Revista Latinoamericana de Tecnología Educativa, 25(2)
https://doi.org/10.17398/1695-288X.25.2.247

RELATEC
Revista Latinoamericana de Tecnología Educativa

Received: March 10, 2026
Reviewed: May 5, 2026
Accepted: May 8, 2026

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ARTICLE / ARTÍCULO

Teacher training as a key factor in the adoption of artificial intelligence in primary education

La capacitación docente como factor clave en la adopción de inteligencia artificial en educación básica

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Abstract: Introduction/Objective: This study examines the relationship between formal artificial intelligence (AI) training and its adoption in teaching practice among primary education teachers in Chile's Maule Region, a territory marked by urban-rural inequalities. Method: A cross-sectional exploratory-descriptive contrasting-groups design was used with a sample of 150 teachers (54% women; 58.7% urban, 41.3% rural), who completed a validated 34-item questionnaire (August-October 2025). Descriptive statistics, Chi-square test, and Cramér's V as effect size measure were applied. Results: Complete group differentiation was observed (χ^2 = 143.96, df = 1, p < .001; Cramér's V = 0.980): 100% of formally trained teachers (n = 31) actively use AI, while no untrained teacher (n = 119) has integrated it. Trained teachers show high-frequency use (90.3%), high confidence (67.7%), and perceived pedagogical improvements (100%). A descriptive pattern of territorial inequality in training access is observed (urban: 25.0% vs. rural: 14.5%; rate ratio = 1.72). Discussion/Conclusions: Findings challenge the teacher-resistance narrative (only 10.1% of untrained teachers express active opposition), pointing to predominantly structural barriers. Formal training emerges as an enabling condition for AI adoption, with direct implications for the design of territorial equity policies governing access to teacher professional development in Latin American contexts marked by urban-rural inequality.

Keywords: Artificial Intelligence, Elementary Secondary Education, Elementary School Teachers, Educational Technology, Territorial Inequality, Equal Education

Resumen: Introducción/Objetivo: Este estudio examina la relación entre capacitación formal en inteligencia artificial (IA) y su adopción pedagógica en docentes de educación básica de la Región del Maule, Chile, territorio con desigualdades urbano-rurales. Método: Diseño transversal exploratorio-descriptivo de grupos contrastantes con 150 docentes (54% mujeres; 58.7% urbanos, 41.3% rurales), quienes respondieron un cuestionario validado de 34 ítems (agosto-octubre 2025). Se aplicó estadística descriptiva, Chi-cuadrado y V de Cramer. Resultados: Se observó una separación prácticamente completa entre grupos (χ^2 = 143.96, gl = 1, p < .001; V de Cramer = 0.980): el 100% de docentes capacitados (n = 31) usa IA activamente; ningún docente sin capacitación (n = 119) la ha integrado. Los capacitados presentan alta frecuencia de uso (90.3%), alta confianza (67.7%) y mejoras pedagógicas percibidas (100%). Se observa inequidad territorial descriptiva en el acceso a capacitación (urbano: 25.0% vs. rural: 14.5%; razón de tasas = 1.72). Discusión/Conclusiones: Los resultados cuestionan la narrativa de resistencia docente, pues solo el 10.1% de no capacitados expresa oposición, señalando barreras predominantemente estructurales. La capacitación formal emerge como factor diferenciador para la adopción de IA, con implicaciones directas para el diseño de políticas de equidad en el acceso al desarrollo profesional docente en contextos latinoamericanos con desigualdad territorial.

Palabras-clave: Inteligencia Artificial, Educación Básica, Docentes de Educación Primaria, Tecnología Educativa, Desigualdad territorial, Igualdad de oportunidades educativas.

1. Introduction

Chile has spent more than three decades investing in educational technology: since 1992, computer labs were built, digital platforms were deployed, and 96% of its schools were connected to the internet. In 2024, the vast majority of its primary education teachers do not use artificial intelligence in the classroom, a paradox that constitutes the starting point of this study, not because AI is a pedagogical obligation, but because the gap between available infrastructure and actual adoption reveals something about how teacher technology training policy works, or fails to work. Organizations such as UNESCO (2021) and the OECD (2023) have for years pointed out that the challenge is no longer access but training. The data from the Maule Region presented here confirm that reading with a force that is worth examining.

