

Conceptualizing pre-service teachers' readiness for AI integration into teaching practices: An intelligent-TPACK approach

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ABSTRACT

Pre-service teachers can play a crucial role in integrating AI-based tools into the new educational landscape. However, there is a need to validate specialized instruments, apply current conceptualizations such as intelligent-TPACK, and address ethical issues, as pre-service teachers are often overlooked in the development of tools for AI integration. To address these gaps, we adapted a previously existing instrument designed for in-service teachers to measure pre-service teachers' integration of AI within their training context. We conducted a quantitative cross-sectional survey with a total of 366 pre-service teachers to evaluate the adapted intelligent-TPACK instrument and examine participants' demographic characteristics related to the framework dimensions. Data analysis included a Confirmatory Factor Analysis to assess the factor model of the adapted instrument, followed by correlations to compare participant variables such as gender, type of university, and stage in the training program with the Intelligent-TPACK model factors. To investigate the differences among groups, the nonparametric ANCOVA test (Quade test) was utilized, enabling the control of covariates like age and academic progress level to ensure comparability across the dimensions of the Intelligent-TPACK model. Findings reveal a high fit of the Intelligent-TPACK model for pre-service teachers (CFI=0.997; TLI=0.997). The data also shows statistically significant effects related to academic progress level and type of institution, while factors -gender, geographic location, and type of major- did not demonstrate noteworthy differences. These results highlight key areas for future curriculum development and support for pre-service teachers in integrating AI education.

1. Introduction

International organizations recognize the potential of artificial intelligence (AI) and its transformative capabilities to reshape teaching and learning practices [1,2]. However, there are still several issues regarding how to implement AI to make this potential concrete in our classes. Furthermore, AI implementation in schools has lacked guidance from pedagogical frameworks [3,4] and has not considered teachers' opinions [5]. Indeed, even though teachers are critical for the successful integration of technology in the classroom [6,7], there is a lack of research centered on how AI integration could take place from their perspective [8], despite the critical role that teachers' beliefs, skills, and

competencies play in the effective integration of technology in the classroom [6,7].

A crucial group that could participate in classroom teaching activities with a refreshed AI-based repertoire is pre-service teachers [9]. According to [10] and [11], if teachers are prepared with a strong AI literacy background, they can foster innovation, critical thinking, and personalized learning, serving as role models for classroom adaptation. Indeed, AI-literate teachers are better prepared to engage with personalized and inclusive learning, supporting students' digital skills, problem-solving and adaptability in the era of AI [9,11–13]. Thus, fostering AI-literacy programs in teacher education may significantly improve pre-service teachers' understanding, application, and

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confidence when using AI tools [10,14,15].

Empirical studies have shown both opportunities and threats when integrating AI-literacy programs into teacher education [13,15,16]. According to [16], pre-service teachers can play an active role in adapting or refining AI-generated learning materials, while [17] assert that pre-service teachers who engage in chatbot-integrated metaverses can develop more authentic, immersive, and interactive pedagogical activities. However [18], reveal that perceived risks regarding the use of AI can negatively influence AI acceptance among some teacher groups. These perspectives delve into the importance of integrating AI into teacher preparation programs, while also emphasizing the need for a carefully guided process that explicitly addresses the benefits and challenges of AI in teacher training experiences.

In this sense, pre-service teacher training should encompass what [19] define as the technological, pedagogical, and content knowledge (TPACK) framework, which covers different aspects of teachers' professional knowledge. Moreover, according to Celik [20] this framework could "explain the necessary knowledge for teachers to integrate AI-based tools in education" (p. 2), expanding the practical and conceptual application of the TPACK model to AI trends through the concept of intelligent-TPACK (iTPACK). Nevertheless, the way in which pre-service teachers shape their professional knowledge while integrating AI-based tools is still an emerging field [18,21].

Authors have addressed the relationship between pre-service teachers and the development of TPACK [22–24]. For example, the study by [22] found that improvements in technology knowledge (TK) affected not only that specific domain but also impacted the entire model, including technological abilities, pedagogical strategies, and subject matter. These findings align with [23], who designed TPACK modules and discovered that integrating technology into subject matter teaching has a positive influence on pre-service teachers' TPACK. They also align with [24], who investigated the enactment of TPACK in pre-service teachers after completing modules based on the framework, yielding positive correlations. However, there is a gap in applying these findings to an AI-based educational environment, particularly as pre-service teachers face new challenges, such as ethical issues related to AI in education [20].

Additionally, studies have revealed the influence of social contexts [25–27] and self-efficacy [28] on the enactment and development of pre-service teachers' TPACK. Thus, when considering the reported positive outcomes of enhancing technology knowledge across the entire TPACK framework [22], the contextual AI-mediated landscape, and the potential of AI to transform teaching and learning [2], it becomes evident that training future teachers with AI-based tools is essential for transforming the overall educational experience. However, evidence is needed to understand how technology knowledge influences TPACK model when AI-based skills are acquired by pre-service teachers in diverse socio-cultural contexts.

When considering individuals' demographic information in AI-literacy assessments of diverse populations, the evidence is contradictory. On one hand, some authors shed light on several variables and their correlation with AI-literacy, like gender [29–31], age [30], or prior experience with AI [29,31], and subject area [30,31]. Here, the evidence is not conclusive. On the other hand [31], assert that gender produces no significant differences when iTPACK-based scales were applied among in-service and pre-service teachers. Nevertheless [29], found that, among English as a foreign language pre-service teachers, gender and prior experience with AI were strong predictors of AI-skills when applying iTPACK-based scales. Meanwhile [30], found that neither age, gender, nor training area was a significant predictor for higher education teachers.

Furthermore, there are also studies consider demographic features of participants solely to build a representative sample for instrument construct validity [9] or for overall data gathering [32,33]. However, they fail to report how those features impact in-service or pre-service AI literacy. From this study's standpoint, relating iTPACK to demographic

or personal subject features can help identify the conditions under which AI-literacy programs could have a more substantial impact. It can also highlight which inequalities should be addressed to close gaps in teacher education.

To address these gaps (instrument adaptation and validation for pre-service teachers; applying an iTPACK framework to pre-service teacher education; considering diverse sociocultural contexts and demographic aspects; understanding the impact of technology knowledge in AI-landscape), as well as other relevant gaps in the literature (including ethical factors and instrument validation in Spanish), this study investigates how pre-service teachers conceptualize the use of AI in teaching by conducting an instrument validation research. Drawing on an adapted version of the empirically developed iTPACK framework [20], which is itself based on the TPACK model proposed by Mishra and Koehler [19], we seek to address the gap in assessing TPACK enhanced with AI among pre-service teachers and to validate an instrument for this purpose. Indeed, this study also explores the opportunities and challenges of integrating AI-based tools into teacher training.

Considering that previous research has found a relationship between teachers' perceptions, school context, and the effectiveness of technology integration [34–36], as well as teachers' skills [37], and demographic aspects like gender [38,39], we will also examine how these factors relate to pre-service teachers' perceptions. Those gaps lead us to guide this study through the following research questions:

RQ1. How can an iTPACK scale designed and empirically developed for in-service teachers be adapted for pre-service teachers within native spanish speakers' educational context, while maintaining the reliability of its factors?

RQ2. How are pre-service teachers' demographics and university context related to their iTPACK dimensions?

By answering these research questions, this study seeks to: (1) advance the conceptual understanding of pre-service teachers' readiness for AI integration, (2) provide practitioners and researchers with a validated quantitative tool for assessing AI-related competencies in teacher education, and (3) understand how factors such as university context, discipline, stage of preparation, and demographic information relate to pre-service teachers' AI pedagogical integration.

In the next sections, we discuss the primary conceptual approaches utilized in this study. Then, a literature review explores key advancements in artificial intelligence, pre-service teacher education, and measurement within this field. Finally, we outline the methods, findings, and discussion, concluding the practical and research implications, future directions, and limitations.

2. Conceptual framework

2.1. PCK and T-PACK models

The conceptualization of the knowledge that teachers need for teaching has been the subject of considerable interest and debate over the years [7]. In this context, the framework proposed by Shulman [40] is one of the most recognized and widely used to describe teacher knowledge across various curricular areas (e.g [41], in science [42] in mathematics) [40]. Highlighted two major types of essential knowledge: Content Knowledge (CK), which refers to the critical understanding of the ideas to be taught; and Pedagogical Knowledge (PK), which involves instructional strategies, classroom management, and pedagogical concepts related to how to teach effectively and engage students with the content.

In this context, Pedagogical Content Knowledge (PCK) is understood as the amalgamation of content knowledge and general pedagogical knowledge, which enables the teacher to transform ideas to make them understandable to students.

Building on [40] and in response to the rapid advancement of

technology along with the growing need for teachers to use it effectively in the classroom [19], proposed the TPACK framework. This model adds a third dimension to [40] proposal, called TK, which encompasses knowledge about technological tools themselves, their operation, applications, and the ability to learn about new technologies [14]. TPACK is one of the most commonly used conceptual frameworks to describe the knowledge teachers need to use technology in the classroom effectively [7]. It proposes that the effective integration of technology in education depends on understanding the synergistic interaction between three key elements: CK, PK, TK [20]. From the intersection of these components, other specialized types of knowledge also emerge: PCK (already defined by Shulman), Technological Content Knowledge (TCK) - which refers to how technology represents or facilitates the learning of specific content - and Technological Pedagogical Knowledge (TPK) - which describes how technology can be used to implement general pedagogical strategies [43].

This synergistic interaction between the TPACK components is essential for effective teaching with technology, allowing for the development of specific instructional strategies or addressing problems students face [20]. It is worth noting that TK, unlike pedagogical and content knowledge, is inherently more dynamic and frequently changes due to the rapid evolution of technology [31], which presents teachers with the challenge of continually updating their knowledge [8]. TPACK is one of the most cited frameworks to support teachers' technology integration [25] and has also been widely used with pre-service teachers [27,28].

Furthermore, the responsible integration of AI in education requires paying special attention to its ethical dimension, which encompasses technical, pedagogical, and social aspects [44,45]. These challenges are particularly relevant in teacher education, as the preparation of future teachers will influence their pedagogical practices and the effective and ethical integration of AI in schools [29,46,47]. In the following section, we will provide a more detailed description of the ethical component of AI integration in education.

2.2. Ethical challenges in AI pedagogical integration

The adoption of AI in educational contexts raises numerous ethical concerns [48,49]. Among the main challenges is the management of privacy and data use [50]. Furthermore, AI systems require large volumes of data, which raises questions about consent, transparency, and the risk of manipulation. Additionally, concerns related to the presence of bias in data and algorithms are critical [51], as AI can amplify human prejudices by reproducing stereotypes. The autonomy of students and teachers can also be affected by decisions made by AI systems [52]. In addition, ensuring adequate levels of transparency and explainability is essential to guarantee the ethical and responsible use of these technologies [1,53].

