

Digital Competencies of Secondary School Teachers in Paraguay: An Analysis Based on the *Saberes Digitales* Framework

Valentina Canese *, Juan Mereles, Jessica Amarilla, and Roberto Páez

Facultad de Ciencias Exactas y Naturales, Universidad Nacional de Asunción, San Lorenzo, Paraguay
Email: vcanese@facen.una.py (V.C.); jimereles@facen.una.py (J.M.); jessa.amarillav@gmail.com (J.A.);
robertopaez@facen.una.py (R.P.)

*Corresponding author

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Abstract—While physical access to technology remains a global challenge, contemporary educational success now depends on the professional digital competencies. This study aims to analyze and contextualize the digital competence levels of 563 secondary school teachers in Paraguay, using the *Saberes Digitales* (Digital Literacies) framework as a theoretical foundation. This study employed a quantitative, non-experimental, and cross-sectional design, and examines the relationship between digital proficiency and various sociodemographic variables such as age and gender. The results indicate a general intermediate level of digital competence, with significant strengths in skills such as digital citizenship, digital literacy, and communication. However, some weaknesses were identified in advanced pedagogical areas, specifically managing Artificial Intelligence (AI), data manipulation, and the use of specialized software. Comparative analyses revealed that gender differences exist where men teachers scored slightly higher in some skills relative to women. Also, the most significant factor influencing technological proficiency is professional experience; a negative correlation exists between years of teaching and digital proficiency, highlighting an important generational gap. These findings highlight the necessity of targeted professional development programs to bridge existing gaps and to focus on the pedagogical appropriation of emerging technologies.

Keywords—education, digital literacies, technology, teacher education

I. INTRODUCTION

The integration of technology into all aspects of daily and professional life has made it an essential factor in our daily performance and has also made digital literacy a key determinant of social inclusion and teaching effectiveness in the knowledge society. The rapid integration of Information and Communication Technologies (ICT) into education has led to a shift in focus, moving from research on infrastructure availability to the study of the set of competencies educators need to transform information into knowledge [1, 2]. It is well known that gaps in access to and integration of ICTs in education still exist, affecting their use and adoption, especially with the emergence of new technologies such as Artificial Intelligence (AI) [3, 4]. However, such developments also give rise to new opportunities for developing new skills in the use of technologies in the classroom.

The use of ICT in the classroom is complex, as it requires not only the availability of infrastructure and the planned implementation of technologies, but also the teacher's ability to apply them to the class content and the context in which it

is taught [5]. To this end, teachers must possess technological capital that enables them to adapt various technological tools to their discipline, thereby enhancing their students' learning. Building on Bourdieu, Pitzalis and Porcu [6] propose that Digital Capital should be integrated into Cultural Capital Theory as a complementary element thus aligning with the *Saberes Digitales* framework of technological capital [7, 8].

Casillas *et al.* [7] define technological capital as “the set of knowledge, savoir-faire, and practical skills used in the learning process (in the sense of how they use ICT in school)”. Possessing it distinguishes individuals, generating greater competitive advantages in both personal and professional spheres. In the educational context, this capital manifests itself specifically in digital literacy. Considering this, Ramirez and Casillas [8] have proposed a digital knowledge framework of ten competencies that enable teachers to manage devices and files, create content, and participate in digital citizenship environments which they labeled *Competencias Digitales Docentes* (Teachers' Digital Literacies).

Framing digital competence as technological capital carries analytical consequences that this study seeks to make explicit. Following Bourdieu, such capital is not an isolated technical skill but an embodied disposition, a *habitus*, accumulated over a teacher's biographical and professional trajectory and conditioned by the institutional resources available to them [6]. Understood in this way, digital competence is unlikely to be evenly distributed across a teaching workforce; rather, its configuration should vary systematically with the dimensions along which teachers' trajectories diverge, including gender, age, years of experience, and geographic location. Therefore, the present study treats the measured competencies as evidence of how technological capital is accumulated and unevenly distributed within a specific Global South educational context [7, 8].

As early as the 1990s, studies distinguished between external and internal barriers to the integration of technology in the classroom. In this context, external barriers relate to a lack of access to computers and software, as well as insufficient time for lesson planning. On the other hand, internal barriers relate to perceptions regarding the use of computers in teaching [9]. This framework led to countless studies and the creation of paradigms that reaffirm the need to train teachers in critical ICT skills [10–12]. Furthermore, research on the importance of teacher training for the appropriate implementation of ICT in the classroom was impacted by the emergence of the COVID-19

pandemic [2, 13, 14]. The pandemic led to the widespread use of technologies regardless of the level of proficiency among educational stakeholders, pushing them to discover, learn, and innovate in their respective disciplines [2, 15, 16]. Thus, teacher education gains importance, particularly with the widespread adoption of ICT tools in education, training teachers in the use of ICT tools has become essential to translate pedagogy into student learning [2, 7, 8].

This study aims to contribute beyond a regional replication of established patterns. First, it operationalizes technological capital empirically, examining how this capital is distributed across demographic and professional intersections at a moment when generative Artificial Intelligence (AI) is reshaping what digital competence requires. Second, it interrogates the rural–urban dichotomy that dominates digital-divide research, asking whether geographic divides persist or are displaced by other sources of variation as mobile access becomes widespread. Third, it translates these findings into differentiated, context-sensitive implications for teacher education and policy.

II. LITERATURE REVIEW

It is now essential to integrate digital technologies into educational practices, as they have become a catalyst for achieving inclusive, equitable, and quality education [17]. The United Nations has highlighted the role of technology in Goals 4 (Education) and 9 (Industry, Innovation, and Infrastructure), which has led to a shift in focus, moving from working toward access to technology to working toward digital literacy and competence. Regarding teachers' adoption of technology, this field of educational research has evolved over the decades, leading to studies on the various factors that hinder or facilitate the use of technology in the classroom, as well as on how best to approach teacher training [18]. However, it remains a challenge to understand the best way to approach technology adoption and how educators' contexts influence the acquisition of digital competencies [19].

Over the years, teacher training has prioritized the development of digital literacy, offering teachers courses focused on the skills that will help them integrate technology into their practice. However, research indicates that courses and paradigms that focus exclusively on technology for teaching and learning may be too limited and ineffective for developing the diverse range of skills needed as new technologies emerge [18, 19]. Similarly, as the field of digital competence matured, definitions began to address the pedagogical aspect of the profession. Krumsvik [20], for example, states that “digital competence is the teacher’s individual ability to use ICT in school with sound pedagogical judgment and their awareness of its implications for students’ learning strategies and digital Bildung”. This definition emphasizes the need not to focus solely on technical skills, but to include pedagogy in teachers’ use of technology and to take into accounts’ development in terms of critical thinking and agency [2].

The adaptation of teacher training courses to include pedagogy led experts to develop frameworks that will help guide teacher training. This resulted in several paradigms that provided a solid foundation for understanding how teachers can use technology in their classrooms. Among the most

frequently cited examples are the Technological Pedagogical Content Knowledge (TPACK) model [21] and the Substitution, Augmentation, Modification, and Redefinition (SAMR) model [22]. The TPACK model focuses on the link between technology, pedagogy, and subject content. This model posits that there are effective ways to integrate technology into the teaching of specific content, provided one has a thorough understanding of the subject matter, the pedagogical strategies best suited to that content, and the tools that can adequately support that pedagogy [3, 4, 10, 21]. Furthermore, due to the model’s lack of an ethical dimension regarding technology implementation, Celik [23] introduced “Smart TPACK”, which includes an ethical knowledge component, to guide the ethical and pedagogical use of emerging AI-based tools.

The SAMR model is a four-level framework for integrating technology into the classroom, which includes: substitution, augmentation, modification, and re-definition [24]. In this model, the focus is more on how technology is used in the classroom than on skills related to technology use in general. For example, the substitution level could be illustrated by replacing paper-based exams with their online versions. At the augmentation level, technology is used to enhance a task, such as using devices to allow students to read and listen to digital stories, etc. [24, 25]. Although this model has gained popularity, there is no clear theoretical basis for understanding, applying, or interpreting it, and researchers have pointed out that it does not account for context and may be an overly rigid hierarchical framework that fails to consider the complexities of technology-enhanced teaching [24]. While the aforementioned models acknowledge the importance of pedagogy and technology together, their lack of more operational considerations limits their implementation, scope, and measurement.

