot of overall AI-TPACK scores.



A global mean of 3.58 on a five-point scale must, however, be read in light of the dimensional disaggregation presented in the section "**Analysis by AI-TPACK Dimensions**": the aggregate figure conceals marked inter-dimensional disparities, and it is these asymmetries, rather than the overall score, that carry the most consequential implications for professional development design.

Analysis by AI-TPACK Dimensions

The dimensional disaggregation of AI-TPACK scores reveals a pattern of structural asymmetry that constitutes the central empirical finding of this study. Descriptive analysis across the seven dimensions of the model yields a coherent and theoretically interpretable profile in which traditional knowledge domains − those predating the emergence of AI-specific competency requirements − are systematically and substantially stronger than their AI-specific counterparts.

Content Knowledge (CK; M = 4.40, SD = 0.50), Pedagogical Knowledge (PK; M = 4.26, SD = 0.50), and Pedagogical Content Knowledge (PCK; M = 4.13, SD = 0.47) all attain mean scores in the upper range of the scale, reflecting a degree of perceived competence that approaches ceiling in the case of CK. In marked contrast, the AI-specific dimensions present substantially lower and more variable scores: AI-TK (M = 3.06, SD = 1.00), AI-TCK (M = 3.03, SD = 1.10), and AI-TPK (M = 3.01, SD = 1.17). The integrative AI-TPACK dimension (M = 3.17, SD

= 1.04) occupies an intermediate position, which is theoretically unsurprising given that integration presupposes command of the constituent knowledge domains.

Table no. 3

Descriptive Statistics of AI-TPACK Dimensions

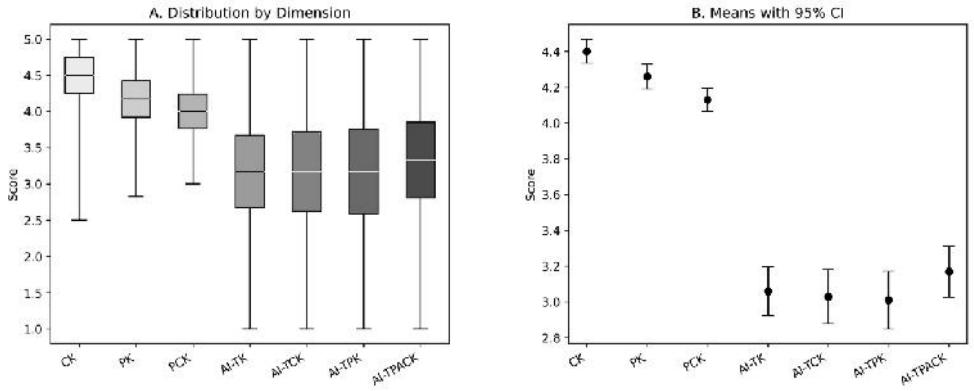
Dimension	***M***	***Mdn***	***Mo***	***SD***	***Var***	***Min***	***Max***
CK	4.40	4.50	5.00	0.50	0.25	2.50	5.00
PK	4.26	4.17	4.00	0.50	0.25	2.83	5.00
PCK	4.13	4.00	4.00	0.47	0.22	3.00	5.00
AI-TK	3.06	3.17	3.67	1.00	0.99	1.00	5.00
AI-TCK	3.03	3.17	4.00	1.10	1.22	1.00	5.00
AI-TPK	3.01	3.17	1.00	1.17	1.36	1.00	5.00
AI-TPACK	3.17	3.33	4.00	1.04	1.09	1.00	5.00

*Not*e: M = mean; Mdn = median; Mo = mode; SD = standard deviation; Var = variance.
CK = Content Knowledge; PK = Pedagogical Knowledge; PCK = Pedagogical Content Knowledge; AI-TK = Artificial Intelligence Technological Knowledge; AI-TCK = Artificial Intelligence Technological Content Knowledge; AI-TPK = Artificial Intelligence Technological Pedagogical Knowledge; AI-TPACK = integrated dimension.

The markedly elevated standard deviations in the AI-specific dimensions — more than double those observed in the traditional domains — carry interpretive significance beyond mere statistical description: they indicate that, in contrast to the broad consensus observable around teachers' competence in conventional pedagogical domains, perceptions of AI-related competence are substantially more heterogeneous, reflecting a teaching population that is internally differentiated with respect to its AI-readiness, likely as a function of differential exposure to and engagement with these technologies.