In Latin America, empirical research on AI adoption in primary education is significantly scarce. The systematic review by Zawacki-Richter et al. (2019) found that only 2.4% of studies on educational AI came from this region, evidencing a critical gap in the production of situated knowledge. Most of the available theoretical frameworks, such as the Technology Acceptance Model (TAM) by Davis (1989) or the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003), were developed in Global North contexts with consolidated digital infrastructure and articulated public policies, conditions that do not characterize Latin American education systems (CEPAL, 2021).

This study is situated in that gap, examining AI adoption among 150 primary education teachers in Chile's Maule Region. The territory concentrates significant inequalities between urban and rural areas: according to ministerial data (MINEDUC, 2023), 89% of urban schools report adequate connectivity compared to 54% in rural areas. This is not a technical problem; it is a structural condition that unequally distributes the possibilities for technological integration depending on where teaching takes place. This study examines what happens, in a specific territory with known structural inequalities, when a minority of teachers gain access to formal AI training and the majority do not. The guiding question and the specific objectives of the study are presented in the Methodology section, where they are articulated with the corresponding research design.

This study does not attempt to settle whether Chilean teachers should use AI or when they should do so. The question is more concrete: what happens, in a specific territory with known inequalities, when a minority of teachers receives formal training and the majority does not. That difference in starting point has consequences that the data allow us to observe with some clarity. The Maule Region is not a singular or peripheral case: its characteristics, consolidated educational infrastructure, persistent urban-rural gaps, insufficient and geographically concentrated continuing education offerings, are repeated with variations across much of the Latin American educational landscape.

1.1. Teacher technology adoption: from individualist models to structural approaches

For decades, research on technology adoption in education was dominated by a single question: why do some teachers use technology and others not? TAM (Davis, 1989) answered with two variables (perceived usefulness and ease of use) and that seemed sufficient. Venkatesh et al. (2003) expanded the model, but the logic remained individual: the teacher as the unit of analysis, their attitudes as the central variable. The problem with that view is not that it is incorrect, but that it is incomplete: Cuban (2001) was among the first to systematically document it, with schools of high computer availability and teachers who barely used them, not out of resistance or ignorance, but because institutional, curricular, and training conditions did not accompany the available technology.

What Cuban opened, others went on to confirm. Teacher training emerges in recent systematic reviews as the most robust predictor of effective technology adoption, above attitudes, pedagogical beliefs, or available infrastructure (Celik et al., 2022). This does not mean that individual variables do not matter: it means that without structural conditions to support them, positive attitudes toward technology rarely translate into real pedagogical use. A teacher convinced of AI's usefulness but without specific training is, in practice, in the same position as an indifferent one. The data from this study illustrate that dynamic with notable clarity.

Celik et al. (2022), in a systematic review of 100 empirical studies on educational AI, conclude that teacher professional development is the most influential and consistent factor for effective adoption, even above attitudinal and self-efficacy variables. Williamson and Eynon (2020) point in the same direction from another angle: AI integration policies tend to reproduce logics of individual accountability, expecting teachers to adopt emerging technologies without systematic investment in the conditions that would make that change possible.

For the Latin American context, the picture is no different. Martínez-Abad et al. (2020) and Pozos-Pérez and Tejada-Fernández (2018) document that limitations to adoption do not lie primarily in individual attitudes, but in structural inequalities of access to continuing education and in working conditions that restrict the time available for pedagogical experimentation. Rivas et al. (2023), in a prospective study with education and AI experts conducted for ProFuturo and the OEI, identified teacher training as the most highly valued priority for equitable AI integration in the region, above connectivity and tool availability, which coincides with CEPAL's (2021) diagnosis regarding access to continuing education as a persistent barrier in contexts with territorial inequality. In primary education specifically, Crompton et al. (2023) confirm in 66 empirical studies that teachers' use of AI is critically determined by access to professional training, and Yadav et al. (2024) document that this factor surpasses attitudes, self-efficacy, and technological access in predictive power.

1.2. Teacher training as a critical enabler for AI adoption

Speaking of teacher training in AI as if it were simply learning to operate tools falls short: Schön (1983) made this point decades ago, what forms a reflective professional is not the transfer of techniques but the construction of knowledge in practice, with real time, with mentorship, and with room to make mistakes. In emerging technologies such as AI, this requirement intensifies because the tools evolve faster than any training curriculum: what a teacher learns today about a specific model may be obsolete in six months. What does not become obsolete is the pedagogical judgment to evaluate and use them; a two-hour workshop on ChatGPT does not build that judgment: it may spark interest, but without sustained practice and mentorship, it rarely changes what happens in the classroom.