Several organizations have published recommendations to define ethical principles that guide the adoption of AI systems [2]. For example [1], draws inspiration from fundamental rights as the basis for defining trustworthy AI. Thus, they establish four ethical principles or imperatives that AI professionals must observe: respect for human autonomy, prevention of harm, fairness, and explainability. Similarly [54], approved a universal framework of values, principles, and actions to guide policy formulation related to AI. Among the principles emphasized are the right to privacy and data protection, awareness and education, collaborative and adaptive governance, to name a few. The various sets of ethical principles show a high degree of overlap [55] and are often covered through already established general domains of technological ethics [56]. Therefore, the difficulties in addressing ethical challenges may be more related to the neglect of fundamental ethical issues than to the understanding of AI itself [44], highlighting the fundamental role of ethical training in shaping the new professional teaching profile.

The ethical implications surrounding the adoption of AI extend

beyond the training space; they require a systemic approach where policies, evaluation, and professional development promote a shared ethic [54]. At the regulatory level, the adoption of international frameworks [1,54] must be translated into verifiable indicators that guide the integration of AI-based technological systems in education and require providers to make algorithmic logic transparent. Training teachers to connect technological innovation with democratic values strengthens transformative educational AI, ensuring it is not dependent on fragmented solutions or the goodwill of external actors.

Regarding the relevance of and ethical dimension, Celik [20] develops an iTPACK framework that deepens into the ethical implications of professional teachers' knowledge in an AI-based landscape. In this sense [20], proposes that the ethical component is as important as technological-pedagogical knowledge when affecting all components of the TPACK framework. This means that the ethical dimension is gaining relevance when examining teachers' professional skills in an AI-mediated educational environment.

2.3. iTPACK model

The conceptualization developed by Schulman [40] and complemented by Mishra & Kohler [19] is enhanced by integrating AI into the TPACK model [20]. According to [20], integrating AI in education involves using new AI-based tools in teaching and learning management, and facing serious ethical issues such as algorithm bias, lack of transparency in AI decision-making, difficulties in the accountability of AI-driven consequences in educational environments, and problems in creating inclusive environments around AI educational access. All these aspects are part of the iTPACK model [20].

Considering this framework, Celik's work redefines each dimension of the TPACK model when embedding it with AI aspects. Thus, according to [20] the intelligent technological knowledge (iTK) is defined as "the knowledge to interact with AI-based tools" (p. 4), intelligent technological-pedagogical knowledge (iTPK) addresses "pedagogical affordances of AI-based tools such as personal and timely feedback, and monitoring students' learning" (P. 4), intelligent technological content knowledge (iTCK) involves the specific field of AI-based tools as "measures to what extent teachers use AI-based tools to update their content knowledge" (p. 4), and iTPACK joins all dimensions enhanced with AI, as is shown in Fig. 1.

In iTPACK model [20], contributes with a new dimension called ETHICS, which "measures the teacher's assessment concerning the decision on AI-based tools" (p. 4). In ETHICS [20], includes aspects such as transparency, fairness, accountability, and inclusiveness, which are problematic when embedded into educational settings. The former TPACK dimensions, including ETHICS are converted into factors for iTPACK scale development and validation, resulting in the "first study to develop an instrument for measuring teacher professional knowledge from a robust theoretical perspective" (p. 9) through the lens of iTPACK.

Moreover [20], analyzed the relationship between the iTPACK model factors. Accordingly, it was found that iTK had a positive effect on iTPK and iTCK, but no significant effect on iTPACK. Also, the ETHICS factor had a positive effect on iTPK, iTCK, and iTPACK. The iTPACK, as a factor that considered all the other factors, explained 69 % of the combination between iTPK, iTCK, and ETHICS. These findings show that the iTPACK model, in its original design context, is accurate and consistent when assessing teachers' AI-literacy from the iTPACK framework.

Since this approach was launched, several studies have adopted the iTPACK scale for measuring AI-literacy among in-service [31,57] and pre-service teachers [31,50]. However, studies have merged different scales, including Celik's [20], but without reporting factor analysis of the original scales [31,50,57]. Still, further scale validation in different contexts [26,27] or involving new control variables [20] is necessary to better comprehend and conceptualize iTPACK in teacher education.

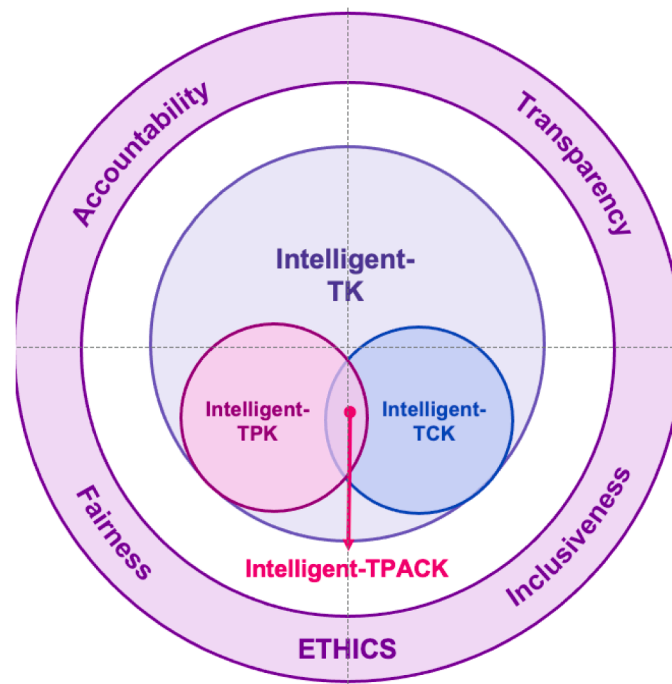


Fig. 1. iTPACK framework (Celik, 2023).

Note. Figure redrawn from Towards Intelligent-TPACK: An empirical study on teachers' professional knowledge to ethically integrate artificial intelligence (AI)-based tools into education, by I. Celik, 2023, Computers in Human Behavior, 138. The original components and relationships were retained.

3. Literature review

3.1. AI in pre-service teachers' education

AI is transforming education at all levels [58], and pre-service teachers are no longer excluded from this change exception. Various trends, such as chatbots [17,59], feedback [60–62], writing skills [63, 64], learning a second language [65–67], and even the use of ChatGPT in pre-service teachers' education [21,68–70], are garnering significant attention in scientific knowledge.

Main findings in the literature agree on identifying the positive effects of AI in pre-professional tasks, such as curriculum planning [68,71] and in shaping the identities of future teachers [16,72]. However, challenges have also been highlighted, including issues in human interaction and ethical concerns [73,74], as well as inconsistencies in AI responses to prompts from pre-service teachers [62].

Deepening into the positive effects and opportunities when merging AI into pre-service teachers training reported in the literature, studies have found enhancements in second language writing [67], in participants confidence within metaverses [17,59], in creative thinking [69], in mathematics problem solving [75], sustainable behaviour [76], teachers' reflections [77], and AI literacy [78]. Additionally, literature reports positive outcomes when training AI to support pre-service teachers' training, as evidenced by the success of ChatGPT's planning recommendations [68].

When addressing the adverse effects or threats of integrating AI into pre-service teachers' training, studies have identified concerns related to human interaction, critical thinking, and ethical issues that arise when pre-service teachers engage with chatbots [73]. Additionally, topics such as anxiety and job replacement emerge as critical concerns among teacher candidates [79]. Moreover, studies confirm that familiarity with AI does not necessarily lead to its pedagogical integration [63], revealing an underestimation of the complexity involved in integrating AI into education [80].

When considering ethical issues, studies have reported that pre-service teachers elicit ethical concerns regarding AI integration in

educational contexts [81]. Although they generally express a favorable attitude toward the use of AI and recognize its usefulness in improving task performance, ethical concerns could be a source of anxiety [51]. For example [82], adopted the Unified Theory of Acceptance and Use of Technology - UTAUT - [83]) to explore how AI-based tools can improve evaluative pre-service teachers' practices. Their results report that participants highlighted the efficiency and usefulness of AI. However, they also report ethical concerns such as plagiarism, decreased creativity, or excessive AI dependence. On the other hand, research has also demonstrated that these concerns may not necessarily significantly impact AI-use intention toward an educational use of AI [84].

Finally, research has identified the variables that influence AI acceptance among pre-service teachers. Therefore, users' level of trust in AI not only impacts AI acceptance but also affects ease of use and the perceived usefulness [18], while other studies emphasize the importance of usefulness in the perceived intention to use ChatGPT [21]. In summary, factors such as trust and usefulness influence pre-service teachers' acceptance of AI, opportunities to develop their pedagogical skills (writing, confidence, creative and sustainable thinking, etc.), and potential threats like ethical issues, fears of job replacement, and anxiety. Addressing pre-service teachers' professional perceptions of AI integration into education through a TPACK approach, as well as considering ethical concerns, is essential.

3.2. Measuring AI in pre-service teachers' education

The TPACK framework serves as an analytical tool for examining the integration of AI literacy into pre-service teacher education [9,85,86] developed and validated an instrument to assess readiness for integrating AI tools from a TPACK perspective, reporting strong psychometric indicators: KMO > 0.80, significant Bartlett's sphericity, and overall model fit (PLS-SEM) with GFI = 0.966, AGFI = 0.991, TLI = 0.996, and RMSEA = 0.068. Meanwhile [29], conducted a comparative analysis of TPACK and iTPACK using structural modeling, reporting highly robust indices: CFI = 0.96, IFI = 0.97, RMSEA = 0.05, SRMR = 0.05, and high alphas for TPACK ($\alpha = 0.97$, KMO = 0.96), with

reliability by iTPACK dimension ranging from 0.76–.82. Similarly [87], directly links digital competence with the iTPACK model [20], reporting very high reliability (iTPACK $\alpha = 0.99$; digital competence $\alpha = 0.94$) and a significant relationship ($\beta = 0.39$) between both dimensions.

There have been significant advances in research and instrument development in integrating AI pre-service teachers' education over the last few years (e.g. [9,20,21,88,89]). The work of [18] addresses the factors that influence AI acceptance among pre-service teachers, highlighting ease of use and perceived usefulness as significant factors. The study also reveals that rural pre-service teachers are negatively affected by perceived risks to their privacy and safety. In this regard, the study by [21] also examines these factors, revealing that the "perception of usefulness for professional development plays a more significant role" (p. 201) in shaping pre-service teachers' willingness to use AI-mediated tools. This research helps identify and interpret factors that explain AI adoption in general; however, it does not necessarily address how AI adoption modifies the identities or professional abilities of pre-service teachers.

When analyzing pre-service teachers' AI competencies or skills [88], offers a model of AI competence that includes theoretical knowledge about AI, legal frameworks and ethics, AI implications, attitudes towards AI, teaching and learning with AI, and ongoing professional development. Conversely [9], employ the existing TPACK model but do not measure its core concepts; instead, they find significant correlations between a deep understanding of AI and problem-solving. Lastly [89], consider [20] iTPACK approach but do not report the specific instrument adaptations, validation, or correlation of factors and participant features. Indeed, research is still evolving or adapting models to assess pre-service teachers' AI skills.

This research reveals different kinds of gaps. From a conceptual point of view, we can see that studies focusing on factors in AI adoption [18, 21] fail to conceptualize pre-service teachers' identities or competencies when integrating AI-based tools into their training. The studies that delve into AI competencies [9] or AI skills [89] also fail when merging the TPACK model with an instrument because concepts are not measured and are only vaguely considered [9], or because adaptation and validation procedures are not presented in their works [89].