In this regard, DigCompEdu [26] was developed by the European Commission and serves as a point of reference for various stakeholders in the education sector in the region. It comprises 22 competencies across six domains and offers a structured approach to assessing and improving educators’ digital competencies. The model provides levels of competence in technology use that serve as a tool for measuring technological knowledge and also as a guide for teachers to reflect on their technological skills. Caena and Redeker [27] note that DigCompEdu is broader than TPACK, as it prioritizes the skills dimension over the knowledge dimension and focuses on the teacher’s work environment. The generic nature of the model allows for its adaptation as new technologies emerge. Furthermore, the updated version of the Digital Competence Framework for Citizens (DigComp 2.2) includes new skills and knowledge due to emerging AI-driven technologies [28]. However, this model views digital competence as a linear, non-cumulative process and focuses on teachers’ self-reflection, which may lead to an overestimation of pedagogical skills.

The *Saberes Digitales* framework [7] comprises 10 core competencies, including: Computer Science (1) Device Management, (2) File Management, (3) Specialized Programs and Systems, (4) Text and Rich Text, (5) Data Management, (6) Multimedia, (7) Communication, (8) Collaboration, (9) Information Literacy, and (10) Digital Citizenship. Because the framework predates the widespread

adoption of generative AI, the present study extends it with an eleventh dimension dedicated to generative AI, capturing a competence area now central to teachers' work but absent from the original model. This model addresses several of the limitations mentioned. For example, it is not a general framework that assumes technological skills are the same or equally necessary across all professions, including teaching. It posits that technological skills vary depending on disciplines and context. This allows for greater "granularity" regarding the skills needed to manage technology and can help define teacher training courses. Furthermore, the *Saberes Digitales* model [7, 8] views technological skills as a form of capital and takes into account educators' backgrounds and prior knowledge regarding the adoption of technology. Thus, it recognizes that learning new skills is not a linear process and is shaped by teachers' prior knowledge and professional backgrounds. Finally, this model explicitly underscores the importance of digital citizenship and digital literacy. This involves fostering an awareness of values and ethics, along with the risks and responsible behaviors related to the use of technology.

Table 1. Comparison of major digital competence frameworks

Framework	Primary operational focus	Limitation in developing contexts
TPACK / SAMR	Integrating technology into specific instructional tasks	Separates technical skill from teachers' social and structural conditions
DigCompEdu	Comprehensive European competency standard	Presupposes institutional infrastructure and support uncommon across Latin America
Saberes Digitales (selected)	Digital competence as context-sensitive technological capital	Region-specific; benefits from wider macro-level validation

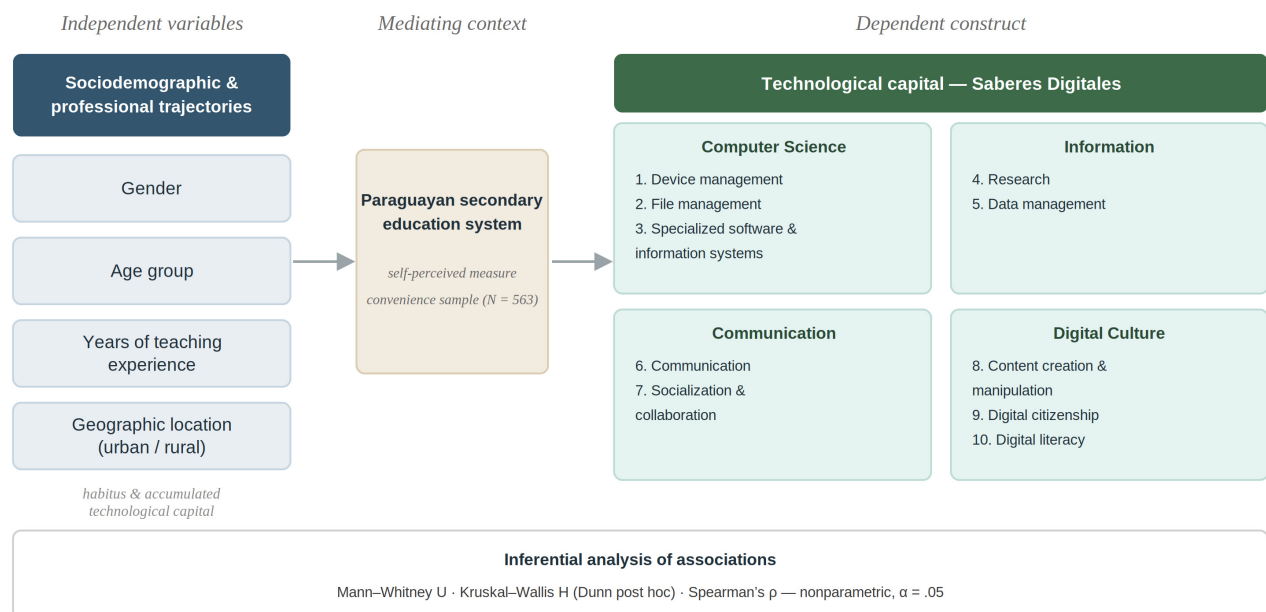
Table 1 synthesizes how these frameworks differ in operational focus and in their fit for developing contexts.

Although each contributes to the educational technology discourse, this study adopts *Saberes Digitales* because it was designed for Latin American educational realities and treats digital competence as a holistic socio-technical practice, a form of technological capital, rather than an abstract set of advanced skills. This makes it more sensitive than the Eurocentric models to contexts marked by infrastructural variability and mobile-centric use.

III. MATERIALS AND METHODS

This study was conducted using a quantitative approach with descriptive, comparative, and correlational objectives, employing a non-experimental, cross-sectional design. The purpose was to analyze the level of digital competencies among secondary school teachers in Paraguay and to examine their relationship with sociodemographic and professional variables, specifically gender, age group, area of residence, and years of teaching experience.

The population consisted of current secondary school teachers or those just beginning to teach at this level, of whom 563 participated in the study. Participants were selected through non-probabilistic convenience sampling, taking into account the digital accessibility required to complete the online survey and the exploratory nature of the study. The sample included teachers from urban, rural, and hard-to-reach rural areas, as well as different age groups and levels of professional experience, which provided sufficient variability for the comparative analysis. Fig. 1 presents the conceptual model guiding the study. Sociodemographic and professional trajectories are treated as independent variables representing the habitus and accumulated technological capital. These operate through the mediating context of the Paraguayan secondary education system. The dependent construct is technological capital, operationalized through the *Saberes Digitales* dimensions grouped into four domains.



Note. Digital competence is modeled as technological capital (Bourdieu) unevenly distributed across demographic and professional trajectories.

Fig. 1. Conceptual model relating sociodemographic and professional variables to technological capital (*Saberes Digitales*).

A structured questionnaire administered digitally via Google Forms was used for data collection. The instrument

consisted of Likert-type items on a transformed 0-to-3-point scale, where 0 represents a lack of competence and 3

represents a high level of proficiency. The items assessed various dimensions of teachers' digital competencies, such as digital citizenship, communication, information management, multimedia production, use of educational software, data manipulation and analysis, digital collaboration, and generative AI. The instrument comprised 110 items distributed across the 11 dimensions, including 10 *Saberes Digitales* and a generative AI dimension (10 items each). Internal consistency analysis confirmed satisfactory reliability across all subscales (Cronbach's α range: 0.761–0.934) and for the full instrument ($\alpha = 0.971$). Based on individual scores, averages were calculated for each dimension, and an overall average score was derived to represent each teacher's global level of digital competence.

The instrument was administered on a voluntary and anonymous basis via an online form. Once the data collection period ended, the data were exported and processed for statistical analysis using R software (version 4.5.2).

The analysis was conducted in several stages. First, a descriptive analysis was performed by calculating means, medians, standard deviations, standard errors, and 95% confidence intervals, as well as by creating graphical representations that allowed for the identification of general trends, such as the skills with the highest and lowest scores. Prior to comparative testing, the normality of each dimension score was evaluated using the Shapiro-Wilk test. Results confirmed that none of the 11 subscale scores nor the overall score followed a normal distribution (all $W < 0.985$, all $p < 0.001$), with skewness values ranging from -2.06 to 0.339 and excess kurtosis ranging from -1.20 to 4.12 . These findings justified the use of nonparametric statistical procedures throughout: Mann-Whitney U for the two-group gender comparison (with rank-biserial correlation r as the effect-size index), Kruskal-Wallis H for comparisons among more than two groups supplemented with Dunn's post-hoc tests with Bonferroni correction (with rank epsilon-squared ϵ^2 as the effect-size index), and Spearman's rank correlation coefficient ρ for bivariate associations with continuous variables. Effect sizes were interpreted following conventional benchmarks: $|r| = 0.10$ – 0.29 small, 0.30 – 0.49 medium [29]; $\epsilon^2 < 0.04$ negligible, 0.04 – 0.16 moderate. Missing data were negligible across all 110 items (mean = 0.02% per item; maximum = 0.4%), and dimension scores were computed as item means across non-missing responses, excluding a participant only when all items within a given dimension were missing. It should be noted that the results of the statistical tests are limited to the given sample, due to the type of sampling used.