Figure 2

Distribution and comparison of AI-TPACK dimensions.
(A) Boxplots representing the distribution of scores across dimensions, with medians (lines) and means (squares). (B) Mean scores with 95% confidence intervals.



The inferential analysis of inter-dimensional differences, conducted via the Friedman test for related samples, corroborates and quantifies the pattern identified in the descriptive data. A Friedman test confirmed statistically significant differences across the seven dimensions ($\chi^2(6) = 412.35$, $p < 0.001$, Kendall's $W = 0.34$).

The magnitude of the effect (Kendall's $W = 0.34$) indicates a moderate-to-large degree of systematic ordering in participants' responses across dimensions − a finding that lends robust statistical support to the theoretical proposition, articulated in H3, that the seven AI-TPACK dimensions constitute qualitatively distinct, hierarchically ordered zones of teacher competence. Post-hoc Bonferroni-corrected pairwise comparisons confirmed that each traditional domain (CK, PK, PCK) attained significantly higher scores than each of the four AI-specific dimensions (all $p < 0.001$), whilst differences among the AI-specific dimensions themselves were smaller in magnitude and, in several pairings, did not reach statistical significance − consistent with the interpretation that these dimensions share a common epistemological substrate of AI-related unfamiliarity that current professional preparation has not systematically addressed.

Taken together, these findings provide clear statistical support for H3, and the practical implication is direct: the specific knowledge required for the purposeful, critical, and ethically grounded integration of GenAI into teaching practice is precisely the knowledge that current teachers, across disciplinary boundaries and age cohorts, report least.

The results revealed strong and statistically significant correlations between the global score and the AI-related technological dimensions, namely AI-TK ($\rho = 0.93$, $p < 0.001$), AI-TCK ($\rho = 0.933$, $p < 0.001$), AI-TPK ($\rho = 0.928$, $p < 0.001$), and AI-TPACK ($\rho = 0.915$, $p < 0.001$). These findings indicate that overall performance on the instrument is highly associated with teachers' perceived technological and pedagogical knowledge applied to Artificial Intelligence.

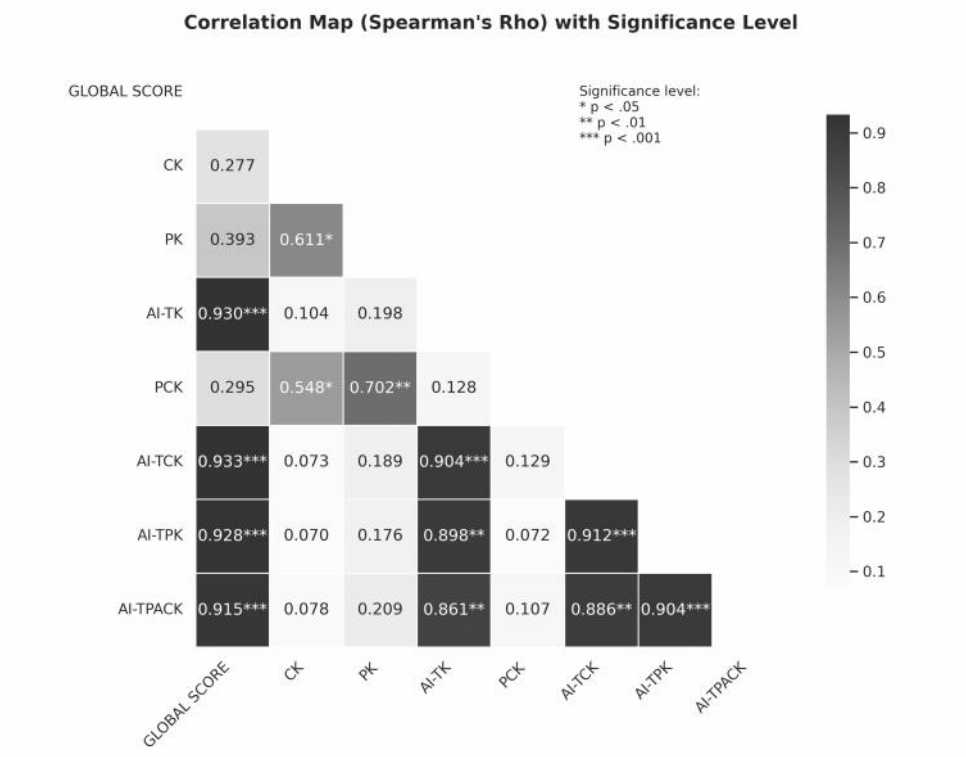
Additionally, very strong correlations were observed between the composite dimensions of the model, including AI-TCK and PCK ($\rho = 0.904$, $p < 0.001$), AI-TPK and PCK ($\rho = 0.898$, $p < 0.01$), AI-TPACK and PCK ($\rho = 0.861$, $p < 0.01$), AI-TPACK and AI-TCK ($\rho = 0.886$, $p < 0.01$), and AI-TPACK and AI-TPK ($\rho = 0.904$, $p < 0.001$). These relationships suggest a high level of internal coherence within the model, indicating that AI-related technological knowledge is strongly interconnected with pedagogical and content knowledge.