Cukurova et al. (2024), in a report for the European Commission, are explicit on this point: teacher professional development in AI requires continuous processes anchored in the institutional context and real pedagogical needs, not one-off events disconnected from practice. The distinction matters because it defines what can be expected from each type of intervention. A continuing training program with follow-up can change teaching practice; an isolated workshop, at best, generates favorable disposition without concrete pedagogical translation. When nearly four out of ten untrained teachers report knowing about AI applications but having had no opportunity to explore them, the diagnosis does not point to a lack of interest but to a training offer that does not reach them, or that reaches them insufficiently to become practice.

In the literature on teacher technology training, this structural perspective has gained increasing relevance. Romero et al. (2023), in a study with 667 Spanish primary, secondary, and university teachers, document that perceived digital competence is at an intermediate level across all experience brackets, and that the need for specific continuing training is transversal across the teaching profession regardless of gender or age. Méndez et al. (2022) add a relevant finding from initial training: prospective teachers perceive the competencies needed to integrate technology in a pedagogically meaningful way as insufficient, suggesting that training deficits do not begin in professional practice but earlier.

1.3. Structural barriers in Latin American contexts with territorial inequality

In Latin America, barriers to AI integration in education exceed individual attitudinal or competency-related dimensions. CEPAL (2021) identifies persistent territorial inequalities: while urban areas concentrate digital infrastructure and professional development opportunities, rural contexts face limited connectivity, lower access to training, and more precarious working conditions. The pattern is not new: it reproduces historical educational inequity logics that the emergence of AI may aggravate if specific policies do not intervene.

Chile's Maule Region constitutes a representative case of these patterns. With a population of approximately 1.3 million inhabitants distributed across 30 municipalities, it presents pronounced urban-rural gaps: 54% of rural schools report insufficient connectivity for digital pedagogical activities, compared to 11% in urban areas (MINEDUC, 2023). Teacher professional development in AI is geographically concentrated in provincial capitals, requiring costly travel for rural teachers; although the Center for Improvement, Experimentation, and Pedagogical Research (CPEIP), the agency of the Chilean Ministry of Education responsible for continuing teacher education, has promoted online formats to expand reach, coverage in rural areas remains insufficient relative to documented demand.

Maule is not an isolated case. Contexts such as Spain, with documented gaps between rural provinces and urban centers in access to continuing teacher technology training (Romero et al., 2023), or Latin American contexts such as Colombia, Peru, and Bolivia share similar structures. What occurs in a territory with consolidated infrastructure but unevenly distributed training matters beyond its borders: any system where teacher training in emerging technology is concentrated in urban centers faces variants of the same problem.

2. Methodology

2.1. Study design and scope

The guiding question of the study is: What differences exist between trained and untrained teachers in the integration of AI in primary education in Chile's Maule Region? The specific objectives are: (a) to characterize differences in effective AI use between the two groups; (b) to describe adoption patterns among trained teachers; (c) to identify the structural barriers perceived by untrained teachers; and (d) to examine contextual differences according to geographic location and type of school.

A cross-sectional exploratory-descriptive contrasting-groups design was used (Stebbins, 2001), aimed at identifying differential patterns between AI-trained and untrained teachers, and at characterizing the structural barriers perceived by the latter. This approach is appropriate given the emerging state of empirical research on AI adoption in Latin American primary education, where exploratory designs allow for the generation of hypotheses for future confirmatory research (Muñiz, 2018). The choice of a cross-sectional design responds to this exploratory logic: it constitutes a first systematic approximation to a phenomenon scarcely documented in the region, without any claim to capture the procedural dimension of adoption, which would require longitudinal designs in later research phases.

Inferences derived from this design are of contextual scope: the findings characterize patterns in the sample studied and should not be causally extrapolated to broader populations without additional longitudinal and quasi-experimental studies. This limitation is explicitly acknowledged and its implications are discussed in the conclusions.

