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A Holistic and Adaptive Pedagogical Model for Developing Digital Competence in Rural Teachers: Integrating IoT, Data Analytics, and Low-Connectivity Learning Environments

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Abstract: This study examines the gap between digitalization agendas and school realities, where connectivity constraints, limited devices, and uneven support restrict pedagogical innovation. It evaluates the Model for Integrative and Predictive Smart Teaching Adaptation, integrating artificial intelligence, learning analytics, and Internet of Things components, within a holopraxic cycle of diagnosis, design, implementation, evaluation, and readaptation driven by field feedback. Over a semester, 120 rural teachers participated in a quasi-experimental study combining a competence questionnaire, interviews, and system usage logs. Baseline competence was comparable between groups, and gain was defined on a zero to one hundred scale as post minus pre. The experimental group showed a median gain of 6.25 points, whereas the control group remained at 0.00; the common-language effect size was 0.765. Engagement was sustained with peaks (twenty-five to thirty-seven sessions per week), indicating selective appropriation rather than linear growth. Results support improvement and emphasize adoption conditions: teacher agency, ethical trust, and institutional sustainability, operationalized through pseudonymization and bias auditing.

Index Terms: Digital Competence, Educational Artificial Intelligence, Internet of Things, Learning Analytics, Rural Education, Ethical Governance, Holopraxic Action Research

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1. Introduction

Global efforts toward digital transformation in education continue to expose a persistent paradox: digital technologies have expanded in availability and policy visibility, yet equitable access to their pedagogical benefits remains uneven, particularly where infrastructural fragility, territorial dispersion, and constrained institutional capacity converge. In Latin America, and especially in Colombia, rural schools still face pronounced technological asymmetries such as intermittent connectivity, limited access to devices, and restricted opportunities for sustained professional development, despite successive modernization initiatives [1–3]. This gap is not reducible to infrastructure alone. Increasingly, it is understood as a problem of pedagogical design under constraint: when training and integration strategies assume stable connectivity and standardized implementation conditions, rural adoption becomes fragile and discontinuous [4,5]. In parallel, policy and governance debates have sharpened around the need to align digital transformation with teacher empowerment, system-level support, and credible safeguards, particularly as artificial intelligence (AI) enters everyday educational practice [6].

Evidence from post-pandemic contexts reinforces that the rural–urban divide is not simply about "using tools," but about whether educators can translate technological resources into viable pedagogical routines that preserve autonomy, professional judgment, and contextual fit [1,2,7,8]. Teachers frequently report a pattern that can be characterized as technological dependency without durable autonomy: external solutions arrive faster than the institutional mechanisms required for appropriation, maintenance, and reflective adaptation [9]. In such settings, international competence frameworks—such as the Digital Competence Framework for Educators (DigCompEdu) and the UNESCO ICT Competency Framework for Teachers (UNESCO ICT-CFT)—are most useful not as plug-in standards, but as reference architectures requiring localized calibration, especially when connectivity is unstable and professional learning must be sustained through lightweight, iterative support designs [2,5]. A related implication is methodological: interventions in rural, quasi-experimental settings must be reported and interpreted with caution; causal language requires explicit baseline checks and design-strengthening strategies rather than inference by visual inspection or policy enthusiasm.

Within this context, the present study introduces the MIPSTA model (Model for Integrative and Predictive Smart Teaching), a holopraxic, adaptive, and ethically guided pedagogical framework designed to strengthen digital competence among rural teachers. The model integrates AI, Internet of Things (IoT) technologies, and predictive learning analytics (PLA) within a holistic cycle of design, implementation, reflection, and readaptation. Its architecture is intentionally oriented toward low-connectivity feasibility through offline-capable routines and deferred synchronization, reducing dependence on always-on platforms and stabilizing implementation under real rural conditions [10,11]. Rather than positioning AI as a substitute for pedagogical judgment, MIPSTA treats intelligent modules as decision-support mediators embedded in reflective practice, an orientation aligned with recent guidance emphasizing human oversight, transparency, and the avoidance of techno-solutionism in educational AI deployments [12,13].

The research addresses a central problem: how to design and validate a pedagogical model that enhances rural teachers' digital competence through AI- and IoT-assisted learning while ensuring ethical transparency, contextual adaptability, and sustainable impact. The guiding research question is therefore: How can a pedagogical model be structured to improve rural teachers' digital competence through the integration of AI, IoT, and adaptive learning strategies in low-connectivity contexts? The study hypothesizes that implementing MIPSTA—combining analytics-informed pedagogical support, IoT-assisted tools, and holopraxic reflection—will improve rural teachers' digital competence and related constructs in ways that remain interpretable under quasi-experimental constraints [7,8,10,11]. Importantly, the term "predictive" is used in an evidence-calibrated sense: anticipatory pedagogical support informed by analytics and usage traces, without presupposing that every component must instantiate a standalone predictive model.

The objective of this research is to propose and empirically validate MIPSTA as an integrative solution that merges pedagogical innovation, intelligent analytics, and responsible governance for AI-supported education. Specifically, the study seeks to: (1) diagnose the current state of digital competence among rural teachers; (2) design and implement the MIPSTA framework as an iterative, holopraxic system; (3) assess its impact through quantitative and qualitative indicators, including platform and tool usage traces; and (4) derive sustainability guidelines for the ethical incorporation of AI and IoT in rural education ecosystems. This logic is consistent with iterative field-based improvement traditions that emphasize refinement grounded in feedback rather than one-shot treatments [25]. Complementarily, recent work on teacher digital competence measurement highlights that self-reflection instruments can support professional learning trajectories when used as formative scaffolds rather than as compliance metrics [15]. In parallel, auditable self-reflection tools and competence frameworks are increasingly used for planning and professional learning design, offering practical structure when implementation capacity is uneven [14].

The theoretical relevance of MIPSTA lies in extending the holopraxic paradigm into digital pedagogy by linking technological mediation with ethical cognition and teacher agency. Practically, it offers an implementation blueprint for rural digital transformation grounded in autonomy, adaptability, and human oversight. Empirical antecedents support this orientation: quasi-experimental didactic models have shown measurable competence improvements under structured pedagogical designs [14], while research on innovation and governance in Colombian science and technology ecosystems underscores the importance of linking institutional capacity, infrastructure, and responsible practice to

sustain change beyond pilot enthusiasm [16–19]. Accordingly, MIPSTA is framed not as a purely technical artifact, but as a methodological stance: disciplined, iterative design under constraint, with claims calibrated to observable evidence.