From a statistical perspective, although all the reported instruments used Likert-based surveys, they performed normality tests when applying confirmatory factor analysis (CFA) without considering the specific characteristics of data distribution in Likert-based responses. Therefore, there is also a gap in addressing Likert-based scales in CFA analysis, which requires the use of robust and appropriate statistical data analysis. In this study, both gaps (conceptual and statistical) will be addressed to develop a reliable instrument for measuring pre-service teachers' iTPACK competence.

In sum, according to our literature review, we found that when addressing AI integration into pre-service teachers' education, the field lacks reliable instruments that 1) measure iTPACK, 2) include ethical factors, 3) are validated for pre-service teachers, and 4) are validated in Spanish. Therefore, our research aims to address these issues using the following methodology.

4. Methods

4.1. Research design

This study employed a quantitative, cross-sectional survey approach with confirmatory factor analysis (CFA). We adapted an iTPACK instrument designed for in-service teachers [20] and evaluated its results when applied to pre-service teachers. Therefore, we treated the different domains or combinations of the iTPACK instrument as factors (iTK, iTPK, iTCK, iTPACK, ETHICS). Then, we assessed the covariance between survey questions and the pre-established factors, fitting the corresponding model. Finally, we compared both the CFA model and the correlations between factors and participants' demographics. This study

was approved by the Ethical Committee of the Pontificia Universidad Católica de Chile (ID 250,310,001).

4.2. Research context

This research was conducted with students enrolled in teacher education programs across eleven universities in Chile. On average, teacher education programs in Chile last five years. Historically, these programs took around six years to complete, but recent reforms have aimed to shorten their duration, with most universities now offering programs that span 10 academic semesters.

Although there is no standardized national curriculum for teacher education, there are several shared characteristics across universities. For instance, teacher education in Chile places significant emphasis on practical experience. Students participate in multiple practicum experiences, each with a specific focus such as teaching and learning methodologies, inclusion and diversity, among others.

During their final year, students spend the majority of their time in practicum placements, working under the supervision of experienced, licensed teachers. In addition, during their last semester, students are required to complete a final research project or thesis seminar ("seminario de tesis").

After completing high school, students in Chile must take a national examination to access higher education, enrolling directly in their chosen subject area of teacher education [90]. For example, students do not enroll in a general "teacher education" program but rather in specialized programs such as "Teacher of Science" or "Teacher of Mathematics."

It is important to note that although some of the universities in this study are private, they are part of Chile's free higher education system [91,92]. Universities, whether public or private, receive government funding based on their accreditation status. Institutions with higher accreditation scores receive greater financial support, regardless of whether they are public or private [93].

Chile is a highly centralized country, with approximately 40 % of the population living in the capital city, Santiago [94]. This centralization is particularly relevant when considering there are 13 other regions across the country, many of which have fewer resources and less access to educational infrastructure compared to the capital.

Chile is also recognized as a regional leader in AI research and integration within Latin America [95]. At the policy level, national regulations have been established to promote AI literacy and ensure data protection [96,97]. Chile has led several initiatives across Latin America, including the development of the Latin American AI Index [98] (Centro Nacional de Inteligencia Artificial, 2024) and the establishment of specialized AI research centers. One of the latest initiatives is the forthcoming launch of LatamGPT, a large language model (LLM) system trained with regional data in collaboration with 13 Latin American countries.

These contextual factors are highly relevant for interpreting the results of this study. For example, although universities were categorized as public or private in the analysis, both types of institutions are subject to national regulations and accreditation standards, making it feasible to establish common requirements for improving teacher preparation. Additionally, the variable of centralization was included in the study, as Chile's pronounced geographic and resource centralization significantly affects higher education, with universities in the capital generally receiving more support and funding than those in other regions.

4.3. Instrument

The present study used the iTPACK scale developed and empirically validated by [20] to assess in-service teachers' professional knowledge to integrate AI into education. It gives specific emphasis to ethical aspects. As our study sought to measure Celik's model in pre-service teachers, and in a different language (with Spanish native teachers

and the instrument reported in English), we adapted and conducted a psychometric assessment.

First, questions oriented specifically to in-service teacher aspects were adapted to pre-service teacher conditions. For example, in the iTPACK item which originally said, “I can take a leadership role among my colleagues” [15, p. 10], it was changed to “I can take a leadership role among my future colleagues” (“Puedo asumir el papel de líder entre mis futuros colegas”, in Spanish). This process was conducted by the first two authors of this paper - both advanced English speakers.

Second, the entire adapted instrument was translated into a Spanish version. This step used cross-cultural adaptation [99], which consists of a contextual translation of the original content. Two external certified translators were hired to conduct the translation of the instrument independently. The research team created a document with each statement of the instrument and met independently with each translator to explain the research, objectives, and the translation procedure. After receiving both versions, we created a comparison table to identify any differences. We found minor differences (e.g., the word *subject* in Spanish can be translated as *asignatura* or *disciplina*). To resolve these minor disagreements, the first and second authors met with both translators. In this meeting, we paid specific attention to the Chilean cultural context, and we finalized a Spanish version of the instrument. This version of the instrument was applied to pre-service teachers and is available in [Appendix A](#).

According to [97], the cross-cultural adaptation process does not ensure the preservation of the original psychometric validity of the scale. Therefore, we also conducted a psychometric analysis using confirmatory analysis to ensure the validity and reliability of the instrument, which is discussed in the finding section.

4.4. Participants and data procedures

Students enrolled in education programs across eleven universities in Chile were invited to complete an online questionnaire using Google Forms voluntarily. The questionnaire consisted of three sections: informed consent, student demographic information, and the adapted iTPACK questionnaire [20]. The student demographic information section asked students to self-identify their gender, age, educational level, university, and program. The questions in this section were carefully designed to avoid collecting personally identifiable information. The adapted Spanish version of the iTPACK consisted of 27 items designed to assess participants' knowledge of effective AI integration in teaching practices, keeping the five dimensions of the original instrument.

The link to the full survey was distributed through various channels, including in-class announcements, the Moodle platform, mass emails to students at participating universities, social media platforms, and outreach to faculty members. As a result, 366 students completed the test. Most participants were between 23 and 30 years old (47.27 %). A total of 117 identified as men (31.97 %) and 238 as women (65.03 %). The vast majority were senior students (61.20 %), enrolled in public higher education institutions (68.58 %) in programs related to STEM education (41.80 %). [Table 1](#) provides more detailed demographic information of the participants.

4.5. Data analysis and analytical strategy

For RQ 1, we conducted a Confirmatory Factor Analysis (CFA) to assess the previous definition of the instrument's factors as outlined by [20]. Although several studies estimated model fit conducting traditional Maximum Likelihood Estimation (MLE) methods when applying CFA [20,60,70], we added to the analysis process a Weighted Least Mean and Variance Adjusted (WLSMV) estimation, which is especially adequate when processing ordinal data like Likert scales [100–102].

Data CFA was conducted using the *lavaan* package in the open-source statistical software R. Both MLE and WLSMV estimations were applied to data. Model fit was assessed considering Chi-square (χ^2/df), robust and

Table 1
Demographic profile of the participants.

Variable	Subgroups	Frequency	Percent
Gender	Male	117	31,97
	Female	238	65,03
	Non-binary	6	1,64
	Prefer not to say	5	1,37
Age	18 - 22 years	136	37,16
	23 - 30 years	173	47,27
	31 - 40 years	44	12,02
	41 years or older	13	3,55
Educational Level	Freshman	35	9,56
	Sophomore	18	4,92
	Junior	63	17,21
	Senior	224	61,20
	Extended Undergraduate	5	1,37
	Graduate	1	0,27
	Postgraduate	2	0,55
University ownership	Other	18	4,92
	Private	115	31,42
University location	Public	251	68,58
	Capital	193	52,73
Program	Region	173	47,27
	Primary and early childhood education	80	21,86
	STEM	153	41,80
	Non-STEM	133	36,34

common Tucker Lewis Index (TLI), robust and standard Comparative Fit Index (CFI), robust and standard Root Mean Square Error of Approximation (RMSEA), and the Standardized Root Mean Square Residual (SRMSR), as proposed in CFA guidelines [103] and in robust analysis for ordinal data [101].

For RQ 2, after validating the instrument, we analyzed group differences for each of the five iTPACK factors across sociodemographic variables. In the data description section, we provide as much detailed information as possible. However, for the data analysis, we generated broader categories to facilitate interpretation. For example, although we have the full distribution of students by semester (which would result in >10 groups), we created two general categories: *Underclassmen* and *Upperclassmen*, with *Upperclassmen* defined as students in their third year or beyond. Similarly, for universities, we grouped them into *public* and *private* categories to avoid describing each institution individually.

Before comparing groups, we evaluated the distribution of the factors using the Shapiro–Wilk test, which indicated non-normal distributions for all variables ($p < .001$). Therefore, we used a non-parametric covariance approach Quade test to examine differences between groups while controlling for covariates such as age and academic level, as appropriate. For descriptive purposes, we also inspected mean differences and confidence intervals for each subgroup. All analyses were carried out in JASP (version 0.19.3), except for the Quade tests, which were implemented in Python using the *pandas*, *scipy.stats*, and *statsmodels* packages.

5. Findings

RQ1. Can an iTPACK instrument designed for teachers be adapted for pre-service teachers while maintaining the reliability of its factors?

The assessment of the model fit showed a lower CFI when applied to all factors and items, rather than when some items were reduced. Models were also tested by removing some items which augmented CFI using both ML and WLSMV estimators. Finally we removed the original instruments' s item 6 (“I can understand the pedagogical contribution of AI-based tools to my teaching field”) and item 7 (“I can evaluate the usefulness of feedback from AI-based tools for teaching and learning”) from the iTPK factor, and item 26 (can understand the justification of any decision made by an AI-based tool.”) from the ETHICS factor. CFA results of the model are presented in [Fig. 2](#).