Likewise, the relationship between years of teaching experience and the overall digital competence score, as well as the relationship between age and overall competence, were explored using Spearman's rank correlation coefficient, which is appropriate for ordinal or non-normally distributed variables. In addition, to examine the combined contribution of multiple sociodemographic and contextual predictors, a hierarchical multiple linear regression analysis was conducted with overall digital competence as the dependent variable. Model 1 included gender, age, years of experience, and residential area; Model 2 added home ICT infrastructure as an additional predictor. Standardized Beta Coefficients (β), 95% confidence intervals, Variance Inflation Factors (VIF),

and the Incremental Explained Variance (ΔR^2) were reported. Finally, the internal consistency of the instrument was assessed using Cronbach's alpha for each of the 11 dimensions and for the full 110-item scale, adopting $\alpha \geq 0.70$ as the threshold for acceptable reliability [30]. All analyses were conducted at a significance level of $\alpha = 0.05$. At this stage, the study constitutes a localized application of a well-established framework, with the primary psychometric focus on internal-consistency reliability. Formal construct-validity verification and scale revision are reserved for follow-up large-sample, multi-institution studies.

To complement the inferential analyses and address the distributional structure of competence across the workforce, a hierarchical cluster analysis was conducted on the 11 dimension mean scores. The analysis aimed to identify naturally occurring teacher profiles representing qualitatively distinct configurations of digital competence, thereby moving beyond point estimates of the average teacher. Prior to clustering, all dimension scores were standardized using z-scores to equalize their contribution to the Euclidean distance metric, given that despite sharing a common 0–3 scale, the dimensions differ in mean and variance. Ward's minimum variance linkage method (ward.D2 in R) was selected because it minimizes within-cluster sum of squares at each agglomeration step and produces compact, internally homogeneous clusters suited to continuous data. The optimal number of clusters was determined by inspecting the dendrogram for large jumps in merge distances, corroborated by three internal validity indices: the Silhouette coefficient (higher = better separation), the Calinski–Harabasz index (higher = better), and the Davies–Bouldin index (lower = better). Solutions from $k = 2$ to $k = 6$ were evaluated. Once cluster membership was assigned, between-profile differences on each dimension were tested with Kruskal–Wallis H supplemented by Dunn's post-hoc tests with Bonferroni correction, and demographic differences across profiles were assessed with Kruskal–Wallis (continuous variables) and chi-square tests (categorical variables).

IV. RESULTS AND DISCUSSION

Fig. 2 shows that the highest average scores are concentrated in dimensions related to instrumental and normative digital competencies: Digital Citizenship ($M = 2.55$, $SD = 0.54$, 95% CI [2.51, 2.60]), Files and Content ($M = 2.39$, $SD = 0.69$, 95% CI [2.34, 2.45]), Devices and Systems ($M = 2.34$, $SD = 0.53$, 95% CI [2.29, 2.38]), Word Processing ($M = 2.32$, $SD = 0.72$, 95% CI [2.26, 2.38]), and Communication ($M = 2.27$, $SD = 0.60$, 95% CI [2.23, 2.32]). At the other end of the spectrum, the lowest scores are observed in generative AI ($M = 1.25$, $SD = 0.81$, 95% CI [1.18, 1.32]), Data and Spreadsheets ($M = 1.58$, $SD = 0.95$, 95% CI [1.50, 1.66]), and Collaboration ($M = 1.56$, $SD = 0.66$, 95% CI [1.51, 1.62]), all with standard errors below 0.05. This pattern suggests a gap between mastery of basic tools and the development of advanced digital competencies geared toward pedagogical innovation and data analysis in the context of secondary education.

The distribution of the overall mean score (Fig. 3) indicates an intermediate level of teachers' digital competence ($M = 2.06$, $SD = 0.50$, $Mdn = 2.09$, 95% CI [2.02, 2.10];

skewness = -0.41 , excess kurtosis = -0.05). The largest concentration of scores falls between 1.8 and 2.5 points, which could be associated with a functional mastery of digital tools, though without reaching advanced levels. The absence of a bimodal distribution suggests that there is no marked polarization between teachers with very low and very high levels of digital competence, but rather a moderate heterogeneity with a predominance of intermediate levels.

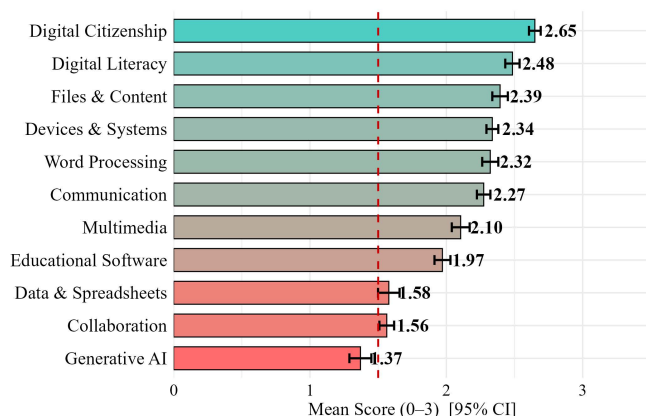


Fig. 2. Average score of teachers in each digital competency.

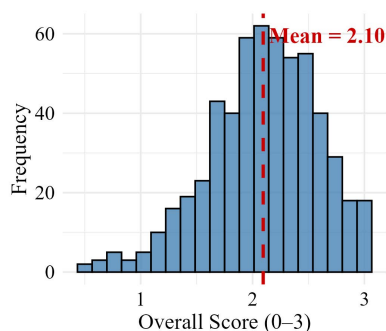


Fig. 3. Distribution of the overall mean score.

A comparison of overall digital literacy scores by gender (Fig. 4) shows that male teachers have a slightly higher average than female teachers, and this difference was statistically significant ($U = 21,106.5$, $p < 0.001$, rank-biserial $r = -0.21$, indicating a small effect size). Male teachers scored higher on average ($M = 2.23$, $SD = 0.51$, $Mdn = 2.26$) than female teachers ($M = 2.06$, $SD = 0.48$, $Mdn = 2.1$), though both groups fall within an intermediate level of digital competence. The data distribution shows a higher prevalence of outliers in the women's group, suggesting greater internal heterogeneity that may reflect the more decisive role of individual technological trajectories rather than gender alone.

A comparison of the overall scores by residential area (Fig. 5) revealed no statistically significant differences (Kruskal-Wallis $H(2) = 3.537$, $p = 0.171$, $\varepsilon^2 = 0.006$), with a negligible effect size indicating that residential area accounts for virtually none of the variability in teachers' digital competence scores. Descriptively, urban teachers ($M = 2.10$, $SD = 0.49$), rural teachers ($M = 2.03$, $SD = 0.51$), and remote rural teachers ($M = 2.34$, $SD = 0.35$) all fall within an intermediate competence level. Although the remote rural group shows a slightly higher descriptive median, the very small sample size of this group ($n = 8$) precludes any substantive interpretation of this difference.

Figs. 6 and 7 highlight the specific competencies with the lowest and highest scores, respectively. The results reveal a

dual structure in teachers' digital competence: while skills related to communication, digital citizenship, and file management reach higher levels, competencies linked to generative AI, digital collaboration tools, data analysis, and specialized software show significantly lower scores. This pattern suggests the existence of well-established instrumental digital literacy, particularly in everyday communication and security practices, alongside a significant gap in the adoption of emerging technologies and advanced pedagogical tools.

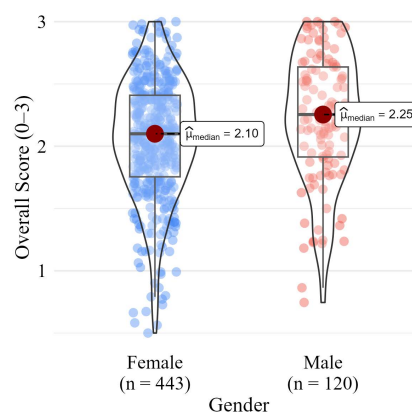


Fig. 4. Comparison of overall digital literacy scores by gender.