2. Literature Review

2.1 Digital Competence Frameworks in Education

Global frameworks conceptualize teachers' digital competence as a multidimensional construct combining pedagogical innovation, technical fluency, and ethical digital citizenship. The UNESCO ICT Competency Framework for Teachers (ICT-CFT), the European DigCompEdu, and the ISTE Standards for Educators remain key references shaping national digital transformation agendas. The DigCompEdu update of 2019 defines six competence areas—professional engagement, digital resources, teaching and learning, assessment, learner empowerment, and digital development—placing digital literacy within a reflective professional profile [1]. However, empirical work consistently shows that these frameworks become methodologically fragile if applied as universal templates, because many assume stable infrastructure, institutional supports, and continuous professional learning that are not structurally available in rural systems. Evidence from diverse contexts suggests that localized adaptations (including self-reflection instruments) can raise awareness and diagnostic clarity, but do not automatically translate into sustained behavioral change unless embedded in ongoing support arrangements [2,4]. This gap has motivated the development of competence-oriented self-reflection tools designed explicitly for formative professional learning rather than assessment; a representative example is SELFIEforTEACHERS, which operationalizes DigCompEdu as a teacher-centered reflection journey [15].

Table 1 remains analytically justified in this section: it does not merely compare frameworks as static taxonomies, but illustrates how ethical orientation and rural feasibility are contingent on implementation scaffolds such as training design, leadership support, and lightweight routines compatible with low-connectivity realities.

Table 1. Comparative Overview of International Frameworks for Teacher Digital Competence

Framework	Core Dimensions	Ethical / Inclusion Focus	Applicability to Rural Contexts
UNESCO ICT-CFT [1]	Knowledge creation, pedagogy, technology literacy	Digital inclusion, sustainability	Moderate – requires localization
DigCompEdu [2]	Professional engagement, digital resources, pedagogy, assessment, learner empowerment	Digital well-being, equity, reflection	High – adaptable via *Selfie for Teachers*
ISTE [4]	Learner, Leader, Citizen, Collaborator, Designer	Implicit ethical guidance on citizenship	Limited – assumes high connectivity

2.2 Technology Integration in Rural and Low-Connectivity Contexts

Persistent infrastructural asymmetries continue to shape the rural digital divide, but the literature increasingly treats connectivity as only one layer of a broader sociotechnical system. Beyond access to devices, exclusion often results from institutional barriers that constrain teacher agency, limit time for experimentation, and weaken maintenance and mentoring ecosystems [3]. Empirical evidence indicates that pedagogical adaptation, peer support, and community collaboration can predict sustainability more reliably than connectivity indicators alone [3]. International reports similarly document that hybrid delivery designs—offline repositories, localized content hosting, delayed synchronization, and community-based mentoring—are among the most frequently cited strategies for maintaining continuity in constrained settings [5]. These findings support a shift in how "integration" is conceptualized: not as linear tool adoption, but as iterative stabilization of practice under constraint, where feasibility must be designed rather than assumed.

2.3 AI and Learning Analytics in Teacher Development

Artificial intelligence (AI) and learning analytics (LA) are reshaping teacher professional learning ecosystems through adaptive feedback, competence trajectory visualization, and analytics-informed decision support. Recent syntheses emphasize that human-centered approaches—interpretability, participatory design, and trust—are not optional add-ons but conditions for adoption, especially when systems mediate pedagogical judgment [7]. At the same time, the literature remains explicit about risks: algorithmic bias, opacity, and governance failures can undermine equity and teacher agency, particularly in contexts where institutional safeguards are weak [20]. For this reason, responsible guidance has increasingly stressed that educational AI systems should preserve human oversight, ensure transparency about data use, and avoid narratives that treat automation as an unquestioned solution [12,13,21]. Within MIPSTA, these principles are operationalized as design constraints shaping how analytics and adaptive feedback are integrated into teacher workflows.

2.4 IoT Applications and Hybrid Architectures for Education

The Internet of Things (IoT) has evolved into enabling infrastructure for hybrid, intelligent, and offline-ready learning environments, particularly when paired with local processing and deferred synchronization. Studies highlight that edge-oriented architectures can reduce dependency on cloud services, improve resilience, and strengthen data sovereignty—features that become especially relevant under rural connectivity volatility [11]. Complementary work on AI/ML-enabled IoT systems emphasizes accessibility-oriented design and efficiency benefits when intelligence is distributed across lightweight devices and local services [10]. However, the educational implication is methodological: IoT cannot be treated only as a technical layer; its pedagogical value depends on whether it is integrated into routines that teachers can appropriate, adapt, and sustain. This is why MIPSTA frames IoT as a support substrate within the holopraxic cycle rather than as an isolated innovation component.

2.5 Ethical AI and Responsible Innovation in Education

Ethical governance has emerged as a central priority in AI-mediated education. Contemporary discussions converge on transparency, accountability, fairness, and explainability—principles that must be embedded by design rather than applied retroactively [22,23]. International analyses warn that techno-solutionism can displace attention from structural constraints and sociocultural realities, reinforcing inequities even when tools are introduced with "inclusion" rhetoric [24]. Consequently, GDPR-aligned data governance and privacy-by-design practices are increasingly treated as baseline requirements for learning analytics pipelines and AI-supported systems in education [22,23]. Compliance with privacy safeguards and responsible data governance across learning analytics pipelines has also become imperative [23]. Within MIPSTA, these considerations function as adoption conditions (trust and agency) rather than as abstract add-ons, particularly in settings where communities may experience heightened vulnerability to extractive data practices.

2.6 Theoretical Synthesis: Toward a Holopraxic, Adaptive, and Ethical Model

Across the literature, three discontinuities remain salient. First, digital competence frameworks are conceptually robust yet often insufficiently adaptable to rural feasibility constraints. Second, AI/analytics research advances personalization and automation but can under-specify teacher agency and governance safeguards. Third, IoT and hybrid infrastructures improve technical resilience but frequently lack explicit pedagogical grounding and sustainability mechanisms. The holopraxic paradigm, articulated through integrative epistemologies and action-research-informed methodologies, offers a coherent bridge by treating innovation as iterative praxis anchored in empirical validation and reflective redesign [9,25–27]. MIPSTA operationalizes this synthesis as a design-and-validation loop in which competence development, analytics-informed support, and governance constraints co-evolve through successive refinement cycles, with claims explicitly calibrated to what the evidence supports under rural implementation conditions.