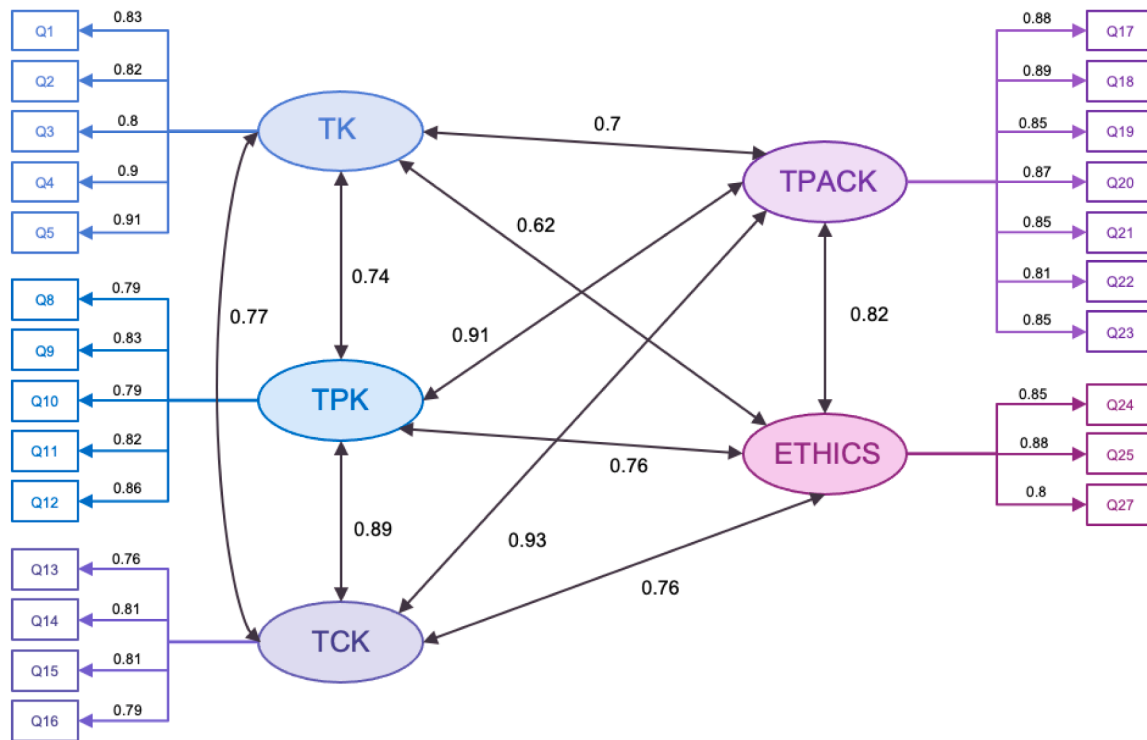


Fig. 2. CFA results of adapted iTPACK scale.

The item-total correlations (r) presented were all statistically significant at $p < .01$. This demonstrates that each item possesses a strong and reliable association with the total score of its respective factor, thereby reinforcing the internal consistency and construct validity of the adapted iTPACK scale. The factor load of every item and factor is described, along with descriptive statistics, are available in [Appendix B](#).

The item removal was carefully conducted regarding not leaving any factor with less than three items. Accordingly, we removed three items regarding keeping all factors with enough items to CFA analysis and considering its relevance when representing the factor load. After this, all statistical indices grew.

Additionally, MLE and WLSMV estimators were applied, taking into account the features of ordinal data, and showed acceptable CFI and TLI values (>0.900) in both. Results of CFA with MLE are shown in [Table 2](#), while CFA with WLSMV are shown in [Table 3](#). In both cases, the CFI and TLI estimators are increased after item modification.

Additionally, WLSMV provided robust estimation across all indices. This estimator, which is most suitable for ordinal data like Likert-scale responses, showed a better fit compared to the MLE. The comparison between estimators is shown in [Table 4](#).

Consequently, results of the CFA demonstrate high validity for the proposed model. Although the scaled chi-square statistic was significant ($\chi^2(242) = 423.423, p < 0.001$), which is common with large sample sizes, the robust fit indices provide a much more favorable assessment. Both the Robust Comparative Fit Index (CFI) and the Robust Tucker-Lewis Index (TLI), with values of 0.997, substantially exceed the recommended threshold of 0.90 (Hair et al., 2019), suggesting an

Table 2
Confirmatory Factor Analysis of Model (with MLE estimator).

Model Fit Index	No Modifications	Modifications
Items	27	24
df	314	224
CFI	0.883	0.915
TLI	0.869	0.904

Note: CFI is Comparative Fit Index, TLI is Tucker–Lewis Index.

Table 3
Confirmatory Factor Analysis of Model (with WLSMV estimator).

Model Fit Index	No Modifications	Modifications
Items	27	24
df	314	242
CFI	0.880	0.930
TLI	0.865	0.920

Note: CFI is Comparative Fit Index, TLI is Tucker–Lewis Index.

Table 4
Index comparison between estimators.

Index	With MLE	With WLSMV
CFI	0.915	0.997
TLI	0.904	0.997
RMSEA	0.091	0.045
SRMR	0.047	0.038

Note: CFI is Comparative Fit Index, TLI is Tucker–Lewis Index, RMSEA is root mean square error of approximation, SRMR is standardized root mean squared residual, LL is 90 % lower limit, and UL is 90 % upper limit.

accurate fit of the model to data. These values indicate that the hypothesized model accurately represents the relationships between the observed and latent variables.

Furthermore, the approximation error indices also support the model's adequacy. The Robust Root Mean Square Error of Approximation (RMSEA) of 0.028, with a 90 % confidence interval ranging from 0.024 to 0.033, is well below the 0.05 threshold typically considered indicative of a good fit. The associated p -value for the Robust RMSEA ($P(H_0: RMSEA \leq 0.050) = 1.000$) further strengthens this conclusion, as it indicates no evidence to reject the hypothesis that the RMSEA is less than or equal to 0.05. Likewise, the Standardized Root Mean Square Residual (SRMR) of 0.038, which is below the 0.08 cutoff, corroborates the model's strong predictive capacity and the low discrepancy between the observed and model-implied covariance matrices.

Collectively, these robust fit indices (CFI, TLI, RMSEA, and SRMR) consistently demonstrate that the model possesses high construct validity. The standardized factor loadings of all observed variables on their respective latent factors are high and statistically significant ($p < 0.001$), with standardized values ranging from 0.760 to 0.914. This signifies a strong representation of the constructs by their respective items. The covariances among the latent factors are also significant and positive, suggesting coherent relationships between them. Therefore, the model provides a valid and robust representation of the theoretical relationships intended for evaluation.

RQ2. How are pre-service teachers' demographics and university context related to their iTPACK dimensions?

The means and standard deviations were estimated for each of the five factors of the iTPACK model: iTK, iTPK, iTCK, iTPACK, and ETHICS, based on the participants' demographic variables (see Table 1). Demographic profile of the participants). We assessed the normality of each factor's distribution using the Shapiro-Wilk test (iTK: $W = 0.923$, $p < .001$; iTPK: $W = 0.974$, $p < .001$; iTCK: $W = 0.961$, $p < .001$; iTPACK: $W = 0.968$, $p < .001$; ETHICS: $W = 0.953$, $p < .001$).

The results of the correlations among the factors of the iTPACK model are presented below to explore how technological and pedagogical skills influence AI ethical knowledge, as is shown in Table 5.

Between-group comparisons were conducted using Quade's nonparametric ANCOVA, adjusting for covariates as appropriate. In this regard, no significant differences by gender were observed when controlling for age (all $p > .05$). Regarding academic level, when controlling for age, Upperclassmen ($N = 255$) obtained higher scores than Underclassmen ($N = 111$) in iTK ($F = 5.18$, $p = .023$, $\Delta = +0.38$), iTPK ($F = 4.26$, $p = .040$; $\Delta = +0.37$) and ETHICS ($F = 10.70$, $p = .001$; $\Delta = +0.65$). The effects for iTCK ($F = 3.71$, $p = .055$) and iTPACK ($F = 3.52$, $p = .061$) were marginal, in favor of the Upperclassmen, as is shown in Table 6 and more detailed in Appendix C.

When institutions are compared by type of ownership (public vs. private), public institutions show higher values in all model factors, most prominently in the ETHIC factor and iTPACK (see Table 7). After controlling for age and level no differences were found (all $p \geq .05$). The means were close: e.g., iTK = 5.33 in the capital vs 5.13 in the regions ($\Delta = +0.19$). Regarding geographic location, after controlling for the covariates of age and level, no significant differences were found (all $p \geq .05$).

These findings suggest that the institutional context significantly impacts the development of teachers' digital competencies, possibly due to curricular differences or the institutional culture regarding the integration of AI into training processes.

Regarding the type of specialization, only iTK showed a global effect (ANOVA: $F(2, 363) = 3.90$, $p = .021$), with an advantage of STEM over Primary and Early Childhood Education ($\Delta = +0.42$; Tukey $p = .020$). After adjusting for age and level, no significant differences were detected between the STEM, Primary and Early Childhood Education, and Non-STEM groups (all $p > .05$).

6. Discussion and conclusions

Global organizations have called for an increase in empirical research to understand potential risks better and for the effective use of

Table 5
Correlations between iTPACK dimensions.

	iTPK	iTCK	iTPACK	ETHICS
iTK	.648*	.678*	.639*	.533*
iTPK		.773*	.827*	.659*
iTCK			.833*	.643*
iTPACK				.725*

Note: Pearson correlation analysis, * $p < .001$.

Table 6

Group differences in iTPACK factors by academic level (Underclassmen vs. Upperclassmen).

Factor	F (Quade)	p-value	Comparison Under vs. Upper
iTK	5.18	.023	4.97 (1.48) < 5.35 (1.18)
iTPK	4.26	.040	4.39 (1.58) < 4.76 (1.34)
iTCK	3.71	.055	4.64 (1.64) < 5.04 (1.24)
iTPACK	3.52	.061	4.27 (1.71) < 4.64 (1.43)
ETHICS	10.70	.001	4.12 (1.82) < 4.77 (1.53)

Table 7

Comparative analysis of iTPACK factors by type of institution (public vs. private).

Factor	Public ($n = 251$) M (SD)	Private ($n = 115$) M (SD)	F (Quade)	p-value
iTK	5.48 (1.09)	4.70 (1.53)	13.87	<0.001
iTPK	4.85 (1.29)	4.20 (1.59)	7.52	.006
iTCK	5.15 (1.21)	4.42 (1.60)	10.40	.001
iTPACK	4.82 (1.35)	3.91 (1.72)	16.88	<0.001
ETHICS	4.99 (1.43)	3.67 (1.73)	35.38	<0.001

AI to support teaching and learning [1,2]. However, there has been limited attention given to understanding the role of pre-service teachers and their perceptions regarding AI in education from an iTPACK approach [20].

To help address this gap, the present study explored the knowledge and perceptions of 366 pre-service teachers from eleven different universities in Chile. Using the empirically validated iTPACK framework [15], we translated the instrument into Spanish, following a rigorous cross-cultural validation process. After conducting a CFA, we confirmed that the five dimensions of the original instrument, designed for in-service teachers, also hold and apply well to pre-service teacher populations.

In the literature, the intercorrelations among iTPACK subdimensions reach very high values. In [87], for example, coefficients of 0.871 (iTK-iTPK), 0.936 (iTPK-iTCK), 0.930 (iTPK-iTPACK), and 0.950 (iTPACK-ETHICS) are reported. In our study, the associations between iTPK-iTPACK ($\rho = 0.827$) and iTCK-iTPACK ($\rho = 0.833$) were high. This pattern is consistent with previous work: in K-12 iTPACK, strong correlations between the factors and coefficients "<0.85" were observed (max. iTCK-iTPK = 0.791; iTPACK-iTCK = 0.781; iTPACK-iPCK = 0.786), which suggests expected overlap but not total redundancy [104]. In iTPACK contexts, "a robust correlation between the constituent elements" and a "strong linear relationship" between iTPK/iTCK and iTPACK are reported, reinforcing the integrative nature of the construct [105]. In sum, the magnitudes > 0.80 observed here are theoretically consistent with TPACK/iTPACK frameworks and empirically reported by recent literature, reflecting conceptual integration rather than factorial redundancy.