In contrast, correlations involving more traditional dimensions, such as Content Knowledge (CK) and technological dimensions, were generally weak and mostly non-significant (e.g., CK–AI-TK: $\rho = 0.104$, $p > 0.05$), which may reflect a relative dissociation between domain-specific content knowledge and emerging technological competencies.

It is noteworthy that inter-correlations among AI-specific dimensions (AI-TK, AI-TCK, AI-TPK, AI-TPACK) appear consistently high in the matrix ($\rho > 0.85$ in several pairings). Whilst such correlations are expected given the theoretical adjacency of these constructs, values approaching 0.90 or above warrant scrutiny regarding discriminant validity — that is, whether the AI-specific dimensions are measuring meaningfully distinct constructs or a more unitary underlying factor. Values of this magnitude imply that the dimensions concerned share more than 80% of their variance, and two implications follow for the dimension-level analyses reported here and in the section "**Influence of Professional and Personal Variables**". First, the profiles observed across AI-TK, AI-TCK, AI-TPK, and AI-TPACK should be read as facets of a possibly more general 'AI knowledge' factor rather than as fully independent constructs. Second, the training-related differences replicated across the four AI-specific dimensions may partly reflect a single association with that general factor rather than four distinct effects. The modelling strategies capable of adjudicating between these interpretations are discussed in the section "**Limitations And Future Research**".

Figure 3

Spearman correlation matrix across AI-TPACK dimensions.
Values represent correlation coefficients (ρ). Asterisks indicate levels of significance (*$p < 0.05$, **$p < 0.01$, ***$p < 0.001$).



Influence of Professional and Personal Variables

The comparison of AI-TPACK knowledge between STEM (n = 84; M = 3.68, SD = 0.61) and non-STEM teachers (n = 119; M = 3.51, SD = 0.66) yielded a descriptively modest and inferentially non-significant difference ($t(201) = 1.97$, $p = 0.051$). Although the p-value approaches the significance threshold, H1 is not supported. This finding is noteworthy not merely as a null result, but as a substantively significant one: it challenges the disciplinary proximity argument and suggests that the structural gap between GenAI familiarity and pedagogical integration competence is broadly distributed across the teaching profession, not concentrated among those whose disciplinary formation might have been expected to confer technological advantage. One interpretation of this pattern is that the AI-specific knowledge domains assessed by the AI-TPACK instrument require a form of applied pedagogical-technological judgment that transcends disciplinary background — a judgment that, in the current professional landscape, most teachers have had limited opportunity to develop regardless of their subject area.

The analysis of age-related differences in AI-TPACK knowledge, conducted across five generational cohorts, produced a comparably non-significant result (Welch's ANOVA: $F(4, 38.21) = 0.549$, $p = 0.702$; $\omega^2 = 0.002$). H2 is not

supported. The negligible effect size − age accounting for essentially zero variance in AI-TPACK scores − is of considerable theoretical import. It problematises the pervasive "digital native" discourse that informs much popular and policy-level thinking about generational differences in technology engagement, suggesting that, in the specific domain of GenAI for educational purposes, chronological proximity to the digital age does not translate into measurable professional competence advantage. This may reflect the recency and pace of GenAI development, which has effectively "levelled the playing field" by confronting teachers of all ages with technologies that exceed their prior experience, rendering generational trajectories of technology socialisation insufficient as predictors of current AI-TPACK knowledge.