3. Methodology

3.1 Research Design

This study adopts a projective research design grounded in holopraxic action research, operationalized as an iterative spiral in which theoretical reflection, pedagogical intervention, and empirical validation inform each other through successive refinement cycles. The design is explicitly oriented toward the construction, implementation, evaluation, and adjustment of the Model for Integrative and Predictive Smart Teaching Adaptation (MIPSTA) in response to contextual constraints typical of rural education, rather than treating the intervention as a fixed "treatment" applied once. In this study, *predictive* denotes anticipatory pedagogical support informed by learning analytics and aggregated system usage traces, without presupposing that the research necessarily trains a standalone predictive model in all components. Holopraxis is assumed as an integrative praxis that frames technology not as an add-on but as an epistemic mediator connecting pedagogical knowledge, institutional learning, and innovation dynamics [25].

The holopraxic logic is expressed as a continuous reflection–action–reflection loop: (i) a theoretically informed diagnosis of needs and constraints, (ii) design of pedagogical and technological components, (iii) pilot implementation under real institutional conditions, (iv) empirical feedback from multiple sources, and (v) systematic refinement of both the model and its implementation strategy. As shown in Fig. 1, this cycle specifies the methodological sequence through which MIPSTA is iteratively designed and validated across action–reflection–action iterations.

Methodologically, the study integrates mixed methods within each cycle. Quantitative evidence captures change patterns in digital competence and related constructs (e.g., self-efficacy, attitudes), while qualitative evidence reconstructs meanings, contextual barriers, and institutional conditions that shape adoption trajectories. In parallel, system usage logs provide behavioral traces that enable triangulation between declared practices and actual interaction with intelligent support modules, strengthening ecological interpretability [26,28,29]. Triangulation is treated as an explicit strategy to reduce single-source bias and stabilize interpretation across instruments and modalities [30].

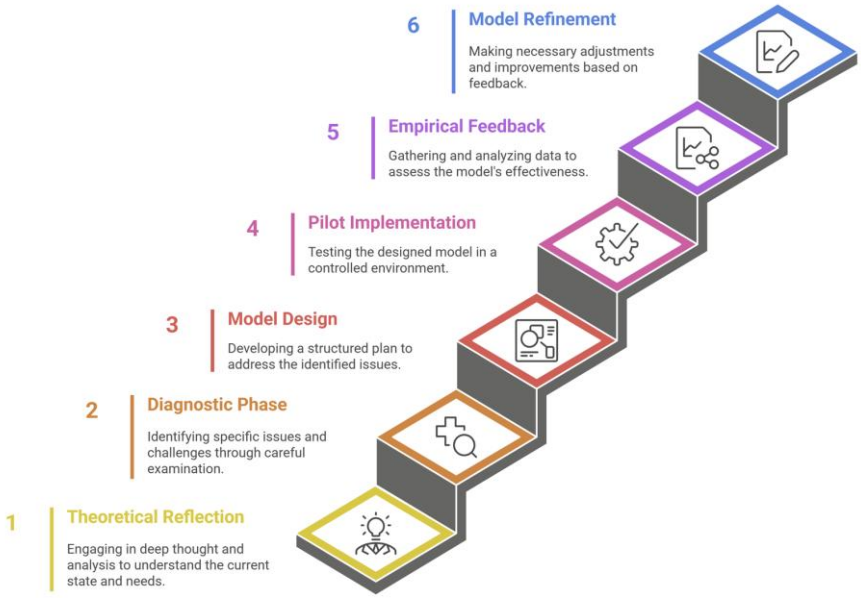


Fig. 1. Holopraxic methodological cycle for the design and validation of the MIPSTA model

3.2 Population and Sampling

The target population comprises rural teachers from public educational institutions in the municipality of Soto Norte (Santander, Colombia). A stratified sampling strategy is applied using two criteria: (a) educational level (primary vs. secondary) and (b) geographic location (populated centers vs. remote rural hamlets). This structure is intended to preserve variability in connectivity, access to devices, and institutional support—conditions expected to moderate feasibility and outcomes of AI-supported pedagogical integration in rural contexts [1].

The proposed sample size (n = 120) is aligned with prior empirical studies evaluating teacher training and technology-mediated pedagogical programs in comparable rural settings [1]. The study uses experimental and control groups of approximately 50–60 participants each. Because allocation in rural institutions is often constrained by feasibility, scheduling, and institutional availability, the design is treated as quasi-experimental with non-equivalent groups. Internal validity is strengthened through (i) stratified recruitment, (ii) explicit documentation of allocation criteria, and (iii) formal baseline comparability testing prior to the intervention, implemented as a condition for interpreting post-intervention contrasts as model-related change rather than pre-existing group differences.

3.3 Data Collection Instruments

3.3.1 Structured Questionnaire

A structured questionnaire assesses digital competence and related constructs using a 5-point Likert scale (1 = "Strongly disagree" to 5 = "Strongly agree"). Items specifically related to educational AI, analytics, and rural teaching practices are adapted from validated instruments in recent empirical work [8]. Content validity is established by expert judgment (CVI $\geq$ 0.80), and reliability is examined via internal consistency (Cronbach's $\alpha \geq 0.70$). To avoid construct opacity in a multidimensional competence framework, reliability is reported by subscale when multidimensionality is theoretically expected [9,14,18].

When sample conditions are adequate, an exploratory factor analysis (EFA) is conducted to evaluate latent structure and strengthen construct validity. Reporting follows established recommendations: assessment of sampling adequacy and correlation structure, explicit specification of extraction method and rotation strategy, transparent criteria for factor retention, and interpretable thresholds for factor loadings [31,32]. The EFA is used as an empirical check on subscale coherence rather than as a post hoc justification mechanism.

3.3.2 Semi-Structured Interviews

A purposive subsample stratified by geographic zone and educational level participates in semi-structured interviews exploring barriers, motivations, expectations, and contextual appropriation of MIPSTA. Initial analytic categories include resistance to change, digital literacy, institutional culture, and technological equity, while allowing inductive expansion during coding. This component examines how teachers conceptualize educational AI integration, including perceived benefits, risks, and ethical–pedagogical tensions in rural STEM-oriented environments [33,34].

3.3.3 Intelligent System Usage Logs

During the pilot phase, the intelligent support system captures interaction logs including access frequency, session duration, navigation paths, and use of adaptive-feedback modules. These data are processed through an end-to-end learning analytics pipeline and analyzed using educational data mining techniques in Python (e.g., pandas, scikit-learn) to characterize adoption patterns and relate behavioral traces to survey and interview evidence [28]. This component is explicitly included to reduce reliance on self-report and support convergent interpretation between intention, perception, and behavior. As summarized in Fig. 2, the log-processing workflow specifies each stage from capture to analysis outputs used in mixed-method integration.