CFA revealed an accurate transposition of Celik's [20] factors assessed in teachers' iTPACK skills when assessing the same factors in pre-service teachers. When analyzing factors, although we did not conduct Structural Equation Modeling (SEM) analysis, our factor correlations grew similarly to Celik's SEM effects. Thus, as [20] confirms that iTK has a weak effect on iTPACK, in our study we found a small to moderate correlation between iTK and iTPACK (0.639). Our study found a moderate correlation between iTK and ETHICS factors among pre-service teachers, similar to [20] with in-service teachers. Additionally, ETHICS shows the highest correlation with iTPACK and the lowest with iTK suggesting that, at the pre-service teachers' level, responsible and accountable decision-making around AI-based tools could be enhanced when such tools are integrated into teaching and learning, rather than focusing solely on their technological properties.

The study also explores the impact of sociodemographic variables on the iTPACK model, specifically focusing on future teachers' digital and

ethical competencies. It finds that gender and age do not significantly affect the various dimensions of the iTPACK model, aligning with previous research indicating an equitable distribution of these competencies among future educators. However, a notable distinction arises with academic level; students in advanced courses achieve higher scores in iTK, iTPK and ETHICS dimensions. This outcome suggests that continued progression in teacher training fosters a more nuanced incorporation of technology and a deeper reflection on the ethical aspects of artificial intelligence use.

Interestingly, while initial differences were noted based on the type of institution and discipline—favoring public universities and STEM programs—these differences diminished when age was controlled for in the analysis. After adjusting for age, the only sustained significant differences were in iTK, iTPK, and ETHICS based on academic level. This indicates that the variations previously observed can largely be attributed to age distribution among groups rather than the institution type or discipline. Overall, the findings emphasize that educational maturity and the trajectory of curricular advancement are more influential in shaping iTPACK competencies during the initial stages of teacher training than other contextual or disciplinary factors.

From our point of view, this could indicate that pre-service teachers' iTK still cannot be transposed to ethical-pedagogical skills because they are still developing professional knowledge as they advance in their teacher training. In fact, all iTK correlations with other factors do not surpass 0.678, which could mean that technological knowledge is dissociated from pedagogical, content, or ethical knowledge in pre-service teachers, at least in the first years of their training.

Our empirical analysis revealed no statistically significant differences based on students' gender, age, or years of study. We found that students' academic progress (i.e., their year in the program) was significantly associated with their knowledge of ethical considerations within the iTPACK framework. While these findings do not establish causality, they suggest that as pre-service teachers advance through their academic training, their understanding of the ethical implications of AI in education also increases.

Our findings differ from other studies that have applied the same scale under diverse cultural contexts. Thus, as [29] found a strong prediction when integrating the gender factor when assessing iTPACK skills, our results align with [30] and [31] which found no significant correlation between gender and iTPACK literacy. However, is important to point out that [29] study focuses on English foreign language pre-service teachers, while our results gather scores of pre-service teachers with diverse backgrounds. This could mean that in English as a foreign language, gender may be a stronger predictor than in the rest of the subject areas.

Previous research has shown that demographic variables can play a critical role in shaping how teachers conceptualize and integrate technology into teaching [38,39]. In this sense, while [39] nearly 20 years ago found that females demonstrated lower confidence and experience when integrating technology into teaching compared to males, the findings of [38] revealed that females no longer expressed that gap just before the emergence of generative AI in the world. Our finding confirms this trend at a time when AI is transforming education.

Furthermore, our analysis differs from [89], who assert in their study with pre-service teachers that "respondents are generally knowledgeable about technologically utilizing artificial intelligence in their teaching field" (p. 48). While they report moderate to high correlations between iTK and the other factors (but without reporting correlations with ETHICS), we found the opposite: a lack of training and skills to transpose iTK competencies into other pedagogical, content, or ethical dimensions.

Although the cultural and contextual factors that drives the current study could be pointed as an explanation for this difference in findings, it is relevant to point out that the study of [89] does not present an instrument validation process, uses purposive sampling, does not assess factors beyond correlations, and fails to explain the study context (e.g.,

whether students were exposed to specific training before responding). In this regard, cultural or contextual reasons cannot be discarded when addressing these different values when correlating iTPACK factors [26], especially iTK and ETHICS. Nevertheless, to be compared appropriately, contextual factors require similar research conditions (methods, frameworks) to be well discussed and scientifically compared.

Finally, expanding Shulman's [40] framework, which originally conceptualized PCK, by adding new dimensions such as technological or ethical knowledge, is essential to recognize that these dimensions cannot be fully understood independently of the pedagogical component. In fact, we are inclined to agree with the perspective that such dimensions may already be embedded within what is defined as PK, without the need to separate them as entirely external or isolated constructs explicitly.

6.1. Limitations

Despite the robust sample size of 366 participants and the institutional diversity represented across 11 universities, the findings of this study are confined to the unique context of Chilean higher education. This specificity limits the direct generalization of the results to other educational systems. However, it offers a vital baseline for future analyses regarding the contextual invariance of the instrument in similar cultural settings, particularly within Latin American countries. Many nations in this region share a common language and cultural patterns. Therefore, while the results cannot be automatically applied from one country to another, validating Celik's [20] scale within a Latin American context serves as a valuable starting point for regional researchers interested in exploring iTPACK literacy among both in-service and pre-service teachers.

A further methodological limitation lies in the exclusive reliance on self-report surveys for data collection. While this approach is efficient for the initial construct validation, self-reported measures may potentially under- or overestimate actual levels of AI literacy—a recognized challenge in competence assessment using such instruments [106]. Nevertheless, the methodological and analytical strategy employed was fully adequate to satisfy the primary research objective of validating Celik's instrument in a new educational setting.

Finally, the validation design focused exclusively on Confirmatory Factor Analysis (CFA), excluding Exploratory Factor Analysis (EFA) nor structural Equation Modeling (SEM). This decision was based on treating the original validation of the instrument as a strong theoretical starting point. While the CFA successfully confirmed the factor structure in the Chilean context, this approach implies that the factors were confirmed rather than being inductively built within the local context. The research team opted for this methodology to maintain the statistical integrity of the CFA, thereby avoiding the sample splitting that adding an EFA would require. This use of the original instrument as a theoretical starting point is a well-established approach, supported by a growing body of literature in scale adaptation and revalidation (e.g. [31, 57]), as well as in scale re-assessment studies using CFA [29].

7. Implications and future work

This study contributes to the field in several ways, showing significant strengths at both the scholar and practitioner levels. First, there is a lack of psychometrically validated, short, and practical instruments that assess pre-service teachers' knowledge and readiness to integrate AI effectively in educational settings. Second, to the best of our knowledge, there were no existing Spanish-adapted instruments suitable for use across Latin American countries. For the international audience of *Computers & Education Open*, this research provides decentralized, context-sensitive findings that may be of interest to practitioners, researchers, and policymakers worldwide.

The practical implications of having a properly adapted survey to measure iTPACK in a Latin American context, such as the Chilean

educational system, offer the entire region a scale that enables a robust comparative study with other realities worldwide. Regarding the research implications, as the scale develops, scholars could consider conducting interventions in the ethical domain of the AI-educational field, which can now be assessed using the iTPACK framework and scale. Regarding practitioners' implications, the approach of integrating ethical aspects to previous TPACK dimensions could help enhance practical AI and general technological acquisition in schools and higher education institutions.

Our findings also reveal significant differences in iTPACK skills based on the type of institution and discipline, with better results seen among students from public universities and those studying STEM fields. These findings motivate us to include contextual variables when designing training programs for integrating AI into initial teacher education (ITE). The variations in model factors according to institution type and discipline suggest that familiarity and prior interaction with technology positively influence this integration [39]. This highlights the need to strengthen the development of pedagogical and technological knowledge as a shared foundation, upon which specialized training can be built, tailored to the characteristics and specific approaches of each discipline. For instance, programs could teach future teachers how to work with AI-based tools, focusing on their technical aspects in specific classroom situations. However, more research is necessary to understand how disciplinary technological skills relate to the pedagogical abilities essential for effective AI integration.

Another important aspect concerns the link between technological knowledge and the ethical considerations of AI use. The weak connection identified in our results highlights the need for enhanced ethical training, encompassing topics such as data privacy, algorithmic fairness, bias, and accountability for AI decisions. This requires designing training experiences that not only build epistemic knowledge but also foster ethical thinking and behavior in real-world scenarios [41]. In this context, there are opportunities to integrate reflection spaces within ITE on ethical dilemmas and controversial issues related to AI adoption in education, which can help strengthen professional judgment and informed decision-making.

At the methodological level, future research directions also emerge. Besides examining the design and effectiveness of training programs, it is important to explore how digital competence develops during initial teacher education, especially in AI-mediated environments. Further research could explore the possible overlap between the new dimension addressed by the iTPACK framework (ETHICS) and other dimensions by conducting exploratory factor analysis in the new contexts where the scale is adapted.

On the other hand, the same dataset was used for both the instrument validation and the exploratory comparative analyses between groups. This decision responds to the cross-sectional nature of the design and the purpose of the research, which focused on describing contextual trends. In this regard, the nonparametric Quade ANCOVA test was applied as a strategy to examine differences. Nevertheless, future studies should incorporate analyses to assess invariance and replicate the results with

independent samples

Finally, longitudinal studies analyzing how the dimensions of iTPACK evolve would provide deeper insight into how technological, pedagogical, disciplinary, and ethical knowledge gradually integrate as students progress through their training and incorporate AI into their practice. This approach would help identify key moments and factors that either facilitate or impede this integration.

Statements on potential conflicts of interest

All authors declare no conflict of interest.

Statements on open data and ethics

Research data can be shared upon request.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the second and third authors utilized generative AI in order to translate the existing text, instructing the AI not to modify or add new content, but to focus solely on translation. After utilizing AI, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article. The used prompt is available in [Appendix D](#).

CRediT authorship contribution statement

José Reyes-Rojas: Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Brayan Díaz:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Camila Ruz-Reveco:** Visualization, Methodology, Investigation, Data curation. **Angela Castro:** Writing – original draft, Investigation. **David Reyes-González:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

*** Validated instrument in spanish, original from Celik (2023).*

1. ¿Con qué género te identificas?
 - a. Mujer
 - b. Hombre
 - c. No binario
 - d. Otro: ¿Cuál: ___?
 - e. Prefiero no decir
2. ¿En qué semestre de la carrera te encuentras?
 - 1ro

- 2do
 - 3ro
 - 4to
 - 5to
 - 6to
 - 7mo
 - 8vo
 - 9no
 - Otro (programa de formación pedagógica o PFP, post-licenciatura, programas advance, etc.)
3. ¿En qué rango de edad te ubicas?
- a. 18 a 22 años
 - b. 23 a 30 años
 - c. 31 a 40 años
 - d. 41 o más
4. ¿En qué universidad estás estudiando?
- a. Universidad Metropolitana de Ciencias de la Educación (UMCE)
 - b. Universidad de Playa Ancha (UPLA)
 - c. Universidad del Bío-Bío (UBB)
 - d. Universidad de La Serena (ULS)
 - e. Universidad de Chile (UCh)
 - f. Pontificia Universidad Católica de Chile (PUC)
 - g. Universidad San Sebastián (USS)
 - h. Universidad Diego Portales (UDP)
 - i. Universidad de O'Higgins (UOH)
 - j. Otra
5. ¿A cuál carrera de pedagogía o mención perteneces?
- a. STEM
 - b. Lenguaje
 - c. Ciencias Sociales
 - d. Idiomas
 - e. Artes
 - f. Educación Física
 - g. Educación Especial
 - h. Educación Básica
 - i. Otra

A continuación, lea atentamente cada afirmación y responda según el nivel de acuerdo que corresponda con su perspectiva personal.