2.2. Participants

The sample included 150 primary education teachers from the Maule Region, selected through convenience sampling with intentional heterogeneity criteria regarding geographic context and type of school. The gender distribution was 81 women (54.0%) and 69 men (46.0%). Teaching experience was heterogeneous: 28 participants with 1-5 years (18.7%), 37 with 6-10 years (24.7%), 34 with 11-15 years (22.7%), 29 with 16-20 years (19.3%), and 22 with more than 20 years (14.7%). Regarding administrative dependency, teachers participated from municipal schools (n = 81, 54.0%), municipal corporations (n = 35, 23.3%), subsidized private schools (n = 18, 12.0%), and foundations (n = 16, 10.7%). Regarding geographic context, 88 teachers (58.7%) work in urban areas and 62 (41.3%) in rural areas. The imbalance between the trained group (n = 31, 20.7%) and the untrained group (n = 119, 79.3%) is inherent to the contrasting-groups design and reflects the actual distribution of training in the territory studied; nonetheless, it has implications for the statistical power of the multivariate analyses specified in the Results section.

Table 1. Demographic and contextual characteristics of the sample (N = 150).

Variable	Category	n	%
Gender	Female	81	54.0
	Male	69	46.0
Teaching experience	1-5 years	28	18.7
	6-10 years	37	24.7
	11-15 years	34	22.7
	16-20 years	29	19.3
	More than 20 years	22	14.7
Type of school	Municipal	81	54.0
	Corporation	35	23.3
	Private	18	12.0
	Foundation	16	10.7
Geographic context	Urban	88	58.7
	Rural	62	41.3

2.3. Instrument

A structured 34-item questionnaire was designed, addressing: (a) demographic and contextual data; (b) participation in formal AI training; (c) patterns of AI use in teaching practice, frequency, nature, specific activities; (d) level of confidence and perceived improvements; and (e) perceived barriers to adoption and interest in future training. The question on AI use (item 12) explicitly asked about any type of use in the preceding three months, including experimental or sporadic uses, with the purpose of not restricting the response to consolidated uses.

A design limitation relevant to the interpretation of the main finding is the possible conceptual interdependence between the training item (item 8) and the AI-use item (item 12). Although both explore distinct dimensions, having received training versus having applied AI in teaching practice, it cannot be ruled out that, during the period studied (August-October 2025), formal training constituted the almost exclusive channel of access to AI in this context, which would explain the observed separation without necessarily implying that training is the direct cause of each instance of use. This distinction is relevant in order not to overinterpret the Cramér's V coefficient of 0.980 as causal evidence.

The instrument was validated through the judgment of five experts in educational technology, all with research experience in ICT integration in primary education, applying Lawshe's (1975) content validity procedure, which led to wording adjustments in 8 of the 34 items. Given the exploratory and multidimensional nature of the questionnaire, reliability was assessed through: (a) content validity with an expert panel; (b) piloting with 15 teachers not included in the final sample; and (c) for the prospective attitude toward AI subscale, the inter-item correlation ($r = .544$) and the Spearman-Brown coefficient ($\alpha = .704$) were calculated, a value considered adequate for exploratory instruments (Nunnally & Bernstein, 1994). The instrument was administered digitally via Google Forms between August and October 2025, with explicit informed consent and guarantees of confidentiality and anonymity.

2.4. Análisis de datos

Descriptive statistics were used to characterize the groups (frequencies, percentages, measures of central tendency). The association between formal training and AI use was analyzed using the Chi-square test with Yates' continuity correction, appropriate given that the 2×2 table presents cells with zero value, and Cramér's V as the effect size measure, considering values > 0.50 as a strong association (Cohen, 1988). This was complemented with Fisher's exact test. To examine whether secondary sociodemographic variables, gender, teaching experience, and type of school, moderate the relationship between training and adoption, a binary logistic regression analysis was performed. To examine territorial inequality in access to training, a Chi-square test of independence between training and geographic context was applied, complemented by the calculation of the urban/rural training rate ratio and the odds ratio. Open-ended responses on perceived barriers were categorized through deductive-inductive content analysis. Data were processed using SPSS v.28 and Microsoft Excel with a significance level of $\alpha = 0.05$.

2.5. Ethical considerations

The study was conducted in accordance with the ethical principles of the Declaration of Helsinki for research involving human subjects. Voluntary participation was guaranteed through explicit informed consent, confidentiality of personal data, anonymity in reporting, and the right to withdraw without consequences. Data are stored with restricted access limited to the researcher and will be deleted after five years in accordance with institutional protocols.