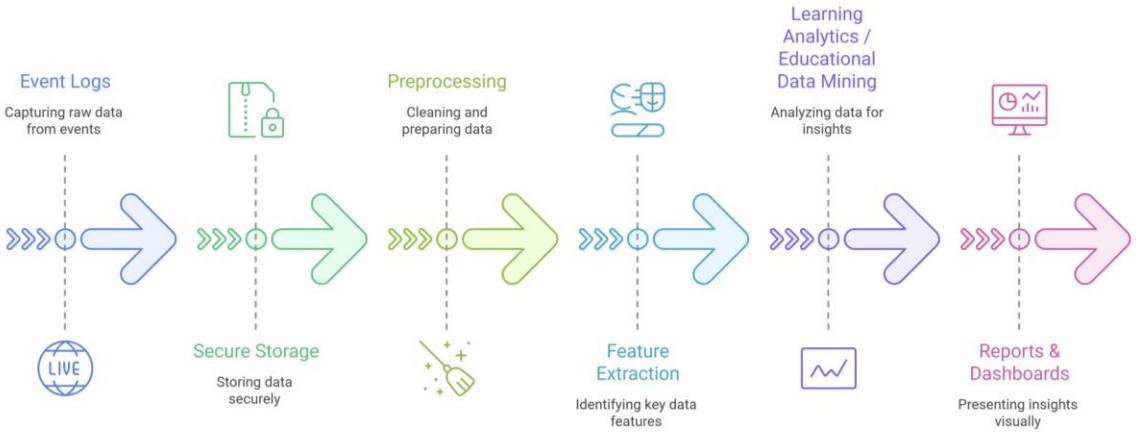


Fig. 2. End-to-end pipeline for intelligent system logs and learning analytics

3.4 Procedure

The intervention is deployed over one academic semester and follows five sequential stages aligned with the holopraxic cycle. As shown in Fig. 3, the stages are structured to preserve the action–reflection–action logic that enables refinement based on empirical feedback.

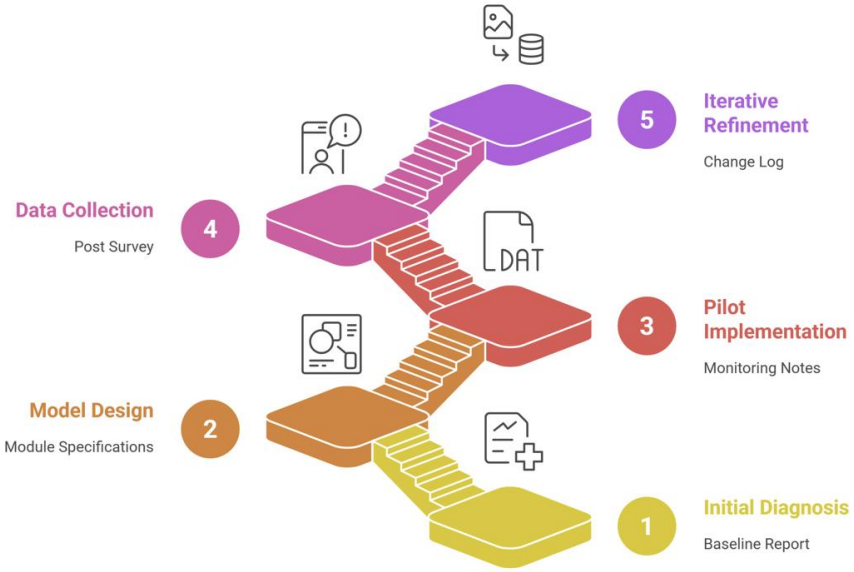


Fig. 3. Procedural timeline and deliverables across the MIPSTA cycle

- Initial Diagnosis: Administration of the questionnaire and exploratory interviews to characterize the baseline of teachers' digital competencies and their relation to technology use.
- Model Design: Construction of the MIPSTA model components (inputs, processes, and outputs) and definition of technological modules integrating AI, educational analytics, and pedagogical IoT.
- Pilot Implementation: Deployment of the model over one academic semester in selected institutions, accompanied by continuous technical support and formative monitoring.
- Post-Intervention Data Collection: Re-administration of the questionnaire, follow-up interviews, and extraction of usage logs from the intelligent system.

- Iterative Refinement: Comparative pre/post analysis and model adjustments derived from findings, completing a cycle of action–reflection–action characteristic of the holopraxic paradigm.

3.5 Data Analysis

Quantitative analysis. Descriptive statistics are reported (mean, standard deviation, skewness, kurtosis), with normality assessed using Shapiro–Wilk ($p < 0.05$). Because Likert-derived constructs and rural-context outcomes often deviate from strict normal assumptions, non-parametric inference is prioritized when appropriate. Associations between ordinal or non-normal variables are estimated using Spearman's rank correlation. Pre/post change within groups is evaluated with Wilcoxon signed-rank tests, and between-group contrasts with Mann–Whitney U tests.

To address baseline comparability as a condition for interpretable between-group contrasts, the study explicitly performs pre-intervention group comparisons on baseline digital competence and key covariates using tests justified by distributional assumptions. This step is treated as design-strengthening rather than ancillary, because post-intervention differences lack interpretive traction if baseline imbalance is not empirically assessed.

In addition to p-values, effect sizes are reported to support practical interpretation. For non-parametric contrasts, effect magnitude is quantified using distribution-based indices such as the common language effect size (Vargha and Delaney, 2000), reported alongside inferential tests [36]. Where multiple related outcomes are tested, familywise error control is addressed using a sequential correction procedure [35], with transparent reporting of adjusted significance decisions. EFA and reliability analyses are conducted in SPSS v29, with reporting aligned to best-practice standards [31,32], including the rationale for factor retention and rotation selection.

For non-parametric between-group contrasts, effect magnitude is summarized using the common language effect size (CLES), defined as the probability that a randomly selected observation from the experimental group exceeds a randomly selected observation from the control group, as in (1) [36]:

$$CLES = P(X > Y) + \frac{1}{2}P(X = Y) \tag{1}$$

where X and Y denote outcomes from the experimental and control groups, respectively.

Qualitative analysis. Interview data undergo open, axial, and selective coding under an inductive logic consistent with grounded theory. Analytic emphasis is placed on how teachers negotiate AI integration in rural contexts—appropriation trajectories, ethical tensions, institutional constraints, and perceived agency. Credibility is strengthened through triangulation across questionnaires, interviews, and usage logs, with explicit attention to discrepant cases and context-sensitive interpretation [30].