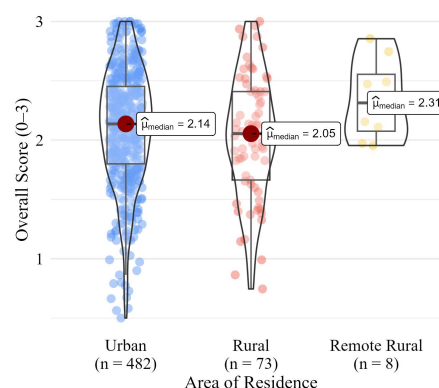


Fig. 5. Comparison of overall digital literacy scores by area of residence.

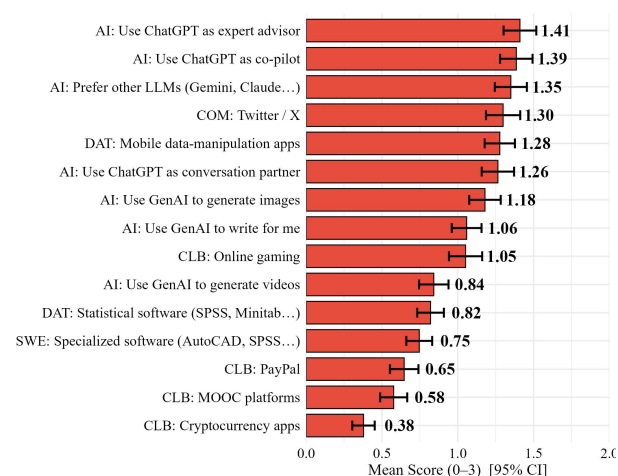


Fig. 6. 15 digital competencies among teachers with the lowest scores.

Analysis by age group revealed statistically significant differences in overall digital competence scores ($H(3) = 41.96$, $p < 0.001$, $\varepsilon^2 = 0.075$, indicating a moderate effect size; Fig. 8). A systematic decreasing trend in digital

competence was observed as teachers' age increased: teachers under 30 scored highest ($M = 2.24$, $SD = 0.41$, $Mdn = 2.24$), followed by the 30–40-year group ($M = 2.18$, $SD = 0.47$, $Mdn = 2.22$), the 40–50-year group ($M = 2.03$, $SD = 0.48$, $Mdn = 2.08$), and teachers over 50 years old, who had the lowest scores ($M = 1.76$, $SD = 0.56$, $Mdn = 1.76$). Dunn's post-hoc tests with Bonferroni correction revealed significant differences in five of the six pairwise comparisons. The group over 50 differed significantly from all other groups: from teachers under 30 ($Z = 5.67$, $p < 0.001$), from the 30–40-year group ($Z = -5.32$, $p < 0.001$), and from the 40–50-year group ($Z = -3.27$, $p = 0.003$). Additionally, teachers under 30 scored significantly higher than those aged 40–50 ($Z = 3.67$, $p < 0.001$). The 30–40 and 40–50 groups also differed significantly from each other ($Z = 3.14$, $p = 0.005$), indicating that the decline in digital competence does not only emerge after age 50 but begins to be detectable already between the 30–40 and 40–50 cohorts. The only non-significant comparison was between teachers under 30 and the 30–40 group ($p = 1.000$). These results confirm a generational gradient in digital competence that intensifies progressively with age, most pronounced among teachers over 50.

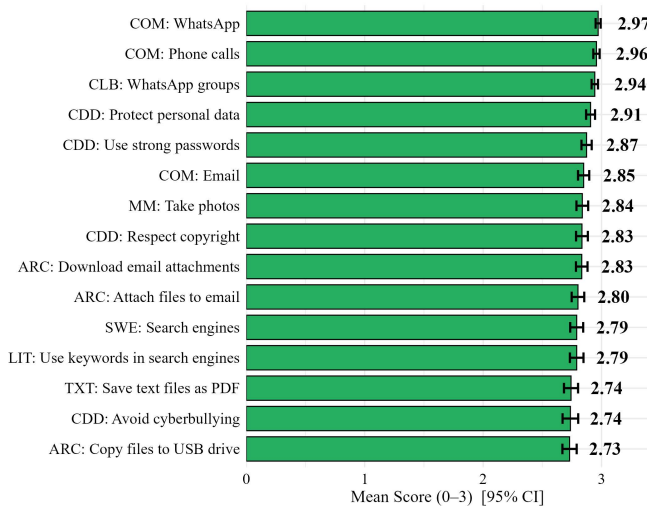


Fig. 7. The 15 highest-scoring digital competencies among teachers.

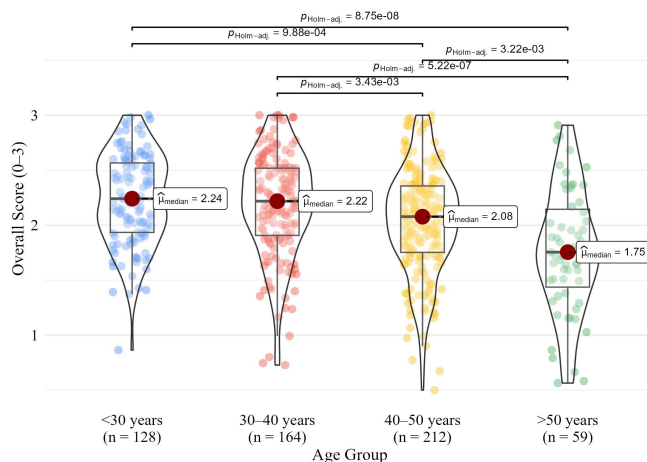


Fig. 8. Relationship between experience and digital competencies.

Fig. 9 highlights a negative and statistically significant correlation between years of teaching experience and overall digital competence ($\rho = -0.163$, $p < 0.001$), indicating a small

inverse effect: as teaching experience increases, perceived digital competence tends to decrease. Age showed a stronger negative correlation with overall competence ($\rho = -0.272$, $p < 0.001$), representing a small-to-medium effect. The high dispersion observed in the scatter plot confirms that neither variable alone fully accounts for the variance in digital competence, pointing to a more complex multivariate structure.

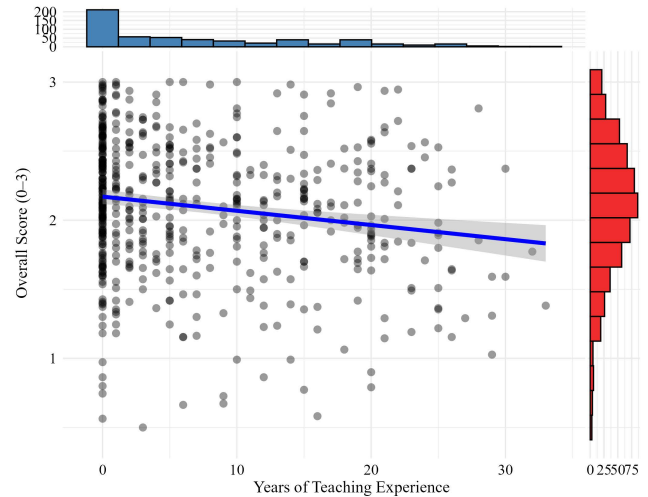


Fig. 9. Overall score by years of teaching experience.

To further disentangle the contribution of these variables, a hierarchical multiple linear regression was conducted ($N = 563$). Model 1, including gender, age, years of experience, and residential area, explained 10.6% of the variance in overall digital competence ($R^2_{adj} = 0.106$, $F(5, 557) = 14.25$, $p < 0.001$). Model 2 added home ICT infrastructure and significantly improved model fit ($\Delta R^2 = 0.030$, $F(1, 556) = 19.21$, $p < 0.001$), yielding $R^2_{adj} = 0.134$, $F(6, 556) = 15.47$, $p < 0.001$. In the full model, age was the strongest predictor ($\beta = -0.014$, $p < 0.001$), followed by home ICT infrastructure ($\beta = 0.114$, $p < 0.001$) and gender ($\beta = 0.134$, $p = 0.005$). Urban residential area showed a marginal effect ($\beta = 0.109$, $p = 0.077$), while remote rural area reached significance ($\beta = 0.359$, $p = 0.036$). Years of teaching experience did not reach significance after controlling for age ($\beta = -0.001$, $p = 0.620$), indicating that the age effect largely subsumes the experience effect. All variance inflation factors were below 1.6 (range: 1.018–1.584), ruling out multicollinearity concerns. These findings confirm that digital competence is shaped by a combination of individual biographical factors and structural conditions, with age and home ICT infrastructure as its primary determinants.