By contrast, participation in AI-specific training emerged as the variable most strongly associated with AI-TPACK knowledge in the study, with effect sizes of a magnitude rarely observed in survey-based educational research. Independent-samples t-tests comparing teachers who had ($n = 81$) and had not ($n = 122$) participated in AI training revealed statistically significant and practically large differences across all four AI-specific dimensions: AI-TK ($t(162.47) = 8.53$, $p < 0.001$, $d = 1.19$), AI-TCK ($t(172.01) = 8.06$, $p < 0.001$, $d = 1.10$), AI-TPK ($t(170.25) = 7.75$, $p < 0.001$, $d = 0.99$), and AI-TPACK ($t(175.68) = 7.55$, $p < 0.001$, $d = 0.95$). The consistency and magnitude of these effects − all exceeding Cohen's (1988) threshold for "large" effects − indicate that formal, structured engagement with AI in professional development contexts is associated with substantial differences in the competency dimensions most directly implicated in the pedagogical integration of GenAI. Crucially, the absence of significant effects of training on traditional knowledge domains (CK, PK, PCK) corroborates the construct validity of the instrument and reinforces the discriminant specificity of the training-related differences to those dimensions − AI-TK, AI-TCK, AI-TPK, AI-TPACK − whose content is most directly developed through deliberate professional learning.

DISCUSSION

The present findings can be productively situated against the rapidly expanding international literature on teachers' AI-related competencies. An interpretive caveat must, however, frame the discussion as a whole: the instrument measures self-perceived knowledge rather than demonstrated competence, and the large training-related differences discussed below may therefore reflect gains in self-efficacy or confidence rather than in enacted competence (see the section "**Limitations And Future Research**"). Five elements of comparison deserve emphasis: the magnitude of overall AI-TPACK self-perception, the asymmetric profile between traditional and AI-specific dimensions, the (non-)role of

disciplinary area and age, the effect of prior training, and the discriminant validity of the AI-specific subscales.

Regarding overall levels, the Portuguese mean of M = 3.58 falls within the moderate range reported across recent international studies using AI-TPACK or closely related instruments. Ning *et al.* (2024), in the validation study with 525 Chinese K-12 teachers, reported overall AI-TPACK means around 3.4–3.7 across dimensions, with comparable internal asymmetries. Choudhury *et al.* (2024), validating the Ning instrument with Indian teachers, also documented moderate scores with the same dimensional pattern (stronger pedagogical/content, weaker AI-technological). The Indonesian vocational adaptation by Setiyawan*et al.* (2025; N = 460) confirmed the seven-factor structure; its participants reported relatively high self-ratings on a seven-point response scale, with in-service teachers scoring above their pre-service counterparts across all dimensions, which precludes a direct comparison of means with the present study but suggests that classroom experience may matter. The convergence of these moderate, asymmetric profiles across China, India and Portugal points to a transnational pattern rather than a Portuguese particularity.

The non-significant effect of disciplinary area (H1) deserves particular attention in the comparative frame. Galindo-Domínguez*et al.* (2024a), surveying 445 Spanish in-service teachers, found that only about 25% reported actively integrating AI in their teaching, with content-creation uses (ChatGPT, DALL·E, Midjourney) dominating across subject areas. Crucially, a related study by the same research group indicated that teachers' digital competence, rather than their personal or professional background variables, was the factor most consistently associated with their attitudes towards AI (Galindo-Domínguez*et al.* 2024b). This converges with the present finding that STEM affiliation does not confer a measurable AI-TPACK advantage in Portugal: in both Iberian contexts, the AI competence gap appears broadly distributed across the profession rather than concentrated in technology-adjacent disciplines. Yue, Jong, and Ng (2024), in a survey of K-12 teachers in Hong Kong (N = 568), reported a parallel pattern, identifying a substantial gap in AI-related content and technological knowledge that cut across teaching areas. Their recommendation that professional development programmes specifically target AI-related TPACK, rather than relying on general technology training, is directly supported by the Portuguese data.