Niveles de acuerdo:

Muy en desacuerdo

Medianamente en desacuerdo

Levemente en desacuerdo

Ni de acuerdo ni en desacuerdo

Levemente de acuerdo

Medianamente de acuerdo

Muy de acuerdo

ÍTEM

- 1: Sé cómo interactuar con herramientas basadas en IA en la cotidianidad.
- 2: Sé cómo ejecutar algunas tareas con herramientas basadas en IA.
- 3: Sé cómo iniciar una tarea con tecnologías basadas en IA mediante texto o voz.
- 4: Tengo el conocimiento necesario para utilizar herramientas basadas en IA.
- 5: Estoy familiarizado con las herramientas basadas en IA y sus capacidades técnicas.
- 6: Puedo comprender la contribución pedagógica de las herramientas basadas en IA con mi campo de enseñanza.
- 7: Puedo evaluar la utilidad de la retroalimentación entregada por las herramientas basadas en IA en la enseñanza y el aprendizaje.
- 8: Puedo seleccionar herramientas basadas en IA para que los estudiantes apliquen sus conocimientos.
- 9: Sé cómo utilizar las herramientas basadas en IA para monitorear el aprendizaje de los estudiantes.
- 10: Puedo interpretar los mensajes entregados por las herramientas basadas en IA para dar retroalimentación en tiempo real.
- 11: Puedo comprender alertas (o notificaciones) de las herramientas basadas en IA para guiar el aprendizaje de los estudiantes.
- 12: Cuento con el conocimiento para seleccionar las herramientas basadas en IA que mantengan la motivación de los estudiantes.
- 13: Puedo utilizar herramientas basadas en IA para buscar material pedagógico en mi campo de enseñanza.
- 14: Conozco diversas herramientas basadas en IA que son utilizadas por profesionales en mi campo de enseñanza.
- 15: Puedo utilizar herramientas basadas en IA para una mejor comprensión de los contenidos enseñados.

(continued on next page)

(continued)

ÍTEM
16: Sé cómo utilizar herramientas basadas en IA que sean específicas en mi área (por ejemplo, tutor inteligente en Matemáticas).
17: Al enseñar contenidos de mi área, sé cómo utilizar diferentes herramientas basadas en IA para entregar una retroalimentación adaptativa.
18: Al enseñar contenidos de mi área, sé cómo utilizar diferentes herramientas basadas en IA para ofrecer un aprendizaje personalizado.
19: Al enseñar contenidos de mi área, sé cómo utilizar diferentes herramientas basadas en IA para entregar una retroalimentación en tiempo real.
20: Puedo enseñar una asignatura utilizando herramientas basadas en IA con diferentes estrategias didácticas.
21: Puedo impartir clases que combinan adecuadamente mi contenido de enseñanza, herramientas basadas en IA y estrategias educativas.
22: Puedo asumir el papel de líder entre mis futuros colegas en el momento de integrar de herramientas basadas en IA en nuestro campo de enseñanza.
23: Puedo seleccionar varias herramientas basadas en IA para monitorear el aprendizaje de los estudiantes en mi proceso de enseñanza-aprendizaje.
24: Puedo evaluar hasta qué punto las herramientas basadas en IA consideran las diferencias individuales (por ejemplo, raza y género) de mis estudiantes.
25: Puedo evaluar hasta qué punto las herramientas basadas en IA actúan de manera justa con los estudiantes.
26: Puedo comprender la justificación de las decisiones tomadas por una herramienta basada en la IA.
27: Puedo identificar quiénes son los desarrolladores responsables del diseño y de las decisiones tomadas por las herramientas basadas en IA.

Appendix B

CFA results of adapted iTPACK scale.

Factor	Ítem	Factor Loading	Item-total r	Mean (SD)
TK	Q1	0.831	0.819**	5.44 (1.36)
TK	Q2	0.823	0.855**	5.42 (1.36)
TK	Q3	0.803	0.728**	5.01 (1.65)
TK	Q4	0.897	0.858**	5.25 (1.43)
TK	Q5	0.914	0.841**	5.07 (1.49)
TPK	Q8	0.792	0.749**	4.94 (1.58)
TPK	Q9	0.831	0.810**	4.30 (1.74)
TPK	Q10	0.786	0.728**	4.81 (1.67)
TPK	Q11	0.822	0.797**	4.57 (1.61)
TPK	Q12	0.859	0.774**	4.63 (1.69)
TCK	Q13	0.760	0.715**	5.39 (1.50)
TCK	Q14	0.810	0.759**	4.72 (1.62)
TCK	Q15	0.813	0.757**	5.23 (1.50)
TCK	Q16	0.794	0.691**	4.32 (1.86)
TPACK	Q17	0.878	0.848**	4.40 (1.72)
TPACK	Q18	0.888	0.880**	4.48 (1.79)
TPACK	Q19	0.850	0.839**	4.24 (1.76)
TPACK	Q20	0.870	0.830**	4.80 (1.69)
TPACK	Q21	0.850	0.812**	4.77 (1.71)
TPACK	Q22	0.807	0.766**	4.63 (1.77)
TPACK	Q23	0.848	0.841**	4.40 (1.77)
ETHICS	Q24	0.852	0.813**	4.69 (1.85)
ETHICS	Q25	0.881	0.839**	4.81 (1.80)
ETHICS	Q27	0.796	0.658**	4.22 (1.84)

Note: **: $p < .01$. CFA conducted with WLSMV estimator.

Appendix C

Variable (covariables)	Dimension	F (Quade)	p	Δ of means (in favor of...)	Interpretation
Gender (age)	iTK	0.53	.659	–	No differences
	iTPK	0.72	.538	–	No differences
	iTCK	0.17	.917	–	No differences
	iTPACK	0.25	.858	–	No differences
	ETHICS	0.29	.831	–	No differences
Academic level (age)	iTK	5.18	.023	+0.38 (Upper > Under)	Significant
	iTPK	4.26	.040	+0.37 (Upper > Under)	Significant
	iTCK	3.71	.055	+0.39 (Upper > Under)	Marginal
	iTPACK	3.52	.061	+0.38 (Upper > Under)	Marginal
	ETHICS	10.70	.001	+0.65 (Upper > Under)	Significant
Type of institution (age + level)	iTK	13.87	<0.001	+0.78 (Public > Private)	Significant
	iTPK	7.52	.006	+0.65 (Public > Private)	Significant

(continued on next page)

(continued)

Variable (covariables)	Dimension	F (Quade)	p	Δ of means (in favor of...)	Interpretation
Geographical location (age + level)	iTCK	10.40	.001	+0.73 (Public > Private)	Significant
	iTPACK	16.88	<0.001	+0.91 (Public > Private)	Significant
	ETHICS	35.38	<0.001	+1.32 (Public > Private)	Significant
	iTK	3.79	.052	+0.19 (Capital > Regional)	Trend
	iTPK	0.25	.617	–	No differences
	iTCK	0.77	.382	–	No differences
Type of specialization (age + level)	iTPACK	1.26	.263	–	No differences
	ETHICS	3.48	.063	+0.24 (Capital > Regional)	Trend
	iTK	2.88	.057	+0.42 (STEM > Primary/Early Ed.)	Marginal
	iTPK	1.10	.334	–	No differences
	iTCK	0.39	.679	–	No differences
	iTPACK	1.14	.323	–	No differences
	ETHICS	1.17	.312	–	No differences

Appendix D

Prompt used to communicate and translate text with the help of AI tools:
“Hello, I am a native Spanish speaker working on a research journal paper that must be written in English. I want your help translating the text from Spanish to English using a native-level or highly advanced bilingual translation. Please do not change or add any text—focus solely on the translation. Also, do not alter the format of the text or modify references or other elements. Please maintain these instructions throughout our entire conversation in this chat”.

References

[1] European Commission. Ethics Guidelines for Trustworthy. AI Publication Office; 2019.

[2] OECD. Recommendation of the Council on Artificial Intelligence. 2019. OECD/LEGAL/0449.

[3] Almasri F. Exploring the impact of artificial intelligence in teaching and learning of science: a systematic Review of Empirical Research. *Res Sci Educ* Oct. 2024;54(5):977–97. <https://doi.org/10.1007/s11165-024-10176-3>.

[4] B. Díaz and C. Delgado, “Artificial intelligence: tool or teammate?,” Dec. 01, 2024, John Wiley and Sons Inc. doi: 10.1002/tea.21993.

[5] UNESCO. *K-12 ai curricula: a mapping of government-endorsed ai curricula*. Paris, 2022.

[6] Niederhauser DS, Lindstrom DL. Instructional technology integration models and frameworks: diffusion, competencies, attitudes, and dispositions. Second handbook of information technology in primary and secondary education. Cham: Springer; 2018. p. 335–55. https://doi.org/10.1007/978-3-319-71054-9_23.

[7] Schmid M, Brianza E, Mok SY, Petko D. Running in circles: a systematic review of reviews on technological pedagogical content knowledge (TPACK). *Comput Educ* 2024;214:105024.

[8] Castro A, Díaz B, Aguilera C, Prat M, Chávez-Herting D. Identifying rural elementary teachers’ Perception challenges and opportunities in integrating artificial intelligence in teaching practices. *Sustain (Switz)* Mar. 2025;17(6). <https://doi.org/10.3390/su17062748>.

[9] Ayanwale M, Adelana O, Molefi R, Adeeko O, Ishola A. Examining artificial intelligence literacy among pre-service teachers for future classrooms. *Comput Educ Open* 2024;6:100179.

[10] Abdulayeva A, Zhanatbekova N, Andasbayev Y, Boribekova F. Fostering AI literacy in pre-service physics teachers: inputs from training and co-variables. *Front Educ (Lausanne)* 2025;10. <https://doi.org/10.3389/educ.2025.1505420>.

[11] Bae H, Jaesung H, Park J, Choi GW, Moon J. Pre-service teachers’ Dual perspectives on generative AI: benefits, challenges, and integration into their teaching and learning. *Online Learn J Sep.* 2024;28(3):131–56. <https://doi.org/10.24059/olj.v28i3.4543>.

[12] Kalniņa D, Nimante D, Baranova S. Artificial intelligence for higher education: benefits and challenges for pre-service teachers. *Front Educ (Lausanne)* 2024;9. <https://doi.org/10.3389/educ.2024.1501819>.

[13] Nuangchalerm P, Prachagool V, Saregar A, Yunus YM. Fostering pre-service teachers’ AI literacy through school implications. *J Philol Educ Sci Dec.* 2024;3(2):77–86. <https://doi.org/10.53898/jpes2024327>.