To move beyond aggregate descriptions and examine the distributional structure of competence across the teaching workforce, a hierarchical cluster analysis was conducted on the 11 standardized dimension scores (Ward linkage, Euclidean distance, $N = 563$). Inspection of the dendrogram identified large merge-distance jumps at $k = 2$ ($\Delta = 20.0$) and $k = 3$ ($\Delta = 11.8$). The $k = 3$ solution was selected over $k = 2$ because it disaggregates the heterogeneity present in the lower half of the distribution into two meaningfully distinct groups while satisfying the theoretical criterion of interpretability [31]. The three-cluster solution yielded the following profiles: Advanced Digital Competence ($n = 194$,

34.5%), Intermediate Digital Competence ($n = 249$, 44.2%), and Basic Digital Competence ($n = 120$, 21.3%). Profile membership was associated with highly significant differences across all 11 dimensions and in the overall score ($H(2) = 415.33$, $p < 0.001$, $\epsilon^2 = 0.738$, large effect).

The Advanced profile scored highly across virtually all dimensions, with particular strength in Files & Content ($M = 2.86$), Word Processing ($M = 2.85$), Digital Citizenship ($M = 2.81$), Digital Literacy ($M = 2.73$), and Communication ($M = 2.70$). Notably, even this most competent group scored below 1.8 in generative AI ($M = 1.77$), confirming that AI integration is an emergent challenge that transcends general digital proficiency. The Intermediate profile, comprising the largest share of the workforce, combined acceptable mastery of foundational skills (DSP: $M = 2.32$; ARC: $M = 2.43$; CDD: $M = 2.39$) with limited performance in advanced domains (DAT: $M = 1.46$; CLB: $M = 1.49$; Gen AI: $M = 0.97$), suggesting that initial digitalization efforts have established a functional digital floor without yet generating competencies for data analysis, collaboration, or AI-assisted pedagogy. The Basic profile scored below 1.8 across most dimensions, with the critical exception of Digital Citizenship ($M = 2.47$), which remained high even among teachers with the lowest overall technical proficiency.

This exception suggests that normative digital behaviors, data protection, copyright, and online safety, are more broadly shared than technical competencies, as they are values-based rather than tool-dependent. The demographic signature of each profile reinforces the regression findings: Advanced profile teachers were significantly younger ($M = 36.6$ years), had fewer years of experience ($M = 6.1$ years), included a higher proportion of male teachers (29.4%), and reported better home ICT infrastructure ($M = 2.73$ on the 0–3 scale) than their Basic counterparts (age $M = 43.7$, experience $M = 10.0$ years, male 12.5%, infrastructure $M = 2.31$); all demographic differences were statistically significant (all $p \leq 0.001$) except residential zone ($\chi^2(4) = 2.91$, $p = 0.574$), which again did not discriminate across profiles.

The results obtained paint an interesting picture regarding perceptions of technological competence. First, it is evident that teachers possess a solid understanding of digital competencies such as digital citizenship and digital literacy, as well as communication skills. These competencies include communication skills using technological tools (WhatsApp and email), and considerations regarding various aspects of digital citizenship, such as protecting personal data and respecting copyright, among others. These results not only demonstrate that teachers possess instrumental skills but also that they are aware of the ethical and moral aspects of technology use. These characteristics are essential as they form part of the skills and values to be conveyed to students during the teaching process. On the other hand, the results show that perceived competence is lower regarding data manipulation and spreadsheets, collaboration, and the use of AI. The results indicate that there is a low perception of competence, primarily in aspects related to AI and, to a lesser extent, communication skills (Twitter) and data manipulation (statistical or specialized software), dimensions conceptualized within the *Saberes Digitales* framework [7, 8].

Similar results related to collaborative use of technology and use of software for content creation were reported by Peña and colleagues [32] and in digital citizenship by Gambi *et al.* [33]. Although there is now a growing abundance of AI-related tools, one might assume that their usefulness remains either unknown or largely unexplored by the general public, including teachers [34, 35]. This leads to a lack of awareness of the potential of such technologies and, consequently, their limited use [23, 36]. To this point, Yim and Wegerif [34] studied 60 teachers' perceptions and found that teachers recognized their limited familiarity with AI, as demonstrated by their self-perceived lack of understanding of operating AI educational tools and their limited experience in using them for teaching AI literacy. Similarly, a study on pre-service teachers reported that AI is not widely used by the participants or there is a lack of awareness of it, or there is a lack of education about it, and concluded that lack of knowledge impacts perceptions and slows AI integration [35].

Among the ten *Saberes Digitales* competencies, those associated with generative AI returned the lowest self-perceived scores, with even the most accessible use cases, consulting a chatbot as an advisor or co-pilot, falling well below the midpoint of the scale (Figs. 2 and 6). Consistent with prior work, the teachers in this sample appear broadly aware that AI tools exist yet report limited capacity to use them pedagogically [34–37]. Looking at this as a technical shortfall, this would restate the familiar observation that advanced tools lag behind basic ones. Interpreted through the lens of technological capital, however, the low AI scores signal something more consequential: generative AI does not merely add another instrument to the teacher's repertoire but reconfigures the conditions of teaching itself, and the competencies required to navigate that reconfiguration, what Zou *et al.* [3] frame as a distinct pedagogic AI competence, are not yet part of these teachers' accumulated capital.

This distinction matters because the capacity to exercise professional agency in AI-mediated settings depends on a teacher's understanding of what such systems can and cannot do. Zhai [38] argues that generative AI is shifting teachers from operators of an auxiliary tool toward negotiators of an active instructional collaborator, a change that redefines their roles and the autonomy with which they enact them. Where AI competence is low, teachers are less equipped to make deliberate, critical decisions about when to draw on AI and when to withhold it, judgments that increasingly constitute pedagogy rather than mere tool selection. The scores observed here therefore point to a constraint on teacher agency when such agency becomes most necessary.

A second consequence concerns the management of cognitive offloading, the delegation of mental work to external systems. Gerlich [39] reports that heavier reliance on AI tools is associated with weaker critical-thinking performance, an effect mediated by offloading and most pronounced among younger users. For teachers this evidence relates to the following has a dual implication: they must regulate their own offloading while also scaffolding how students delegate cognitive effort to AI without surrendering the reasoning that learning is meant to cultivate. Performing that regulatory role is itself a competence, one that presupposes a working grasp of how generative systems

produce knowledge. The limited proficiency documented here suggests that many teachers are not yet positioned to assume it.

These pressures converge most visibly on assessment. The capacity of generative AI to produce fluent, extended responses to open prompts has destabilized conventional assessment practices and raised questions of academic integrity. Kofinas *et al.* [40] find that even authentic, work-relevant assessment designs do not by themselves safeguard integrity in an AI-rich environment. Responding to this is not reducible to detection or prohibition. It requires teachers to redesign tasks, including AI-supported unit and lesson design [4], to communicate norms of legitimate use, and to integrate AI ethically into their practice [23]. Such work draws on domains such as digital citizenship and ethical awareness in which the present sample scored most highly, suggesting an underused foundation on which AI-specific competence might be built. The gap, then, is less a matter of values than of translating an established ethical disposition into the concrete technical practices that responsible AI integration now demands.

Situating these findings within the generational pattern reported below clarifies what is at stake. The teachers least likely to report AI competence are also those whose pedagogical *habitus* formed in a pre-digital era, for whom generative AI represents not an incremental tool but a disruption to their practice. Framing the AI gap as an epistemological and pedagogical transition rather than a discrete skills deficit implies that professional development cannot treat AI as one more software module; it must instead support teachers in developing their judgment, agency, and assessment practices under conditions that AI has fundamentally altered.

Moreover, these findings are consistent with the study by Napal Fraile and colleagues [41]. The authors note that teachers are more competent in areas such as interacting and sharing information (communication) and navigating, storing, and retrieving digital data and content (information), but not in problem-solving or content creation. In addition, teachers demonstrated lower competence in matters of digital literacy (*netiquette*) [41]. The results also align with those of Moorhouse and Kohnke [37]. Regarding AI, the authors report that teachers perceive their own mastery of these technologies as limited [37]. However, other studies indicate that while teachers possess knowledge regarding the use of computers and ICTs, the level of integration is higher in dimensions related to planning and ethics but not in innovation and communication [42], which differs from the results of the present study.