The absence of a significant age effect (H2) is similarly aligned with recent international evidence. Erol*et al.* (2025), using structural equation modelling on a Turkish teacher sample, found that AI self-efficacy and AI attitudes rather than demographic variables were the strongest predictors of AI-TPACK. Karataş and Ataç (2025), modelling TPACK and AI-TPACK simultaneously, reached a comparable conclusion: AI-specific competence is shaped primarily by exposure and training rather than by age cohort. The Portuguese null result therefore

replicates rather than contradicts the emerging consensus that AI-TPACK is not a primarily generational construct.

The large effect of training observed here (Cohen's d = 0.95–1.19) is broadly consistent with the international evidence, though the magnitude reported here is at the upper end of what has been reported elsewhere. Yue, Jong, and Ng (2024), in a pre/post intervention design with pre-service teachers in Hong Kong, found significant gains in AI awareness after a one-semester AI-TPACK programme. Bautista *et al.* (2024), in a Philippine TPACK-AI study, reported moderate-to-large training effects on pre-service teachers' readiness to integrate AI. Caution remains warranted: the present effect, measured cross-sectionally, may reflect self-selection into AI training of teachers who already possessed higher motivation, stronger digital competence, or greater interest in innovation, and it captures self-efficacy rather than demonstrated competence (see the section "**Limitations And Future Research**"). The fact that effect sizes elsewhere are usually smaller when measurement is more rigorous (e.g., pre/post designs, performance-based assessment) supports this interpretive caution.

Finally, the discriminant-validity concern raised by the high inter-correlations among AI-specific subscales ($\rho > 0.85$) is not unique to the Portuguese adaptation. Choudhury *et al.* (2024) and the Indonesian validation (Setiyawan*et al.* 2025) both reported similarly high correlations among AI-TK, AI-TCK, AI-TPK and AI-TPACK, and called for more fine-grained measurement approaches. Karataş and Ataç (2025) explicitly proposed a bifactor structural model to disentangle a general "AI knowledge" factor from dimension-specific variance. This suggests that the issue may be at least partly inherent to the construct's current operationalisation, and not solely an artefact of the Portuguese adaptation.

Taken together, these comparisons strengthen the substantive contribution of the present study in two ways. First, they show that the asymmetric AI-TPACK profile constitutes a transnational rather than Portuguese-specific phenomenon, supporting its interpretation as a structural feature of the contemporary teaching profession rather than a local deficiency. Second, they situate the Portuguese contribution at the cross-cultural frontier of AI-TPACK research, alongside parallel adaptations in China (Ning *et al.* 2024), India (Choudhury *et al.* 2024), Indonesia (Setiyawan*et al.* 2025) and Turkey (Erol*et al.* 2025; Karataş and Ataç 2025), and complementing survey-based evidence from Spain (Galindo-Domínguez*et al.* 2024a, 2024b) and Hong Kong (Yue, Jong, and Ng 2024). The accumulation of this evidence base now permits future meta-analytic synthesis — a step that the field has not yet been in a position to undertake, but for which the present study contributes a methodologically transparent European data point. Stated explicitly, the study's primary contribution is contextual — the first validation of the Ning *et al.* (2024) instrument in a European, Portuguese-speaking school system — while its conceptual contribution is more modest but not negligible: by replicating the asymmetric profile in a markedly different educational system, it strengthens the

interpretation of that profile as a structural feature of the contemporary teaching profession rather than a context-specific finding.

IMPLICATIONS FOR TEACHER EDUCATION

The findings carry substantive implications for both initial and continuing teacher education. The asymmetric profile identified — strong traditional pedagogical and content knowledge alongside markedly weaker AI-specific competencies — signals a systemic misalignment between current professional preparation and the demands of AI-mediated classrooms. Responding to this requires training programmes that move beyond a tool-orientation paradigm towards an integration-orientation centred on pedagogical orchestration of AI in disciplinary contexts, critical evaluation of AI-generated content, design of AI-enhanced learning environments that preserve epistemic agency, and ethical navigation (Redecker 2017; UNESCO 2023). In Portugal, these orientations align with the DigCompEdu-based Referencial, which, however, predates Generative AI and lacks AI-specific competencies. The present findings provide an empirical basis for its revision and inform Portugal's implementation of the European Commission's Digital Education Action Plan 2021–2027 (European Commission 2020) and of the Plano de Ação para a Transição Digital (PATD), including its school-level instrument, the Plano de Ação para o Desenvolvimento Digital das Escolas (PADDE; Direção-Geral da Educação 2020).