3. Results

3.1. AI training and effective use: complete differentiation between groups

Only 31 teachers (20.7%) reported having received formal AI training applied to education, and 100% of this subgroup reported actively using AI in their teaching practice. In contrast, none of the 119 untrained teachers (79.3%) reported AI use in their pedagogical activities, even though the item explicitly explored experimental or sporadic uses in the preceding three months.

The Chi-square test with Yates' continuity correction revealed statistically significant differences ($\chi^2 = 143.96$, df = 1, $p < .001$). Fisher's exact test confirmed this result ($p < .001$). Cramér's V of 0.980 indicates a practically perfect association between both variables, configuring a categorical separation with no overlap: the group with formal training and the group without it represent completely differentiated adoption profiles in this specific context and moment.

It is important to note that the magnitude of this differentiation, higher than the typical ranges reported in technology-integration research where Cramér's V values of 0.30-0.50 already indicate moderate to large effects (Cohen, 1988), invites interpreting this result as an emerging contextual pattern. The separation may be partially influenced by the fact that the instrument explored use during a specific period (the preceding three months), which may not capture prior attempts at self-taught adoption.

Table 2. Differentiation in AI use according to formal training (N = 150).

Group	Uses IA	Does not use AI	Total
Trained	31 (100.0%)	0 (0.0%)	31 (20.7%)
Untrained	0 (0.0%)	119 (100.0%)	119 (79.3%)
Total	31 (20.7%)	119 (79.3%)	150 (100.0%)

Note. χ^2 = 143.96 (Yates correction), df = 1, p < .001; Fisher's exact test p < .001; Cramér's V = 0.980. The magnitude indicates practically complete differentiation between groups in this specific context and period.

3.2. Contextual profile of the groups

To verify that no sociodemographic variable moderates or confounds the main association, a binary logistic regression was performed including as predictors: formal training, gender, teaching experience (ordinal), type of school, and geographic context. The model presents a Nagelkerke pseudo R^2 of .988. In the multivariate model, only formal training was a statistically significant predictor (B = 9.03, OR = 8.321, p < .001); gender (OR = 0.65, p = .794), teaching experience (OR = 0.80, p = .745), type of school (OR = 0.92, p = .964), and geographic context (OR = 0.72, p = .853) did not reach statistical significance. These results should be interpreted with caution: the reduced size of the trained subgroup (n = 31) limits the statistical power of the model to detect real effects of secondary sociodemographic variables, so non-significance does not necessarily equate to the absence of effect.

Regarding the distribution of the trained subgroup by teaching-experience bracket, the 31 teachers are distributed as follows: 1-5 years (n = 4, 12.9%), 6-10 years (n = 4, 12.9%), 11-15 years (n = 9, 29.0%), 16-20 years (n = 8, 25.8%), and more than 20 years (n = 6, 19.4%). The distribution is relatively dispersed, with no extreme concentration in any bracket, which reduces the risk of instability in the logistic model's coefficients. A descriptive pattern of interest emerges when calculating training rates by bracket: teachers with 11-15 years (26.5%), 16-20 years (27.6%), and more than 20 years (27.3%) show notably higher rates than those with 1-5 years (14.3%) and 6-10 years (10.8%), suggesting that AI training is not concentrated among younger teachers but among those with greater professional trajectory. This pattern is consistent with the literature identifying professional experience as a predictive variable for participation in continuing training (Romero et al., 2023).

Table 3. Distribution of trained teachers by experience bracket and access indicators (n = 31).

Experience bracket	n trained	% within group	Training rate by bracket
1-5 years	4	12.9%	14.3%
6-10 years	4	12.9%	10.8%
11-15 years	9	29.0%	26.5%
16-20 years	8	25.8%	27.6%
More than 20 years	6	19.4%	27.3%
Total	31	100%	20.7%

Note. The Training rate by bracket column indicates the percentage of trained teachers out of the total number of teachers in that bracket in the sample (N = 150).

Analysis of contextual variables revealed differences in the geographic distribution of trained teachers. Among the 31 trained teachers, 22 (71.0%) work in urban contexts and 9 (29.0%) in rural contexts. Training rates are 25.0% among urban teachers (22/88) versus 14.5% among rural teachers (9/62), representing a rate ratio of

1.72 (urban teachers have a 72% higher probability of having received training than rural teachers). The Chi-square test of independence between training and geographic context did not reach statistical significance (χ^2 = 1.84, df = 1, p = .175; Fisher's exact test: OR = 1.96, p = .152), which should be interpreted with caution given the reduced size of the trained subgroup (n = 31).