Regarding differences in digital literacy between men and women, it is evident that men score higher than women. However, there is greater variability within the group of women due to the presence of more outliers. Gender and technology competence has been widely studied [42–46]. Almerich and colleagues [42] indicate that men have greater technical and operational proficiency with the tools, but women prioritize the pedagogical dimension and its relationship to the use of technologies. However, Scherer and colleagues [43] note that gender differences can be affected by factors such as educational level, country-level gender inequality, and economic development, thus not supporting

male teachers' advantage in all aspects of technology-related teaching competencies. To this point, Cabero-Almenara and colleagues [44] noted that female teachers have a higher self-assessment in the digital competence in teaching than male teachers in several areas including professional commitment and digital pedagogy.

Regarding geographical differences, no significant differences were observed, suggesting that, according to the data in this study, there is no digital divide between rural and urban areas, but rather differences among individuals resulting from the accumulation of technological capital. These results coincide with those of Wang [47] who noted that no significant differences emerged between rural and urban teachers regarding their competencies and attitudes; however, technology integration experiences differed by school location. However, the issue of urban and rural divide is still debatable until today. For example, in their study of 11,784 teachers in China, Lin and colleagues [48] found that the digital divide existed in relation to ICT attitude, ICT skills, data literacy, and digital teaching competence with rural teachers scoring lower compared to their urban peers.

According to the results, teachers' perceived digital literacy skills decrease as they get older. However, this trend is more pronounced among teachers over the age of 50, consistent with other studies [42, 33, 45]. This generational gap may be attributed to the emergence of new artificial intelligence technologies as well as specific skills related to the manipulation of digital content [49]. Research on digital literacy indicates that among surveyed teachers, younger teachers achieve higher scores than older teachers, even after participating in digital literacy training [8, 42]. Similar results were also found by Peng and colleagues [50] who reported that teachers aged 31–35 years demonstrated higher digital abilities, the use of digital tools and the ability to integrate ICT compared to those aged 20–30 years or older than 35 years. Furthermore, the intergenerational divide may also stem from sociocultural factors, as younger people tend to use technology in social settings more regularly, while adults tend to use it almost exclusively in professional contexts. This creates a skills gap, as young people engage with the digital world for recreational, social, and exploratory purposes, while adults do so only for instrumental purposes, thus limiting the implementation of tools and their efficient use [51].

Furthermore, the regression analysis sharpens this account by showing that the strongest structural correlate of competence is not where teachers live but what they can access: home ICT infrastructure significantly predicted overall competence and improved model fit beyond the demographic variables alone. This reframes the null result for residential areas. Geography, treated as an urban–rural binary, conceals the resource that actually matters, reliable access to devices and connectivity, which is distributed unevenly across, and within, all three zones. Inequality in digital competence thus appears to operate less through location than through the material conditions under which technological capital is accumulated, consistent with this study's central framing. At the same time, the modest total variance explained ($R^2_{adj} = 0.134$) indicates that the measured variables capture only part of the picture; much of what shapes digital competence lies in factors not modelled here,

school-level support, subject specialism, and individual training histories.

Beyond Average Scores: Three Profiles of Technological Capital The cluster analysis adds a distributional dimension that aggregate scores obscure. Rather than a workforce spread along a single continuum, the population resolves into three qualitatively distinct configurations: an Advanced profile (34.5%), an Intermediate profile (44.2%), and a Basic profile (21.3%), each with its own demographic signature, the Advanced group being younger, less experienced, and better resourced at home than the Basic group. This is what a capital-based account predicts: competence clusters according to the trajectories and conditions through which it is accumulated.

Two features are telling. First, the Advanced group scored below the midpoint on generative AI ($M = 1.77$), confirming that AI competence does not accrue as a by-product of general digital proficiency; it is a distinct demand that even the most capable teachers have not yet met. Second, the Basic profile, weak across almost every technical dimension, nonetheless retained high Digital Citizenship ($M = 2.47$). This suggests that the normative, values-based components of digital competence, that is, data protection, copyright, online safety, are more evenly distributed than tool-dependent skills, perhaps because they travel through professional and ethical socialization rather than through access to technology. In capital terms, some dispositions are less contingent on material resources than others. This is a distinction with direct implications for what training must supply.

Taken together, the findings suggest a rethinking of where educational inequality now resides in the Paraguayan secondary system. The absence of a significant rural–urban difference is important against a literature that frequently refers to geography as the primary axis of the digital divide [47, 48]. Rather than indicating an absence of inequality, this result suggests that the divide has migrated: as mobile-based connectivity and ubiquitous platforms such as WhatsApp have levelled basic instrumental access, reflected in the uniformly high communication scores in Fig. 6, the differences that remain are organized less by location than by individual trajectories of capital accumulation and, possibly, by institutional quality. For policy, this marks a shift in target, from provisioning access (the historical concern of the “first-order” divide) toward cultivating the higher-order competencies through which teachers convert access into pedagogical value.

This reframing has important consequences for professional development. The generational pattern documented here, competence declining with age and experience, and most pronounced among teachers over 50, indicates that uniform, “one-size-fits-all” training is poorly matched to the workforce it serves [45]. The *Saberes Digitales* structure offers a basis for differentiation. Teachers whose capital was accumulated in a pre-digital context may benefit most from consolidating foundational competencies, such as data management, specialized software, and the secure management of digital information, whereas. By contrast, teachers already fluent in basic and communicative competencies are better served by advanced, pedagogically oriented training in the ethical integration of generative AI. Tiering provision in this way treats professional development

as the targeted accumulation of specific forms of capital rather than as undifferentiated exposure, aligning support with each teacher’s profile instead of an assumed average.

At the system level, these findings argue for embedding digital competence within institutional structures rather than leaving it to individual initiative, since it is individual, non-institutional trajectories that appear to drive the residual variation, including the greater heterogeneity observed among female teachers. Curriculum and teacher-preparation policy might therefore treat competencies such as data literacy and AI integration not as optional enrichment but as core professional standards, supported by sustained institutional resourcing rather than isolated courses, a caution reinforced by evidence that participation in training does not by itself guarantee transformed practice [2]. According to the OECD’s 2023 Digital Education Outlook [2], approximately 20% of secondary school teachers express a need for additional training in digital education, despite 60% having completed relevant professional development over the preceding year, confirming that participation alone does not guarantee transformed practice. These implications should nonetheless be read against the study’s reliance on self-perceived competence: because such measures are subject to social-desirability and confidence effects, they are best understood as indicators of teachers’ perceived readiness, and the priorities they suggest would be sharpened by future work using performance-based assessment.

These readings are offered as a theoretically informed interpretation of the observed patterns rather than as a direct empirical test of Bourdieu’s constructs; the present design measures self-perceived competence and cannot, on its own, confirm the mechanisms of capital accumulation it invokes.

V. CONCLUSION, LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

The aim of the study was to analyze the digital competence of secondary teachers in Paraguay using the *Saberes Digitales* framework. Overall, teachers show a solid foundation in basic tools and digital citizenship but clear weaknesses in advanced pedagogical applications such as AI, data processing, and collaborative tools. Demographically, no significant rural–urban divide was observed, but a clear generational gradient emerged, with digital competence declining as age and teaching experience increase. A cluster analysis further identified three distinct teacher profiles, Basic, Intermediate, and Advanced.

The study’s contribution is primarily empirical, extending and localizing an established framework to an underrepresented context, and the technological-capital lens is best understood as interpretive scaffolding for future theory-building rather than as a generative theoretical claim in itself. Thus, three contributions follow from these results. Conceptually, the study shows the analytical value of treating digital competence as technological capital: the competencies teachers report are patterned not by geography but by the trajectories through which that capital is accumulated, a finding that shifts the digital divide from access to capacity. Practically, it argues for differentiated, profile-sensitive professional development in place of uniform provision, foundational consolidation for teachers formed in a pre-digital era, and advanced, ethically grounded AI training

for those already digitally fluent. Methodologically, it points to the need for performance-based and longitudinal evidence to corroborate self-perceived measures. Above all, the rapid diffusion of generative AI lends urgency to this agenda: equipping teachers to exercise informed pedagogical judgment over emerging technologies is fast becoming a precondition, rather than an enhancement, of quality secondary education in Paraguay and comparable contexts.