[14] Davila-Moran RC, et al. Brief prompt-engineering clinic substantially improves AI literacy and reduces technology anxiety in first-year teacher-education students: a pre–Post pilot study. *Educ Sci (Basel)* Aug. 2025;15(8). <https://doi.org/10.3390/educsci15081010>.

[15] Younis B. Effectiveness of a professional development program based on the instructional design framework for AI literacy in developing AI literacy skills among pre-service teachers. *J Digit Learn Teach Educ* 2024;40(3):142–58. <https://doi.org/10.1080/21532974.2024.2365663>.

[16] Lee S, Jeon J, Choe H. Generative AI (GenAI) and pre-service teacher agency in ELT. *ELT J Apr.* 2025;79(2):287–96. <https://doi.org/10.1093/elt/ccaf005>.

[17] Hwang Y, Lee S, Jeon J. Integrating AI chatbots into the metaverse: pre-service English teachers’ design works and perceptions. *Educ Inf Technol (Dordr)* Mar. 2024. <https://doi.org/10.1007/s10639-024-12924-4>.

[18] Zhang C, Hu M, Wu W, Kamran F, Wang X. Unpacking perceived risks and AI trust influences pre-service teachers’ AI acceptance: a structural equation modeling-based multi-group analysis. *Educ Inf Technol (Dordr)* Feb. 2024. <https://doi.org/10.1007/s10639-024-12905-7>.

[19] Mishra P, Koehler M. Technological pedagogical content knowledge: a framework for teacher knowledge. *Teach Coll Rec* 2006;108(6):1017–54.

[20] Celik I. Towards intelligent-TPACK: an empirical study on teachers’ professional knowledge to ethically integrate artificial intelligence (AI)-based tools into education. *Comput Hum Behav Jan.* 2023;138. <https://doi.org/10.1016/j.chb.2022.107468>.

[21] Alrishan AMH. Determinants of intention to use ChatGPT for professional development among Omani EFL pre-service teachers. *Int J Learn Teach Educ Res Dec.* 2023;22(12):187–209. <https://doi.org/10.26803/ijlter.22.12.10>.

[22] Wang W, Schmidt-Crawford D, Jin Y. Preservice Teachers’ TPACK Development: a Review of literature. *J Digit Learn Teach Educ Oct.* 2018;34(4):234–58. <https://doi.org/10.1080/21532974.2018.1498039>.

[23] Lachner A, et al. Fostering pre-service teachers’ technological pedagogical content knowledge (TPACK): a quasi-experimental field study. *Comput Educ* 2021;174:104304.

[24] Stinken-Rösner L, Hofer E, Rodenhauer A, Abels S. Technology implementation in Pre-service science teacher education based on the transformative view of TPACK: effects on Pre-service teachers’ TPACK, behavioral orientations and actions in practice. *Educ Sci (Basel)* Jul. 2023;13(7). <https://doi.org/10.3390/educsci13070732>.

[25] McDougall T, Phillips M. Contextual considerations in TPACK: collaborative processes in initial teacher education. *Comput Educ Open* 2024;7:100207.

[26] Petko D, Mishra P, Koehler M. TPACK in context: an updated model. *Comput Educ Open* 2025;8:100244.

[27] Tschönnens F, Backfisch I, Fütterer T, Lachner A. TPACK in action: contextual effects of pre-service and in-service teachers’ knowledge structures for technology integration. *Comput Educ Open* 2024;7:100219.

[28] Schubatsky T, Burde J-P, Große-Heilmann R, Lachner A, Riese J, Weiler D. From knowledge to intention: the role of TPACK and self-efficacy in technology integration. *Comput Educ Open* 2025;8:100246.

[29] Karataş F, Ataç BA. When TPACK meets artificial intelligence: analyzing TPACK and AI-TPACK components through structural equation modelling. *Educ Inf Technol (Dordr)* May 2024. <https://doi.org/10.1007/s10639-024-13164-2>.

[30] Lérias E, Guerra C, Ferreira P. Literacy in artificial intelligence as a challenge for teaching in higher education: a case study at Portalegre Polytechnic University. *Inf (Switz)* Apr. 2024;15(4). <https://doi.org/10.3390/info15040205>.

[31] Ning Y, Zhang C, Xu B, Zhou Y, Wijaya TT. Teachers’ AI-TPACK: exploring the relationship between knowledge elements. *Sustain (Switz)* Feb. 2024;16(3). <https://doi.org/10.3390/su16030978>.

[32] Jeon J, Lee S. Large language models in education: a focus on the complementary relationship between human teachers and ChatGPT. *Educ Inf Technol (Dordr)* Dec. 2023;28(12):15873–92. <https://doi.org/10.1007/s10639-023-11834-1>.

[33] Ng DTK, Wu W, Leung JKL, Chiu TKF, Chu SKW. Design and validation of the AI literacy questionnaire: the affective, behavioural, cognitive and ethical approach. *Br J Educ Technol May* 2024;55(3):1082–104. <https://doi.org/10.1111/bjet.13411>.

[34] Díaz B, Nussbaum M, Greiff S, Santana M. The role of technology in reading literacy: is Sweden going back or moving forward by returning to paper-based reading? *Comput Educ* 2024;105014–213.