3.6 Ethical and Contextual Considerations

All procedures were authorized by the participating educational institutions and conducted in compliance with applicable educational research requirements and personal data protection provisions. Adult participants provided written informed consent prior to data collection; when minors were involved, written permission was obtained from parents or legal guardians and age-appropriate assent was obtained from the students. Participation was voluntary and unrelated to academic evaluation or employment conditions. Data collection followed minimization and purpose limitation principles: only variables necessary for the study objectives were gathered, identifiers were removed, and records were pseudonymized at collection and fully anonymized prior to analysis and external dissemination to prevent traceability to individuals or institutions. Digital traces from the intelligent system were processed in aggregated form, and access to non-aggregated records was restricted to the research team for the stated purposes of model evaluation and research reporting. Data handling followed privacy-by-design and governance principles aligned with widely adopted standards for educational data use (lawfulness, transparency, purpose limitation, data minimization, and accountability) [22,23].

Ethical AI design safeguards—fairness, privacy preservation, non-discrimination, explainability, and human oversight—were integrated to reduce risks of automated bias and preserve teacher agency; routine auditing procedures were applied to monitor potential differential impacts across contextual subgroups, consistent with documented concerns about algorithmic bias and governance implications in education [20]. The study also recognizes the ethical tension between innovation and techno-solutionism and therefore frames intelligent modules as decision-support mediators embedded in reflective practice and contextual feasibility [37], consistent with UNESCO-oriented perspectives emphasizing inclusivity, equity, and participatory governance [24]. Given rural infrastructural constraints (unstable connectivity and uneven device availability), an offline-operational approach was implemented through locally hosted resources, delayed synchronization protocols, and lightweight services to support sustainable digital inclusion under real low-connectivity conditions [38].

4. Results and Discussion

4.1 Baseline Comparability and Outcome Definition

To evaluate the impact of the Model for Integrative and Predictive Smart Teaching Adaptation (MIPSTA), individual improvement was defined as the absolute pre–post change on the 0–100 digital competence scale, as in (2):

$$\Delta_i = Post_i - Pre_i \tag{2}$$

where Δ_i represents the competence gain for teacher i.

Before interpreting post-intervention differences, baseline equivalence was formally tested. Pre-intervention digital competence did not differ between groups (Mann–Whitney U = 1747.0, p = 0.625; effect size r = 0.057), supporting initial comparability and reducing the plausibility that post differences reflect pre-existing imbalance (see Fig. 4 for the baseline distribution). Reporting baseline tests alongside effect sizes follows the general expectation that causal language in quasi-experimental work must be calibrated to demonstrable pre-treatment comparability rather than visual inspection alone.

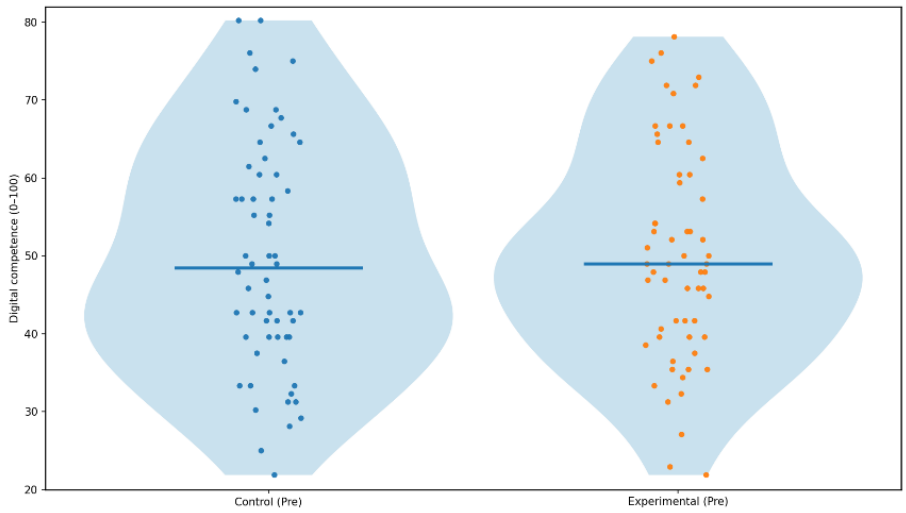


Fig. 4. Baseline (Pre) distribution of teachers' digital competence (0–100) by group: initial comparability

4.2 Competence Gains: Within-Group Change and Between-Group Impact

Fig. 5 shows the distribution of Δ scores. The experimental group exhibited a clear positive displacement, with median gain $\tilde{\Delta} = 6.25$(Q1 = 1.56, Q3 = 8.34; IQR = 6.78). In contrast, the control group clustered around null change ($\tilde{\Delta} = 0.00$; Q1 = −1.04, Q3 = 2.08; IQR = 3.12).

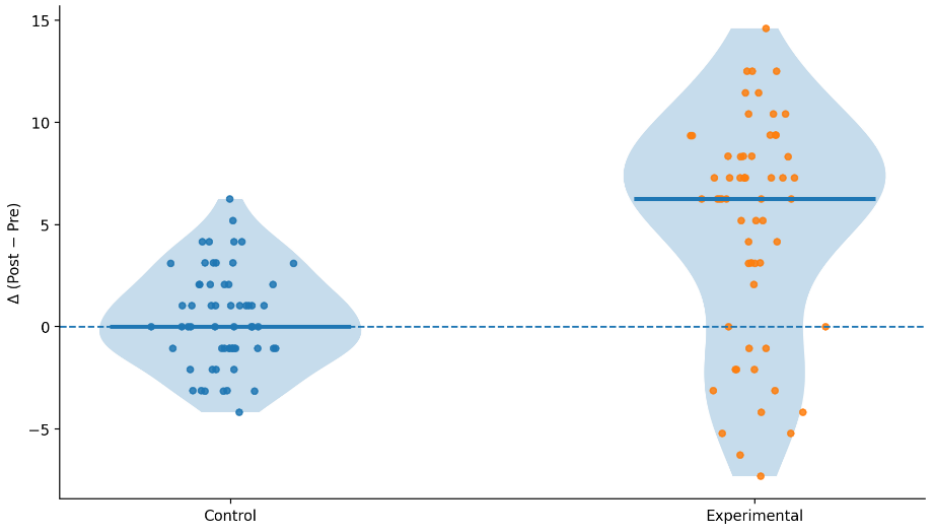


Fig. 5. Pre–post change in digital competence by group (Δ = Post − Pre)

The between-group difference in change distributions was statistically robust (Mann–Whitney U = 2753.5, p < 0.001). Consistently, the post-intervention distributions exhibit a clear group separation (Fig. 6), supporting the interpretation that the experimental group's post-test values shifted upward relative to the control group. To quantify practical magnitude (not only statistical significance), two complementary effect-size indices were computed for Δ, including a probabilistic common-language interpretation [36].