Regarding type of school, among trained teachers the municipal sector predominates (n = 20, 64.5%), followed by corporations (n = 5, 16.1%), private schools (n = 5, 16.1%), and foundations (n = 1, 3.2%). This distribution does not differ markedly from the overall sample, suggesting that administrative dependency is not a significant differentiating factor in access to training in this context.

Table 4. Contextual profile of trained and untrained teachers.

Variable	Category	Trained (n=31)	Untrained (n=119)	Total (N=150)
Geographic context	Urban	22 (71.0%)	66 (55.5%)	88 (58.7%)
	Rural	9 (29.0%)	53 (44.5%)	62 (41.3%)
Training rate		25% urban / 14.5% rural		
Type of school	Municipal	20 (64.5%)	61 (51.3%)	81 (54.0%)
	Corporation	5 (16.1%)	30 (25.2%)	35 (23.3%)
	Private	5 (16.1%)	13 (10.9%)	18 (12.0%)
	Foundation	1 (3.2%)	15 (12.6%)	16 (10.7%)

Note. Training rates calculated on the total number of urban (88) and rural (62) teachers respectively.

3.3. Adoption patterns among trained teachers (n = 31)

The data in this section correspond to a subgroup of 31 teachers and should be read as exploratory indications, not as a consolidated adoption profile. With that limitation in mind, what the data show is a trend toward regular use: 9 out of 10 trained teachers (90.3%) report daily or weekly use, suggesting that adoption, where it occurs, tends to be sustained over time rather than dissipating after training.

Regarding the nature of use, slightly more than half the subgroup combines stable use with experimental or mixed use, and the average number of pedagogical activities in which AI is used is 5.3 per teacher. The most frequent activity is the creation of educational materials, followed by lesson planning and activity design. Two out of three trained teachers describe themselves as confident or very confident in using AI, and the entire subgroup reported having observed some improvement in their pedagogical activities. These data, given the size of the subgroup, point to an integration that goes beyond immediate instrumental use, although its interpretive scope is necessarily limited.

Table 5. Summary of adoption patterns among trained teachers (n = 31).

Variable	Indicator	n	%
Frequency of use	Daily or several times/week	28	90.3
	Once/week or less	3	9.7
Nature of use	Stable use (regularly integrated)	13	41.9
	Experimental use (exploring)	10	32.3
	Mixed use	8	25.8
Activities (multiple responses; avg. 5.3/teacher)	Create educational materials	26	83.9
	Plan lessons and units	20	64.5
	Design activities and exercises	20	64.5
	Prepare presentations	18	58.1
	Create assessments and rubrics	18	58.1
	Search for information and resources	16	51.6
Level of confidence	Confident or very confident	21	67.7
	Moderately confident	7	22.6
	Not very confident	3	9.7
Perceived pedagogical improvements	Significant	15	48.4
	Moderate	16	51.6
	No improvements	0	0.0

Note. Activity percentages are calculated on n = 31.

3.4. Barriers perceived by untrained teachers (n = 119)

Among the 119 untrained teachers, six categories of barriers to AI adoption were identified. The most frequent was «lack of opportunity despite conceptual knowledge» (n = 47, 39.5%). The second was «unfamiliarity with specific pedagogical applications» (n = 31, 26.1%). Together, these two categories represent 65.6% of barriers, pointing to deficits in the professional development offering rather than negative individual attitudes.

Other barriers identified were: «tools not adapted to pedagogical needs» (n = 14, 11.8%); «unsatisfactory results in trial experiences» (n = 13, 10.9%); «preference for current methodologies without the need to incorporate AI» (n = 12, 10.1%); and «lack of clarity about what AI is» (n = 2, 1.7%). Only the 10.1%, the subgroup that prefers its current methodologies, could be interpreted as an expression of active resistance, while the remaining 89.9% faces barriers of a structural or training-related nature.

Table 6. Reasons for not using AI among untrained teachers (n = 119).

Main reason	n	%
I know about AI applications but have not had the opportunity to explore them	47	39.5
I understand what AI is but do not know specific applications in education	31	26.1
I have explored tools but they do not fit my pedagogical needs	14	11.8
I have tried tools but the results did not meet my expectations	13	10.9
I prefer my current methodologies without incorporating AI	12	10.1
I have no clarity about what Artificial Intelligence is	2	1.7

Nota. Categorías mutuamente excluyentes; cada docente seleccionó una razón principal.