- [35] Sidabutar M, et al. Reading digital texts vs. Reading printed texts: which one is more effective in Iranian EFL context? *Educ Res Int* 2022;2022. <https://doi.org/10.1155/2022/7188266>.
- [36] Syahrial S, Kurniawan DA, Asrial A, Sabil H, Maryani S, Rini EFS. Professional teachers: study of ICT capabilities and research competencies in urban and rural? *Cypriot J Educ Sci Jul*. 2022;17(7):2247–61. <https://doi.org/10.18844/cjes.v17i7.7590>.
- [37] Schmitz M-L, Antonietti C, Consoli T, Cattaneo A, Gonon P, Petko D. Transformational leadership for technology integration in schools: empowering teachers to use technology in a more demanding way. *Comput Educ* 2023;204: 104880.
- [38] Šabić J, Baranović B, Rogošić S. Teachers' Self-efficacy for using information and communication technology: the interaction effect of gender and age. *Inform Educ* 2022;21(2):353–73. <https://doi.org/10.15388/infedu.2022.11>.
- [39] Zhou G, Xu J. Adoption of educational technology: how does gender matter? *Int J Teach Learn High Educ* 2007;19(2):140–53 [Online]. Available, <http://www.isetl.org/jtlde/>.
- [40] Schulman L. Knowledge and teaching: foundations of the new reform. *Harv Educ Rev* 1987;57(1):1–22.
- [41] Park S, Oliver JS. Revisiting the conceptualisation of pedagogical content knowledge (PCK): PCK as a conceptual tool to understand teachers as professionals. *Res Sci Educ* 2008;38(3):261–84. <https://doi.org/10.1007/s11165-007-9049-6>.
- [42] D. Loewenberg, M. Hoover, and G. Phelps, "Content knowledge for teaching: what makes it special?," 2008, SAGE Publications Inc. doi: 10.1177/0022487108324554.
- [43] Koehler MJ, Mishra P. What is technological pedagogical content knowledge? Contemporary Issues in technology and Teacher education. *Contemp Issues Technol Teach Educ* 2009;9(1):60–70. <https://doi.org/10.1177/002205741319300303>.
- [44] Alonso-Rodríguez AM. Towards an ethical framework of Artificial intelligence in education. *Teor Educ* 2024;36(2):79–98. <https://doi.org/10.14201/teri.31821>.
- [45] Flores-Vivar JM, García-Peñalvo FJ. Reflections on the ethics, potential, and challenges of artificial intelligence in the framework of quality education (SDG4). *Comunicar* 2023;30(74):35–44. <https://doi.org/10.3916/C74-2023-03>.
- [46] A. Brandão, L. Pedro, and N. Zagalo, "Teacher professional development for a future with generative artificial intelligence – An integrative literature review," Jul. 01, 2024, *Universitat de Barcelona*. doi: 10.1344/der.2024.45.151-157.
- [47] Bustamante Bula R, Camacho Bonilla A. Inteligencia artificial (IA) en las escuelas: una revisión sistemática (2019-2023). *Enunciación Aug*. 2024;29(1):62–82. <https://doi.org/10.14483/22486798.22039>.
- [48] Mouta A, Torrecilla-Sánchez EM, Pinto-Llorente AM. Comprehensive professional learning for teacher agency in addressing ethical challenges of AIED: insights from educational design research. *Educ Inf Technol (Dordr)* Feb. 2024. <https://doi.org/10.1007/s10639-024-12946-y>.
- [49] Sperling K, Stenberg C-J, McGrath C, Åkerfeldt A, Heintz F, Stenliden L. In search of artificial intelligence (AI) literacy in teacher education: a scoping review. *Comput Educ Open Jun*. 2024;6:100169. <https://doi.org/10.1016/j.caeo.2024.100169>.
- [50] F. Karataş and E. Yüce, "AI and the future of teaching: preservice teachers' Reflections on the use of artificial intelligence in open and distributed learning," 2024.
- [51] Agca RK, Korkmaz O. Experimental perspective on artificial intelligence anxiety. *Int J Technol Educ Jan*. 2025;8(1):22–44. <https://doi.org/10.46328/ijte.846>.
- [52] Babanoğlu MP, Karataş TÖ, Dündar E. Ethical considerations of AI through a socio-technical lens: insights from ELT context as a higher education system. *Cogent Educ* 2025;12(1). <https://doi.org/10.1080/2331186X.2025.2488546>.
- [53] Blonder R, Feldman-Maggor Y. AI for chemistry teaching: responsible AI and ethical considerations. *Chem Teach Int Dec*. 2024. <https://doi.org/10.1515/cti-2024-0014>.
- [54] UNESCO, *Recommendation on the ethics of artificial intelligence*. Paris, France, 2022.
- [55] Floridi L, Cowls J. A unified framework of five principles for AI in society. *Harv Data Sci Rev Jun*. 2019. <https://doi.org/10.1162/99608f92.8cd550d1>.
- [56] Sætra HS, Danaher J. To each technology its own ethics: the problem of ethical proliferation. *Philos Technol Dec*. 2022;35(4). <https://doi.org/10.1007/s13347-022-00591-7>.
- [57] Mah DK, Groß N. Artificial intelligence in higher education: exploring faculty use, self-efficacy, distinct profiles, and professional development needs. *Int J Educ Technol High Educ Dec*. 2024;21(1). <https://doi.org/10.1186/s41239-024-00490-1>.
- [58] Wang S, Wang F, Zhu Z, Wang J, Tran T, Du Z. Artificial intelligence in education: a systematic literature review. *Expert Syst Appl* 2024;252(A):124167.
- [59] Lee S, Jeon J, Choe H. Enhancing Pre-service teachers' Global englishes awareness with technology: a focus on AI chatbots in 3D metaverse environments. *TESOL Q Mar*. 2024. <https://doi.org/10.1002/tesq.3300>.
- [60] Fidan M, Gencel N. Supporting the instructional videos with chatbot and peer feedback mechanisms in online learning: the effects on learning performance and intrinsic motivation. *J Educ Comput Res Dec*. 2022;60(7):1716–41. <https://doi.org/10.1177/07356331221077901>.
- [61] Kinder A, et al. Effects of adaptive feedback generated by a large language model: a case study in teacher education. *Comput Educ: Artif Intell* 2025;8:100349.
- [62] Kurt G, Kurt Y. Enhancing L2 writing skills: chatGPT as an automated feedback tool. *J Inf Technol Educ: Res* 2024;23:024. <https://doi.org/10.28945/5370>.
- [63] Hesse F, Helm G. Writing with AI in and beyond teacher education: exploring subjective training needs of student teachers across five subjects. *J Digit Learn Teach Educ* 2024. <https://doi.org/10.1080/21532974.2024.2431747>.
- [64] Martono N, Rochsantiningsih D, Wijaya SA. Intertextuality in pre-service teachers' Argumentative essay in raising AI: practices and beliefs. *Regist J* 2023; 16(2):186–206. <https://doi.org/10.18326/rgt.v16i2.186-206>.
- [65] Al-Nofaie H, Alwerthan TA. Appreciative inquiry into implementing artificial intelligence for the development of language student teachers. *Sustain (Switz)* Nov. 2024;16(21). <https://doi.org/10.3390/su16219361>.
- [66] Chung JY, Jeong SH. Exploring the perceptions of Chinese pre-service teachers on the integration of generative AI in English language teaching: benefits, challenges, and educational implications. *Online J Commun Media Technol Oct*. 2024;14(4). <https://doi.org/10.30935/ojcm/15266>.
- [67] Teng MF, Huang J. Incorporating ChatGPT for EFL writing and its effects on writing engagement. *Int J Comput-Assist Lang Learn Teach* 2025;15(1). <https://doi.org/10.4018/IJCALLT.367874>.
- [68] Biberman-Shalev L. Prompting theory into practice: utilizing ChatGPT-4 in a curriculum planning course. *Educ Sci (Basel)* Feb. 2025;15(2). <https://doi.org/10.3390/educsci15020196>.
- [69] Liu ZY, Vobolevich A, Oparin A. The influence of AI ChatGPT on improving teachers' Creative thinking. *Int J Learn Teach Educ Res Dec*. 2023;22(12): 124–39. <https://doi.org/10.26803/ijlter.22.12.7>.
- [70] Nissim Y, Simon E. The diffusion of artificial intelligence innovation: perspectives of preservice teachers on the integration of ChatGPT in education. *J Educ Teach* 2025. <https://doi.org/10.1080/02607476.2025.2469128>.
- [71] Broutin M. Exploring mathematics teacher candidates' Instrumentation process of generative artificial intelligence for developing lesson plans. *Yuksekogetrim Derg Oct*. 2023. <https://doi.org/10.53478/yuksekogetrim.1347061>.
- [72] Lan Y. Through tensions to identity-based motivations: exploring teacher professional identity in Artificial intelligence-enhanced teacher training. *Teach Teach Educ* 2024;151:104736.
- [73] Duran V. Analyzing teacher candidates' arguments on AI integration in education via different chatbots. *Digit Educ Rev Jul*. 2024;(45):68–83. <https://doi.org/10.1344/der.2024.45.68-83>.
- [74] Segal R, Biton Y. The contribution that utilizing generative AI for problem posing makes to pre-service high school mathematics teachers' TPACK. *Int J Educ Math Sci Technol Sep*. 2024;1559–82. <https://doi.org/10.46328/ijemst.4591>.
- [75] Filiz A, Gür H. Students' Perceptions and applications of metacognitive awareness levels in problem solving with ChatGPT. *Educ Process: Int J* 2025;14. <https://doi.org/10.22521/edupij.2025.14.63>.
- [76] Polat E, Zircirli M, Zengin E. Examining the interaction between artificial intelligence literacy and individual entrepreneurial orientation in teacher candidates: the mediating role of sustainable development. *Int J Manag Educ Jul*. 2025;23(2). <https://doi.org/10.1016/j.ijme.2025.101156>.
- [77] H. Cai, L. Lu, B. Han, L.H. Wong, and X. Gu, "Exploring pre-service teachers' reflection mediated by an AI-powered teacher dashboard in video-based professional learning: a pilot study," *Educational Technology Research and Development*, Apr. 2024, doi: 10.1007/s11423-024-10442-1.
- [78] Dilek M, Baran E, Aleman E. AI literacy in teacher education: empowering educators through critical Co-discovery. *J Teach Educ May* 2025. <https://doi.org/10.1177/00224871251325083>.
- [79] Hopcan S, Türkmen G, Polat E. Exploring the artificial intelligence anxiety and machine learning attitudes of teacher candidates. *Educ Inf Technol (Dordr)* Apr. 2024;29(6):7281–301. <https://doi.org/10.1007/s10639-023-12086-9>.
- [80] Martínez-Moreno J, Petko D. What motivates future teachers? The influence of artificial intelligence on student teachers' career choice. *Comput Educ: Artif Intell Dec*. 2024;7. <https://doi.org/10.1016/j.caeai.2024.100296>.
- [81] Kayaalp F, Durali M, Gökbulut B. Enhancing competence for a sustainable future: integrating artificial intelligence-Supported educational technologies in pre-service teacher training for sustainable development. *Eur J Educ* 2024;60(1): e12865.
- [82] Erdem G. Artificial intelligence literacy in assessment: empowering pre-service teachers to design effective exam questions for language learning. *Br Educ Res J* 2025. <https://doi.org/10.1002/berj.4177>.
- [83] D. Marikyan and S. Papagiannidis, "Unified Theory of Acceptance and Use of Technology: a review," in *TheoryHub book*, S. Papagiannidis, editor, 2025.
- [84] Zhang C, Schießl J, Plöbl L, Hofmann F, Gläser-Zikuda M. Acceptance of artificial intelligence among pre-service teachers: a multigroup analysis. *Int J Educ Technol High Educ Dec*. 2023;20(1). <https://doi.org/10.1186/s41239-023-00420-7>.
- [85] Kim S-W. Development of a TPACK educational program to enhance pre-service teachers' Teaching expertise in Artificial intelligence convergence education. *Int J Adv Sci Eng Inf Technol Feb*. 2024;14(1):1–9. <https://doi.org/10.18517/ijaset.14.1.19552>.
- [86] Bautista A, et al. Preservice teachers' Readiness towards integrating AI-based tools in education: a TPACK approach. *Educ Process: Int J* 2024;13(3):40–68. <https://doi.org/10.22521/edupij.2024.133.3>.
- [87] Hava K, Babayigit Ö. Exploring the relationship between teachers' competencies in AI-TPACK and digital proficiency. *Educ Inf Technol (Dordr)* Feb. 2025;30(3): 3491–508. <https://doi.org/10.1007/s10639-024-12939-x>.
- [88] Delcker J, Heil J, Ifenthaler D. Evidence-based development of an instrument for the assessment of teachers' self-perceptions of their artificial intelligence competence. *Educ Technol Res Dev* 2024. <https://doi.org/10.1007/s11423-024-10418-1>.
- [89] Gregorio T, Alieto E, Natividad E-R, Tanpoco M. Are preservice teachers 'totally Packed'? A quantitative study of pre-service teachers' Knowledge and skills to ethically integrate artificial intelligence (AI)-based tools into education. In: Motahhir S, Bossoufi B, editors. *International Conference on Digital Technologies*

- and Applications. Springer Nature Switzerland; May 2024. https://doi.org/10.1007/978-3-031-68660-3_5. editors.
- [90] Corradi B, Espinosa D, Rodríguez C, Espinoza O. Is admission enough? University persistence of students admitted through affirmative action policies in Chile. *High Educ Policy* Jan. 2025. <https://doi.org/10.1057/s41307-024-00393-w>.
- [91] Bellei C, Muñoz G. Models of regulation, education policies, and changes in the education system: a long-term analysis of the Chilean case. *J Educ Change* Mar. 2023;24(1):49–76. <https://doi.org/10.1007/s10833-021-09435-1>.
- [92] Clasing-Manquian P. How free tuition became a policy in Chile: the importance of policy actors and their beliefs. *High Educ (Dordr)* Nov. 2024. <https://doi.org/10.1007/s10734-024-01188-z>.
- [93] Barroilhet A, Ortiz R, Quiroga BF, Silva M. Exploring conflict of interest in university accreditation in Chile. *High Educ Policy* 2022;35:479–97. <https://doi.org/10.1057/s41307-020>.
- [94] INE, “Resultados nacionales CENSO 2024,” Santiago, Chile, 2024.
- [95] Guzmán-Valenzuela C. Navigating public goods: Chilean public universities and their transformative role in Latin America. *High Educ (Dordr)* Jan. 2024. <https://doi.org/10.1007/s10734-024-01298-8>.
- [96] Ministerio de Ciencia. La Inteligencia Artificial entra al catálogo de ChileValora con 5 perfiles propuestos por el Ministerio de Ciencia,”. 2025. <https://www.mincien.cl/noticias/la-inteligencia-artificial-entra-al-catalogo-de-chilevalora-con-5-perfiles-propuestos-por-el-ministerio-de-ciencia/>.
- [97] Ministerio de Ciencia, “Política Nacional de Inteligencia Artificial,” Santiago, 2021.
- [98] Centro Nacional de Inteligencia Artificial C. Índice Latinoamericano de Inteligencia Artificial,” 2025. <https://indicelatam.cl/>.
- [99] Beaton DE, Bombardier C, Guillemin F, Ferraz MB. Guidelines for the process of Cross-Cultural adaptation of self-report measures. *Spine (Phila Pa 1976)* 2000;25(24):3186–91.
- [100] Kemp A, Palmer E, Strelan P, Thompson H. Testing a novel extended educational technology acceptance model using student attitudes towards virtual classrooms. *Br J Educ Technol* Sep. 2024;55(5):2110–31. <https://doi.org/10.1111/bjet.13440>.
- [101] Li CH. Confirmatory factor analysis with ordinal data: comparing robust maximum likelihood and diagonally weighted least squares. *Behav Res Methods* Sep. 2016;48(3):936–49. <https://doi.org/10.3758/s13428-015-0619-7>.
- [102] Rodway P, Schepman A. The impact of adopting AI educational technologies on projected course satisfaction in university students. *Comput Educ: Artif Intell* Jan. 2023;5. <https://doi.org/10.1016/j.caeai.2023.100150>.
- [103] Kline R. *Principles and practice of structural equation modeling*. 5th Edition. New York: The Guilford Press; 2023.
- [104] Yue M, Jong MSY, Ng DTK. Understanding K–12 teachers’ technological pedagogical content knowledge readiness and attitudes toward artificial intelligence education. *Educ Inf Technol (Dordr)* Oct. 2024;29(15):19505–36. <https://doi.org/10.1007/s10639-024-12621-2>.
- [105] Xie M, Luo L. The status quo and future of AI-TPACK for mathematics teacher education students: a case study in Chinese universities [Online]. Available, <http://arxiv.org/abs/2503.13533>; Mar. 2025.
- [106] Lintner T. A systematic review of AI literacy scales. *NPJ Sci Learn* Dec. 2024;9(1). <https://doi.org/10.1038/s41539-024-00264-4>.