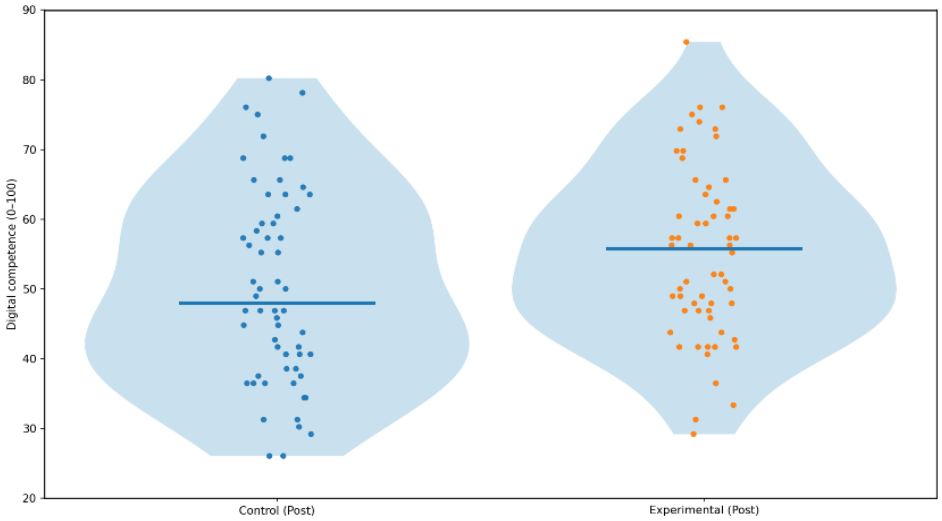


Fig. 6. Post-intervention (Post) distribution of teachers' digital competence (0–100) by group

- **Rank-based effect size:** $r = 0.458$ (moderate-to-large separation of distributions)
- **Vargha–Delaney:** $A = 0.765$ (a randomly selected experimental participant has a higher Δthan a randomly selected control participant about 76.5% of the time, counting ties as 0.5)

Within-group inference confirmed a statistically reliable pre–post improvement in the experimental cohort (Wilcoxon signed-rank $W = 1522.0$, $p < 0.001$), with a rank-biserial correlation $r_{rb} = 0.814$ (large). The control cohort also showed a statistically detectable shift (Wilcoxon $W = 821.0$, $p = 0.006$), but its magnitude was small ($r_{rb} = 0.198$) and its median change remained at 0, consistent with minimal practical movement around baseline. When multiple inferential checks are reported within the same family of outcomes, transparent control of error rates should be considered as part of analytic hygiene [35].

To avoid ambiguity in "percentage improvement" claims, results are reported primarily as absolute points on the 0–100 scale. If a percentage expression is used, the denominator must be stated explicitly (e.g., percent of baseline mean vs. percent of the full scale). In this dataset, the experimental group's mean increase was approximately +4.93 points (from 50.12 to 55.05), corresponding to ~9.8% of the baseline mean. This value is not interchangeable with percent-of-scale expressions or any normalized transformation and should not be mixed across sections.

4.3 Descriptive Statistics (Baseline, Post, and Change)

Table 2 reports central tendency and dispersion for baseline, post-intervention, and change.

Table 2. Descriptive statistics of baseline, post-intervention, and change (Δ) by group

Group	N	Baseline Mean	Baseline SD	Post Mean	Post SD	Δ Median	Δ IQR
Experimental	60	50.12	11.38	55.05	12.04	6.25	6.78
Control	60	49.86	11.45	50.28	13.81	0.00	3.12

Note. SD = standard deviation. Δ= post–pre difference. IQR = interquartile range. Baseline comparability: Mann–Whitney $U = 1747.0$, $p = 0.625$, $r = 0.057$. Between-group Δ: Mann–Whitney $U = 2753.5$, $p < 0.001$, $r = 0.458$, Vargha–Delaney $A = 0.765$ (Vargha & Delaney, 2000). Within-group change: Wilcoxon $W = 1522.0$, $p < 0.001$ (experimental), $r_{rb} = 0.814$; Wilcoxon $W = 821.0$, $p = 0.006$ (control), $r_{rb} = 0.198$.

4.4 Subscale Correlations: Differentiated Coherence (S1–S6)

Fig. 7 and Table 3 describe Spearman associations among subscales (S1–S6). The pattern is not uniform: some subscales relate weakly, while others exhibit strong coupling. The largest correlations observed were between S2 and S5 ($\rho = 0.82$) and between S3 and S6 ($\rho = 0.70$). This structure matters analytically because it suggests the instrument captures partially distinct dimensions rather than a single undifferentiated construct—an important guardrail against over-claiming "total coherence" when interpreting composite readiness.

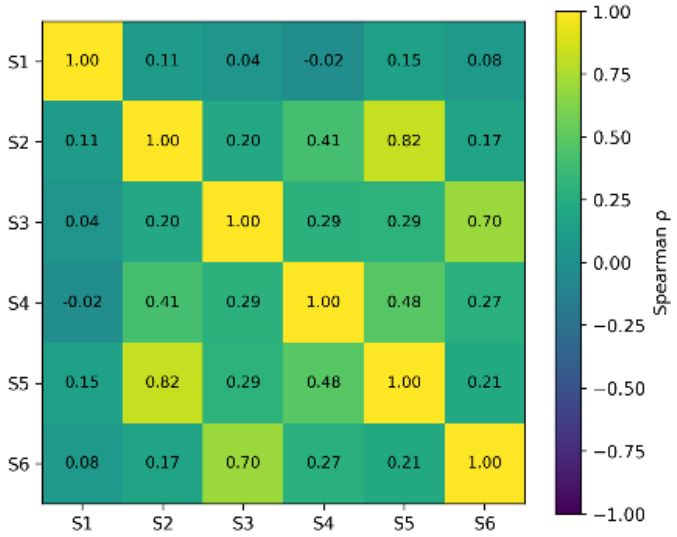


Fig. 7. Spearman correlation among questionnaire subscales (S1–S6)

Table 3. Spearman correlation matrix among questionnaire subscales (S1–S6)

Subscale	S1	S2	S3	S4	S5	S6
S1. Digital Literacy	1.00	0.14	0.06	−0.05	0.07	0.14
S2. Technological Self-Efficacy	0.14	1.00	0.19*	0.41*	0.82*	0.17
S3. Attitude toward AI	0.06	0.19*	1.00	0.16	0.26*	0.70*
S4. Use of Intelligent Tools	−0.05	0.41*	0.16	1.00	0.53*	0.32*
S5. Collaborative Learning Practices	0.07	0.82*	0.26*	0.53*	1.00	0.28*
S6. Ethical and Privacy Awareness	0.14	0.17	0.70*	0.32*	0.28*	1.00

Note. Values are Spearman's ρ. * indicates $p < 0.05$.