While this study leverages a substantial and historically underrepresented sample size ($N=563$) to map teacher digital profiles in Paraguay, its structural conclusions must be interpreted within specific methodological boundaries and limitations qualify these findings. First, the study measures self-perceived rather than demonstrated competence. Self-assessment is vulnerable to social-desirability bias and to gendered confidence effects, whereby respondents may over- or under-estimate their ability independently of actual skill; the scores reported here should be read as indicators of perceived readiness rather than objective capability, and the gender difference in particular requires cautious interpretation. Second, the use of non-probability convenience sampling, while yielding a substantial and varied sample, limits statistical generalizability to the national teaching population, so the results are best understood as indicative structural trends rather than population parameters. Third, the cross-sectional design precludes causal inference about the relationships between demographic variables and competence. Future research would benefit from performance-based or observational measures to complement self-report, from probability-based sampling, and from multivariate and longitudinal designs capable of disentangling the intertwined effects of age, experience, and institutional context. Fourth, the hierarchical regression explained only a modest share of the total variance ($R^2_{adj} = 0.134$), indicating that much of the variation in digital competence is attributable to factors beyond those modelled, among them school-level resourcing, subject specialism, and prior training, which future models should incorporate. Fifth, the cluster solution is exploratory and sample-specific: the three-profile structure should be read as a hypothesis about how competence is organized in this population rather than as a fixed typology, and its stability requires confirmation in independent samples. Finally, because the design is cross-sectional, the association between age and competence cannot separate a developmental (aging) effect from a cohort (generational) one; the “generational gap” interpretation, though plausible, awaits longitudinal confirmation.

To complement, validate, and expand upon the structural trajectories identified in this study, several critical pathways are proposed for subsequent research within the Latin American educational ecosystem. First, future initiatives must transition from a reliance on self-perceived evaluations to the incorporation of objective, performance-based validation tools. Implementing mixed-method designs, task-based simulations, or direct classroom observation protocols will allow researchers to calibrate the exact distance between an educator’s perceived digital self-efficacy and their practical instructional execution, thereby mitigating the systemic social desirability and confidence response biases inherent in self-reports. Second, given the rapid evolution of educational technology, researchers should employ

longitudinal tracking frameworks. Tracking the same cohort of secondary educators over extended temporal intervals will provide vital data on how technological capital actively shifts, adapts, or depreciates over time, particularly regarding the long-term classroom adoption, pedagogical integration, and sustained usage patterns of generative AI tools. Finally, to move beyond the exploratory boundaries of non-probability convenience sampling, future research must implement highly rigorous probability-based designs. Utilizing stratified random sampling across a balanced matrix of public, private, and subsidized institutions will ensure a truer proportional representation of the diverse teaching workforce. This statistical scaling is essential to validate the localized structural trends identified in this cohort at a mathematically definitive, nationally generalizable parameter level.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

V.C. organized and conducted the study and the writing of this article; J.M. organized and analyzed the data and wrote the results section; J.A. conducted the review of literature and wrote the discussion section; R.P. organized the research methods and data collection; all authors approved the final version.

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REFERENCES

- [1] UNESCO. (2018). UNESCO ICT Competency Framework for Teachers. [Online]. Available: <https://unesdoc.unesco.org/ark:/48223/pf0000265721>
- [2] OECD. (2023). OECD Digital Education Outlook 2023: Towards an Effective Digital Education Ecosystem. [Online]. Available: https://www.oecd.org/content/dam/oecd/en/publications/reports/2023/12/oecd-digital-education-outlook-2023_c827b81a/c74f03de-en.pdf
- [3] D. Zou, H. Xie, and L. Kohnke, “Navigating the future: Establishing a framework for educators’ pedagogic artificial intelligence competence,” *Eur. J. Educ.*, vol. 60, e70117, 2025. doi: 10.1111/ejed.70117
- [4] W. Wen and H. Wen, “Bridging Generative AI Technology and Teacher Education: Understanding Preservice Teachers’ Processes of Unit Design with ChatGPT,” *Contemp. Issues Technol. Teach. Educ.*, vol. 24, no. 4, 2024.
- [5] H. R. Kaffash, Z. A. Kargiban, S. A. Kargiban, and M. T. Ramezani, “A close look into role of ICT in education,” *Int. J. Instruction*, vol. 3, no. 2, pp. 63–82, 2010.
- [6] M. Pitzalis and M. Porcu, “Digital Capital and Cultural Capital in Education: Unravelling Intersections and Distinctions That Shape Social Differentiation,” *Br. Educ. Res. J.*, vol. 50, pp. 2753–2776, 2024, doi: 10.1002/berj.4050
- [7] M. A. Casillas, A. Ramirez-Martinell, and V. Ortiz. (2014). Technological capital, a new species of cultural capital: A proposal for