The null effects of age and disciplinary background carry a clear policy corollary: AI competency development cannot be delegated to generational renewal or disciplinary specialisation. It must be treated as a system-wide professional learning priority across the full teaching workforce, consistent with UNESCO (2019, 2023) frameworks that explicitly caution against assuming digital nativity or technical background substitutes for structured professional learning.

The large training-related differences ($d > 0.95$) suggest that the gap may be less a matter of individual cognitive limitation than of unequal access to structured professional development opportunities − an interpretation that, given the cross-sectional design, must remain associative rather than causal. Three complementary models warrant prioritisation: (a) discipline-integrated peer coaching, in which teachers from the same subject area collaboratively design and reflect on AI-enhanced lesson sequences (Voogt*et al.* 2013); (b) cross-school communities of practice convened around shared integration challenges, providing the longitudinal and socially scaffolded learning that one-off workshops cannot replicate (Lawless and Pellegrino 2007; Wenger 1998); and (c) modular micro-credentialing programmes targeted at the dimensions most deficient in this study (AI-TK, AI-TCK, AI-TPK), certifiable within the DigCompEdu framework for scalable system-wide upskilling.

LIMITATIONS AND FUTURE RESEARCH

Several limitations qualify the interpretation of these findings. The non-probabilistic sampling strategy introduces potential self-selection bias: teachers volunteering for an AI-focused survey may differ from those who decline, likely attenuating the magnitude of the gaps identified. In particular, teachers with a pre-existing interest in digital technologies are likely overrepresented, which implies that the AI-specific knowledge levels reported here should be read as an upper bound for the wider teaching population − and the gap identified, correspondingly, as a conservative estimate − and that generalisation beyond similarly self-selected groups should be made with caution. Information on the regional distribution of participants across Portugal was, moreover, not collected, which precludes the analysis of territorial variation and further constrains external validity. The cross-sectional design precludes causal inference about how AI-TPACK is acquired or consolidated. Most importantly, the instrument − consistent with Ning *et al.* (2024) − measures self-perceived knowledge rather than demonstrated competence, a construct closer to domain-specific self-efficacy (Bandura 1997). This carries two interpretive consequences. First, the observed gap may partly reflect differential calibration: teachers can more accurately assess long-practised pedagogical domains than emergent AI competencies, producing potential Dunning-Kruger over-estimation in novel domains or impostor under-estimation in complex ones. Second, the large training effect may reflect gains in confidence rather than enacted competence − a distinction that matters for policy, since raised self-efficacy without corresponding competence would not deliver improved learning outcomes.

A further limitation concerns the psychometric evidence for the discriminant validity of the AI-specific subscales. Complementary indices such as Average Variance Extracted, Composite Reliability, and HTMT ratios were not computed in the present study, and alternative measurement models were not tested against the seven-factor solution. Re-analysing the existing data using second-order or bifactor models, complemented by these indices, therefore constitutes a priority for future research: such a re-analysis would help clarify whether a general 'AI knowledge' factor underlies the AI-specific dimensions or whether these dimensions capture meaningfully distinct constructs.

The contextual boundedness of the study − its situatedness within the particular institutional, cultural, and policy landscape of the Portuguese educational system − constitutes an additional constraint on the generalisability of its findings. Whilst this specificity is an asset insofar as it enables contextually grounded interpretation, it implies that the knowledge profiles, competency asymmetries, and training effects identified here may not straightforwardly transfer to educational systems characterised by different patterns of technology integration, different professional development cultures, or different regulatory frameworks governing AI use in schools.