4.5 Exploratory Factor Analysis (EFA): Factorial Adequacy and Structure (Instrument Transparency)

To address factorial validity with sufficient methodological detail, EFA was conducted at the item level (24 items). As summarized by the scree profile (Fig. 8), the retained solution was three-factor, consistent with the item-level factorability diagnostics reported in the audited dataset. Sampling adequacy was supported by KMO = 0.926, and Bartlett's test indicated that the correlation matrix was factorable ($\chi^2 \approx 2601.21$, df = 276, $p < 0.001$). Factors were extracted using Principal Axis Factoring (PAF) with oblimin rotation (delta = 0), retaining three factors, which together explained 74.72% of the variance in the solution. These reporting elements (adequacy diagnostics, extraction method, rotation disclosure, and loading transparency) align with standard methodological guidance for EFA interpretability and replicability [31,32].

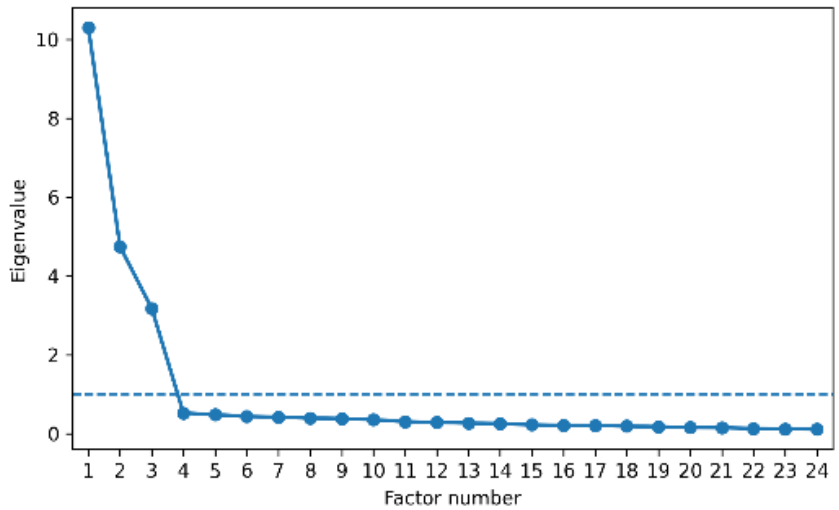


Fig. 8. Scree plot of exploratory factor analysis (item-level, 24 items)

For transparency and replicability, a full factor loading table should be included (main text or supplementary), reporting (i) loadings, (ii) cross-loadings, and (iii) the rule used to interpret salient loadings (e.g., $|\lambda| \geq 0.40$). In this dataset, items clustered into three interpretable dimensions consistent with: (a) literacy/tool operation, (b) AI-related stance and integration, and (c) training/support and institutional enabling conditions (labels should match the manuscript's construct definitions).

4.6 Learning Analytics: Usage Trajectories and Robustness Of the Trend Claim

Weekly platform usage in the experimental group is summarized in Fig. 9. Across 16 weeks, total sessions ranged from 25 to 37 (mean = 28.9; SD = 3.1), with episodic peaks rather than a strictly monotonic increase.

To avoid over-interpreting fluctuations as a "steady rise" or "doubling," trend robustness was tested. A linear time trend on weekly sessions was not statistically supported (slope ≈ +0.34 sessions/week; $p = 0.41$), and a nonparametric monotonic association (Kendall's τ) likewise did not confirm a consistent upward trend ($\tau = 0.09$; $p = 0.65$). Accordingly, the defensible interpretation is that the system maintained stable engagement with intermittent intensification, compatible with task-driven usage cycles during implementation. This cautious framing is consistent with learning analytics literature that calls for interpretive restraint and transparent linkage between claims and evidence when usage data are used to infer adoption dynamics [7].

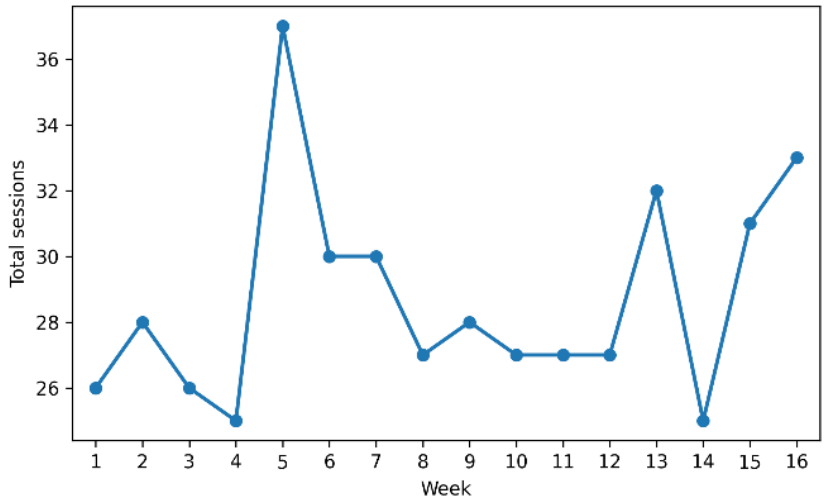


Fig. 9. Weekly usage of the intelligent support system (Experimental)

4.7 IoT Component: Empirical Footprint and Operational Performance Indicators

The IoT toolkit showed lower uptake than other modules. Based on session logs, IoT-related interactions comprised 15.9% of total sessions (vs. 35.4% for analytics and 48.7% for adaptive feedback). Rather than treating this as a deficiency per se, the result is more defensibly interpreted as selective appropriation under contextual constraints (e.g., intermittent connectivity, limited devices, or prioritization of immediate pedagogical supports), a recurrent theme in IoT-for-education deployments and field implementations [10,11].

Importantly, the IoT component can be empirically characterized beyond usage share using the available operational metrics: offline events represented 27.8% of IoT events (80/288), and estimated event loss was 2.25% (7/311). These indicators provide an initial, testable baseline of resilience under connectivity limitations, while still leaving room for stronger benchmarking in future deployments (e.g., latency distributions, packet loss by site, robustness under stress tests).

4.8 Qualitative Findings: Barriers, Enablers, and Contextual Dynamics (With Transparent Coding Structure)

The thematic analysis yielded four major themes with the following coded frequencies: ethical perception of AI (121), pedagogical agency (113), institutional sustainability (98), and contextual constraints (91). Fig. 10 synthesizes thematic composition and the most frequent subcodes per theme (top 3), making the qualitative structure auditable rather than impressionistic.