- its measurement. *Talk to me About ICT: Digital Technology in Higher Education*. A. Ramírez-Martínell and M. A. Casillas, Eds. Argentina: Brujas—Social TIC. [Online]. Available: <https://www.uv.mx/personal/mcasillas/files/2016/05/20.pdf> (in Spanish)
- [8] A. Ramírez and M. Casillas. (2017). *Digital Knowledge of Basic Education Teachers: A Proposal for Discussion from Veracruz*. Veracruz: SEV. [Online]. Available: <https://www.uv.mx/personal/mcasillas/files/2017/04/Los-Saberes-Digitales-SEV.pdf> (in Spanish)
- [9] P. A. Ertmer, "Addressing first- and second-order barriers to change: Strategies for technology integration," *Educ. Technol. Res. Dev.*, vol. 47, no. 4, pp. 47–61, 1999. doi: 10.1007/BF02299597
- [10] S. Malik, D. Rohendi, and I. Widiaty, "Technological pedagogical content knowledge (TPACK) with information and communication technology (ICT) integration: A literature review," in *Proc. 5th UPI Int. Conf. Tech. Vocational Educ. Training (ICTVET 2018)*, 2019. doi: 10.2991/ictvet-18.2019.114
- [11] E. Ifinedo, J. Rikala, and T. Hämäläinen, "Factors affecting Nigerian teacher educators' technology integration: Considering characteristics, knowledge constructs, ICT practices and beliefs," *Comput. Educ.*, vol. 146, 103760, 2020. doi: 10.1016/j.compedu.2019.103760
- [12] T. J. Kopcha, K. L. Neumann, A. Ottenbreit-Leftwich, and E. Pitman, "Process over product: The next evolution of our quest for technology integration," *Educ. Technol. Res. Dev.*, vol. 68, no. 2, pp. 729–749, 2020. doi: 10.1007/s11423-020-09735-y
- [13] M. Á. Negrín-Medina, A. Bernárdez-Gómez, A. Portela-Pruaño, and J. J. Marrero-Galván, "Teachers' perceptions of changes in their professional development as a result of ICT," *J. Intelligence*, vol. 10, no. 4, 90, 2022. doi: 10.3390/jintelligence10040090
- [14] B. L. Moorhouse, "Teachers' digital technology use after a period of online teaching," *ELT J.*, vol. 77, no. 4, pp. 445–457, 2023.
- [15] T. Trust and J. Whalen, "Should Teachers Be Trained in Emergency Remote Teaching? Lessons Learned from the COVID-19 Pandemic," *J. Technol. Teach. Educ.*, vol. 28, no. 2, pp. 189–199, 2020.
- [16] A. Bozkurt et al., "A global outlook to the interruption of education due to COVID-19 pandemic: Navigating in a time of uncertainty and crisis," *Asian J. Distance Educ.*, vol. 15, no. 1, pp. 1–126, 2020. doi: 10.5281/zenodo.3878572
- [17] United Nations. (2015). *Transforming Our World: The 2030 Agenda for Sustainable Development*. A/RES/70/1. [Online]. Available: <https://undocs.org/A/RES/70/1>
- [18] G. Falloon, "From digital literacy to digital competence: The teacher digital competency (TDC) framework," *Educ. Technol. Res. Dev.*, vol. 68, no. 5, pp. 2449–2472, 2020. doi: 10.1007/s11423-020-09767-4
- [19] L. Castañeda, F. M. Esteve-Mon, J. Adell, and S. Prestidge, "International insights about a holistic model of teaching competence for a digital era: The digital teacher framework reviewed," *Eur. J. Teacher Educ.*, vol. 45, no. 4, pp. 493–512, 2022. doi: 10.1080/02619768.2021.1991304
- [20] R. J. Krumsvik and L. Ø. Jones, "Teachers' digital competence in upper secondary school: (Work in progress)," in *Proc. Int. Conf. Inf. Commun. Technol. Educ. (ICITE 2013)*, 2013, pp. 171–183.
- [21] M. J. Koehler, P. Mishra, and W. Cain, "What is technological pedagogical content knowledge (TPACK)?" *J. Educ.*, vol. 193, no. 3, pp. 13–19, 2013. doi: 10.1177/002205741319300303
- [22] R. Puentedura. (2014). Building transformation: An introduction to the SAMR model. [Online]. Available: http://www.hippasus.com/rrpweblog/archives/2014/08/22/BuildingTransformation_AnIntroductionToSAMR.pdf
- [23] I. Celik, "Towards Intelligent-TPACK: An empirical study on teachers' professional knowledge to ethically integrate Artificial Intelligence (AI)-based tools into education," *Comput. Human Behav.*, vol. 138, 107468, 2023. doi: 10.1016/j.chb.2022.107468
- [24] E. R. Hamilton, J. M. Rosenberg, and M. Akcaoglu, "Examining the Substitution Augmentation Modification Redefinition (SAMR) model for technology integration," *TechTrends*, vol. 60, pp. 433–441, 2016. doi: 10.1007/s11528-016-0091-y
- [25] T. Aldosemani, "Inservice teachers' perceptions of a professional development plan based on the SAMR model: A case study," *Turkish Online J. Educ. Technol.*, vol. 18, no. 3, pp. 46–53, 2019.
- [26] C. Redecker, *European Framework for the Digital Competence of Educators: DigCompEdu*, JRC107466, Seville: Joint Research Centre, European Commission, 2017.
- [27] F. Caena and C. Redecker, "Aligning teacher competence frameworks to 21st century challenges: The case for the European Digital Competence Framework for Educators (DigCompEdu)," *Eur. J. Educ.*, vol. 54, no. 3, pp. 356–369, 2019. doi: 10.1111/ejed.12345
- [28] R. Vuorikari, S. Kluzer, and Y. Punie, *DigComp 2.2: The Digital Competence Framework for Citizens—With New Examples of Knowledge, Skills and Attitudes*, EUR 31006 EN. Luxembourg: Publications Office of the European Union, 2022. doi: 10.2760/115376
- [29] J. Cohen, *Statistical Power Analysis for the Behavioral Sciences*, 2nd ed. Hillsdale, NJ, USA: Lawrence Erlbaum Associates, 1988.
- [30] J. C. Nunnally, "An overview of psychological measurement," *Clinical Diagnosis of Mental Disorders: A Handbook*, pp. 97–146, 1978.
- [31] O. Arbelaitz, I. Gurrutxaga, J. Muguerza, J. M. Pérez, and I. Perona, "An extensive comparative study of cluster validity indices," *Pattern Recognition*, vol. 46, pp. 243–256, 2013.
- [32] T. M. C. Peña, O. A. F. Tellez, and A. L. Padrón. (2022). Teachers' Teaching Digital Competence: Case of Pichincha canton, Manabí, Ecuador. *Rev. Cubana Educ. Super.* [Online]. 41(1). pp. 422–439. Available: <https://revistas.uh.cu/rces/article/view/10007?articlesBySimilarityPage=65> (in Spanish)
- [33] G. D. N. Gambi, T. F. Pabón, V. G. S. Sira, M. L. Keuylian, and M. J. R. García, *An Approach to Teachers Digital Competency in Latin America*, Washington, DC: Inter-American Development Bank, 2025. doi: 10.18235/0013638
- [34] I. H. Y. Yim and R. Wegerif, "Teachers' Perceptions, Attitudes, and Acceptance of Artificial Intelligence Educational Learning Tools: An Exploratory Study on Artificial Intelligence Literacy for Young Students," *Future Educ. Res.*, vol. 2, no. 4, pp. 318–345, 2024. doi: 10.1002/fer3.65
- [35] D. Kalniņa, D. Nīmanis, and S. Baranova, "Artificial Intelligence for Higher Education: Benefits and Challenges for Pre-Service Teachers," *Front. Educ.*, vol. 9, 1501819, 2024. doi: 10.3389/educ.2024.1501819
- [36] A. Güneşli, N. S. Burgul, S. Dericioğlu, N. Cenkova, S. Becan, Ş. E. Şimşek, and H. Güneralp, "Exploring Teacher Awareness of Artificial Intelligence in Education: A Case Study from Northern Cyprus," *Eur. J. Investig. Health Psychol. Educ.*, vol. 14, no. 8, pp. 2358–2376, 2024. doi: 10.3390/ejihpe14080156
- [37] B. L. Moorhouse and L. Kohnke, "The effects of generative AI on initial language teacher education: The perceptions of teacher educators," *System*, vol. 122, 103290, 2024. doi: 10.1016/j.system.2024.103290
- [38] X. Zhai, "Transforming teachers' roles and agencies in the era of generative AI: Perceptions, acceptance, knowledge, and practices," *J. Sci. Educ. Technol.*, 2024. doi: 10.1007/s10956-024-10174-0
- [39] M. Gerlich, "AI tools in society: Impacts on cognitive offloading and the future of critical thinking," *Societies*, vol. 15, no. 1, 6, 2025. doi: 10.3390/soc15010006
- [40] A. K. Kofinas, C. H.-H. Tsay, and D. Pike, "The impact of generative AI on academic integrity of authentic assessments within a higher education context," *Br. J. Educ. Technol.*, vol. 56, pp. 2522–2549, 2025. doi: 10.1111/bjet.13585
- [41] M. N. Fraile, A. Peñalva-Vélez, and A. M. M. Lacambra, "Development of digital competence in secondary education teachers' training," *Educ. Sci.*, vol. 8, no. 3, 104, 2018. doi: 10.3390/educsci8030104
- [42] G. Almerich, J. M. Suárez-Rodríguez, J. M. Jornet, and N. Orellana, "Teachers' competencies and use of ICT: A structural model," *Rev. Invest. Educ.*, vol. 29, no. 1, pp. 169–189, 2011. (in Spanish)
- [43] R. Scherer, D. G. Campos, T. Fütterer, and F. Siddiq, "Unraveling Gender Disparities in Teachers' Technological Pedagogical and Content Knowledge: A Large-Scale Meta-Analytic Review," *Educ. Res. Rev.*, vol. 50, 100765, 2026. doi: 10.1016/j.edurev.2026.100765
- [44] J. Cabero-Almenara, J. J. Gutiérrez-Castillo, J. Barroso-Osuna et al., "Digital Teaching Competence According to the DigCompEdu Framework. Comparative Study in Different Latin American Universities," *J. New Approaches Educ. Res.*, vol. 12, pp. 276–291, 2023. doi: 10.7821/naer.2023.7.1452
- [45] A. Hurtado-Mazeyra, R. Núñez-Pacheco, A. Barreda-Parra, E.-P. Guillén-Chávez, and O. Turpo-Gebera, "Digital competencies of Peruvian teachers in basic education," *Front. Educ.*, vol. 7, 1058653, 2022. doi: 10.3389/educ.2022.1058653
- [46] M. Navío-Inglés, S. Tirado-Olivares, J. del Olmo-Muñoz et al., "The Digital Competence Landscape of Teachers: A Large-Scale Analysis on Self-Perceived Competence and Gender Differences," *Technol. Knowl. Learn.*, 2025. doi: 10.1007/s10758-025-09928-5
- [47] P.-Y. Wang, "Examining the Digital Divide Between Rural and Urban Schools: Technology Availability, Teachers' Integration Level and Students' Perception," *J. Curric. Teach.*, vol. 2, no. 2, pp. 127–139, 2013. doi: 10.5430/jct.v2n2p127
- [48] R. Lin, J. Chu, L. Yang et al., "What Are the Determinants of Rural-Urban Divide in Teachers' Digital Teaching Competence? Empirical Evidence from a Large Sample," *Humanit. Soc. Sci. Commun.*, vol. 10, 422, 2023. doi: 10.1057/s41599-023-01933-2

- [49] F. Baier-Mosch, L. Schulze-Vorberg, and J. Schneider, "The Relationship Between Teachers' Age, Gender and Their Will and Skill to Teach Artificial Intelligence," *Technol. Knowl. Learn.*, 2026. doi: 10.1007/s10758-025-09943-6
- [50] R. Peng, R. A. Razak, and S. H. Halili, "Factors Influencing In-Service Teachers' Technology Integration Model: Innovative Strategies for Educational Technology," *PLoS ONE*, vol. 18, no. 8, e0286112, 2023. doi: 10.1371/journal.pone.0286112
- [51] M. Garrido-Lora, J. B. Duran, and R.-A. M. Ramos, "From ICT to ICRT. A study of ICT use and the digital divide among adults and adolescents in Spain," *Anàlisi*, no. 54, pp. 44–57, 2016. doi: 10.7238/a.v0i54.2953

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