3.5. Interest in future training

When asked about interest in receiving training in AI applied to education, the 119 untrained teachers responded: very interested (n = 58, 48.7%), interested (n = 37, 31.1%), moderately interested (n = 19, 16.0%), slightly interested (n = 4, 3.4%), and not interested at all (n = 1, 0.8%). Overall, 79.8% express high interest. The gap between this declared interest (79.8%) and actual access to training (20.7% of the total sample) evidences an unmet demand for professional development that current policies have failed to address.

4. Discussion

4.1. Training as a structural factor: scope and limitations of the finding

That 100% of trained teachers use AI and 0% of untrained teachers do is a result that somewhat unsettles anyone accustomed to reading educational research. Perfect effects almost never occur and, when they do, they must be examined carefully; the literature on teacher professional development in technology, Celik et al. (2022), Tammets and Ley (2023), and Cukurova et al. (2024), identifies training as the most influential factor in AI adoption, but none of those studies reports such complete separations. There are at least two non-exclusive explanations: a methodological one, related to the data-capture period and the possible interdependence between items; and a substantive one, related to the specific structural conditions of the Chilean context, where the AI training offer is so scarce that whoever accesses it represents an already actively motivated teacher profile.

The practically perfect differentiation may be partially explained by design features: the instrument captured use during the preceding three months, a period in which formal training availability was limited and recent for most participants. It is plausible that some untrained teachers had engaged in self-taught use attempts prior to or outside the studied period, not captured by the item. The absence of such self-taught adoption contrasts, on the other hand, with patterns observed in technologies of lower perceived complexity, reflecting the particularities of AI as a technology that requires a minimum training threshold for effective pedagogical use (Crompton & Burke, 2023).

Classic theoretical models, TAM (Davis, 1989) and UTAUT (Venkatesh et al., 2003), posit multiple concurrent variables: attitudes, pedagogical beliefs, self-efficacy, infrastructure. In this specific context, training emerges as the condition that marks the difference between users and non-users, displacing the rest. Romero et al. (2023) document something similar in Spain: even teachers with intermediate digital competence require focused continuing training to integrate emerging technologies. The European Commission (Cukurova et al., 2024) arrives at the same recommendation: teacher training in AI must be continuous, contextualized, and institutionally sustained.

4.2. Characteristics of pedagogically robust adoption

The adoption patterns observed among trained teachers suggest an integration that transcends superficial experimentation. 90.3% show high-frequency use, 41.9% have consolidated stable use, and the average of 5.3 pedagogical activities per teacher indicates versatility in appropriation. The most valued activity, the creation of educational materials (83.9%), is consistent with the priority teaching function and with prior research documenting this use as a preferred entry point for AI integration (Tammets & Ley, 2023).

The unanimity in the perception of pedagogical improvements (100%), although based on subjective self-assessment rather than objective measurements of student learning, is a relevant indicator of the perceived legitimacy of the technology among those who have adopted it. This pattern contrasts with evaluations of other educational innovations where greater heterogeneity of perceptions tends to emerge.

4.3. Territorial inequality and differential access to training

The difference in training rates between urban (25.0%) and rural (14.5%) teachers, with a rate ratio of 1.72, did not reach statistical significance in this sample ($\chi^2 = 1.84$, $p = .175$). This lack of significance should be interpreted with caution: the trained subgroup is small (n = 31) and the statistical power of the analysis is limited to detect real differences of this magnitude. A sample with at least 120 trained teachers would have sufficient power to test this hypothesis with confidence. Therefore, non-significance does not equate to absence of effect, but rather to insufficient evidence in the available sample.

Nonetheless, the direction and descriptive magnitude of the pattern are consistent with the frameworks of territorial inequality documented for Chile (MINEDUC, 2023) and for Latin America in general (CEPAL, 2021): rural teachers access professional development opportunities in technology in lower proportion, which, in a context where training is a necessary condition for adoption, has implications that go beyond technological access. If training operates as an enabler, the territorial gap in access to training translates into a gap in the quality of learning opportunities available to rural students.