These limitations, whilst not vitiating the findings of the present study, delineate a productive agenda for future research. Longitudinal designs, capable of tracking the trajectory of AI-TPACK development in response to targeted professional learning interventions, would substantially advance the evidence base beyond the descriptive snapshot provided by cross-sectional surveys. Mixed-methods approaches − combining psychometric assessment of perceived knowledge with observational or portfolio-based evidence of enacted practice − could address the construct validity challenge posed by the reliance on self-report and illuminate the mechanisms through which professional knowledge is translated, or fails to be translated, into instructional action. Cross-cultural and cross-systemic comparative studies, meanwhile, would enable the identification of those features of professional development systems and institutional cultures that most effectively foster AI-TPACK competencies, thereby providing an empirical basis for policy learning across national contexts.

CONCLUSIONS

This study set out to map Portuguese teachers' knowledge of Generative Artificial Intelligence through the AI-TPACK framework. Results reveal a moderate overall level characterised by a structurally asymmetric profile: well-consolidated traditional pedagogical and content domains contrast sharply with substantially weaker AI-specific technological and integrative knowledge.

The inferential analyses reveal a pattern of null and significant findings that, taken together, carry important theoretical and policy implications. Neither disciplinary area nor age emerges as a meaningful predictor of AI-TPACK knowledge − a double null result that challenges prevailing assumptions about disciplinary proximity and generational digital advantage, and that reframes AI-related competency development as a universal professional learning challenge rather than a targeted intervention for specific subpopulations. By contrast, participation in formal AI training is associated with large and consistent differences across all AI-specific dimensions, providing the study's most actionable finding: that the competency gap is not intractable, but appears responsive to deliberate professional learning.

The contribution of this study lies in both its findings and its method: the adaptation and validation of the Ning *et al.* (2024) instrument for the Portuguese context extends the cross-cultural applicability of AI-TPACK measurement. The gap identified cuts across disciplines and generations and is associated with substantially higher scores among teachers who have undertaken structured training ($d > 0.95$). It is measurable and appears addressable, although longitudinal evidence will be required to confirm the effectiveness of training. Future research extending the sample, adopting longitudinal designs, or complementing self-report

with observational measures will be essential to consolidate the evidence base for system-wide, pedagogically grounded GenAI integration.

Disclosure on the Use of Artificial Intelligence

Artificial intelligence (AI) tools were used in the preparation of this manuscript exclusively for language support purposes, including translation assistance, grammatical revision, and adaptation to Chicago style guidelines. Specifically, the Claude Opus 4.7 model was employed. All intellectual content, analysis, interpretation, and final editorial decisions remain the sole responsibility of the authors.

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Conflicts of Interest

The authors declare no conflicts of interest.

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Inteligența Artificială Generativă (GenAI) este adoptată rapid în școli, ridicând semne de întrebare urgente cu privire la pregătirea cadrelor didactice pentru a o integra din punct de vedere pedagogic. Acest studiu examinează nivelurile și structura cunoștințelor autoevaluate privind GenAI în rândul cadrelor didactice din învățământul primar și secundar din Portugalia, utilizând cadrul AI-TPACK. Un chestionar online structurat a fost aplicat unui eșantion de 203 cadre didactice din domenii disciplinare diverse. Analizele descriptive și inferențiale au evaluat cunoștințele generale, diferențele dintre dimensiuni și rolul variabilelor personale și profesionale. Rezultatele indică un scor general moderat (M = 3,58, SD = 0,64), cu medii semnificativ mai ridicate în dimensiunile tradiționale (CK: M = 4,40; PK: M = 4,26; PCK: M = 4,13) comparativ cu cele specifice IA (AI-TK: M = 3,06; AI-TCK: M = 3,03; AI-TPK: M = 3,01). Nici aria disciplinară și nici vârsta nu au fost predictori ai scorurilor AI-TPACK. Cu toate acestea, formarea anterioară specifică în domeniul IA a fost asociată cu diferențe majore în toate dimensiunile legate de IA (d-ullui Cohen=0,95-1,19). Concluziile relevă un profil de competențe asimetric din punct de vedere structural, care traversează disciplinele și cohortele de vârstă și răspunde în mod robust la formarea structurată. Sunt discutate implicațiile pentru formarea cadrelor didactice, politicile de dezvoltare profesională și cadrul portughez al competențelor digitale.

Cuvinte-cheie: *AI-TPACK; Inteligență Artificială Generativă; Cunoștințele cadrelor didactice; Formarea cadrelor didactice; Competențe digitale; Dezvoltare profesională.*

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