4.4. Dismantling the teacher-resistance narrative

Only 10.1% of untrained teachers express a preference for their current methodologies without the need to incorporate AI, which could be interpreted as active resistance in Selwyn's (2019) sense. The remaining 89.9% face barriers of a structural or training-related nature: lack of training opportunities (39.5%), unfamiliarity with specific pedagogical applications (26.1%), perceived inadequacy of available tools (11.8%), or unsatisfactory initial experiences (10.9%). The declared interest in training (79.8% with high interest) reinforces this interpretation.

Williamson and Eynon (2020) had already pointed out the problem: narratives that individually hold teachers responsible for non-adoption of technology obscure the structural conditions that limit their possibilities for integration. Hence, strategies centered on attitudinal persuasion have little traction if they are not accompanied by investment in accessible training and institutional conditions that make change possible.

5. Conclusions

The data from this study say something that admits no nuance: in the Maule Region, no teacher without formal AI training uses it in their practice, and none with training fails to use it. Such a categorical separation, with Cramér's V = 0.980, is not common in educational research, and that warrants taking it seriously before relativizing it. The exploratory design and the convenience sample preclude causal generalizations, but the pattern is sufficiently clear to formulate three conclusions with direct implications for teacher training policy in Chile.

First, the practically complete separation between groups (Cramér's V = 0.980) indicates that, in this specific context and period, formal training emerges as the differentiating factor between adoption profiles. This association does not allow strict causality to be established given the cross-sectional design, but its magnitude and consistency point to training as a structurally relevant condition. Trained teachers show a robust adoption profile: high frequency of use (90.3%), wide diversity of pedagogical applications (average 5.3 activities), growing autonomous confidence (67.7%), and unanimous positive pedagogical valuation (100%).

Second, a significant territorial inequality persists: the training rate in urban contexts (25.0%) practically doubles the rural rate (14.5%), even though the overall distribution of the sample is more balanced. This gap is not merely a problem of technological access: it is a condition that reproduces and widens inequalities in the quality of teaching available to students depending on their territory.

Third, the teacher-resistance narrative finds no empirical support in this sample. 79.8% of untrained teachers express high interest in receiving training, and only 10.1% express a preference for not incorporating AI. The obstacles are predominantly structural, which directs policy design toward removing access barriers rather than toward persuasion or attitude-change strategies.

Chile has infrastructure. 95.2% of educational establishments have internet connectivity (MINEDUC, 2023). What it lacks, or has very unevenly, is accessible and territorially distributed teacher training in AI. The 79.8% of untrained teachers who declare high interest in training is not a minor finding in a system where the dominant narrative tends to attribute non-adoption of technology to teacher resistance or disinterest. That interest does not automatically translate into adoption; it needs to find a training offer that reaches teachers, that is continuous, and that considers the real conditions of both rural and urban teachers equally. As long as that offer does not exist or is insufficient, available infrastructure will remain a necessary but not sufficient condition for AI integration in Chilean classrooms.

Among the limitations of the study are its exploratory scope and cross-sectional design, which do not allow for establishing causality or temporal follow-up of adoption. The convenience sample limits the generalization of the findings beyond the context studied. The instrument did not include the variable of teacher age, which restricts the depth of the sociodemographic profile of the trained group; future research should incorporate both age and teaching experience to examine their differential contribution to AI adoption. Likewise, the lack of statistical significance of teaching experience in the logistic model should be interpreted with caution, as it may stem from statistical power limitations derived from the reduced size of the trained subgroup (n = 31) rather than from a real absence of effect. Future research should incorporate longitudinal and quasi-experimental designs that allow evaluation of the causal impact of specific training programs, objective measurements of student learning, and comparative analyses between regions with different levels of investment in teacher professional development.

The contribution of this study to existing knowledge can be articulated in three dimensions. In empirical terms, it provides contextualized evidence on a phenomenon scarcely documented in Latin American primary education, from a territory with characteristics replicable across multiple education systems in the region. In methodological terms, it validates an instrument adapted to contexts with territorial inequality, suitable for application in comparative studies between Latin American countries with similar structures. In terms of educational policy, it identifies a pattern of inequity in access to training that transcends the Chilean case: any system in which teacher training in emerging technology is geographically concentrated in urban centers faces variants of the same problem of inequity in the quality of learning opportunities available to students according to their territory.

6. Declaration on the use of artificial intelligence

During the preparation of this work, the author used generative artificial intelligence tools as support for stylistic review and improvement of academic writing. Data analysis, methodological design, interpretation of results, and conclusions are the exclusive responsibility of the author. The final content was fully reviewed and validated by the author.

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