Contextual constraints concentrated on infrastructure, connectivity, and time/workload pressures. Pedagogical agency reflected shifts in how teachers positioned intelligent tools: from initial caution around professional autonomy to a more pragmatic framing as support for planning, feedback, and reflective practice. Ethical perception emphasized privacy, fairness, and transparency concerns, which participants treated as conditions for continued use. These concerns are consistent with peer-reviewed discussions on ethics, bias, and data governance in AI-supported education [19,20,23,37,38]. Institutional sustainability foregrounded training support, leadership, and maintenance arrangements

as prerequisites for continuity, aligned with work emphasizing ethical integration and teacher empowerment in AI-era teaching [28].

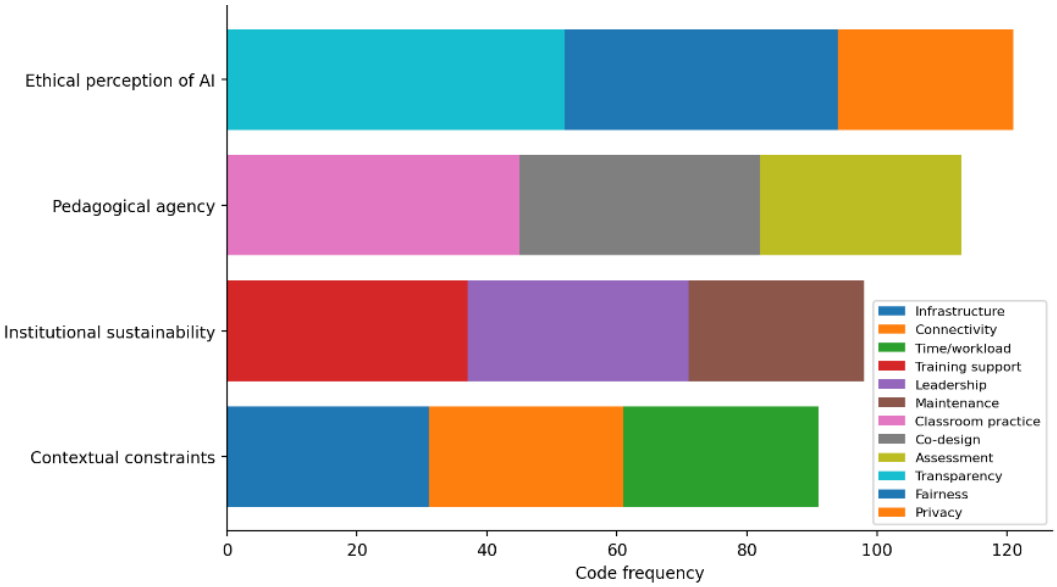


Fig. 10. Thematic composition of qualitative findings by subcodes (stacked)

4.9 Mixed-Method Integration: Joint Interpretation Without Overstating Convergence

Integration was conducted through an explicit alignment of quantitative indicators (competence gains, usage stability, module distribution, and IoT operational metrics) with qualitative themes that plausibly explain enabling and constraining conditions. The combined reading supports a bounded claim: the experimental group's competence gains co-occur with qualitative evidence of increased agency and with persistent structural constraints that shape how (and which) modules are used. Given that integration can be a locus of interpretive overreach, the manuscript treats the qualitative component as explanatory context and boundary-setting rather than as proof of causal mechanisms.

To address transparency concerns regarding "normalized qualitative relevance," (Fig. 11) the qualitative salience index is defined explicitly as a descriptive visualization aid, as in (3):

$$\mathrm{Rel}_{\mathrm{theme}} = 10 \times \frac{c_{\mathrm{theme}}}{\max(c_{\mathrm{theme}})} \tag{3}$$

where c_{theme} is the code count per theme. This yields a 0–10 index that is strictly a descriptive salience visualization, not a latent score.

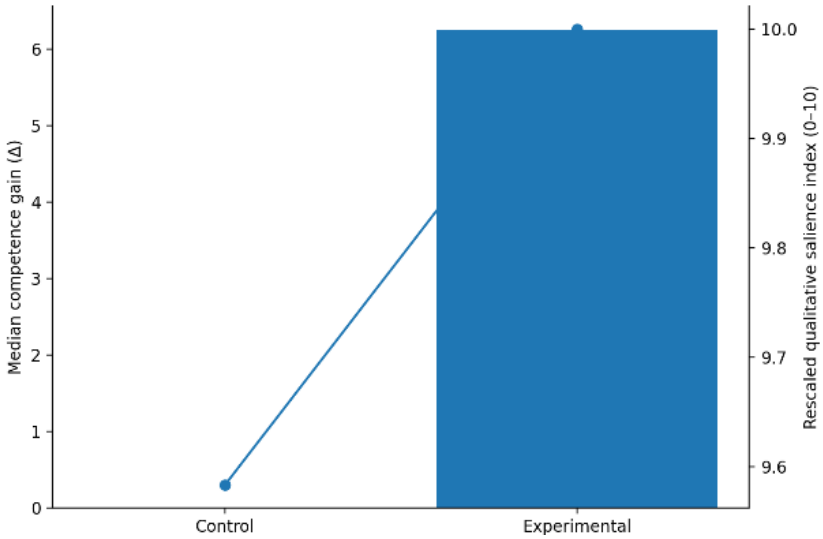


Fig. 11. Integrated summary of quantitative and qualitative outcomes in the MIPSTA implementation
Note. Bars represent median improvement in competence ($\tilde{\Delta}$) by group. The line represents a rescaled salience index derived from qualitative code counts (0–10), computed as $10 \times c_{\mathrm{theme}}/\max(c_{\mathrm{theme}})$. It is a visualization aid, not a causal or psychometric measure.

4.10 Limitations and Implementation Pathway (Claims Calibrated to Evidence)

Several constraints delimit inference. First, the study is geographically concentrated in a single municipality (Soto Norte), limiting external validity; therefore, statements about scalability are framed as a design rationale supported by preliminary evidence, not as demonstrated transferability across regions. Second, implementation covered one academic semester, restricting conclusions about retention, longer-term behavioral consolidation, and institutionalization. Third, although learning analytics show sustained engagement, trend tests do not support a monotonic growth narrative; interpretations remain consistent with observed variability rather than with a "doubling" claim.

Fig. 12 summarizes the operational pathway (Diagnosis → Design → Implementation → Reflection and evaluation → Re-adaptation) that structures the holopraxic action–reflection loop. The forward direction is to evaluate transferability through multi-site replications, strengthen IoT benchmarking under constrained connectivity, and predefine mixed-method integration rules to minimize interpretive drift. In action-research-informed implementations, explicit methodological justification and reporting transparency are commonly treated as necessary conditions for credibility and reproducibility across cycles [25,30].

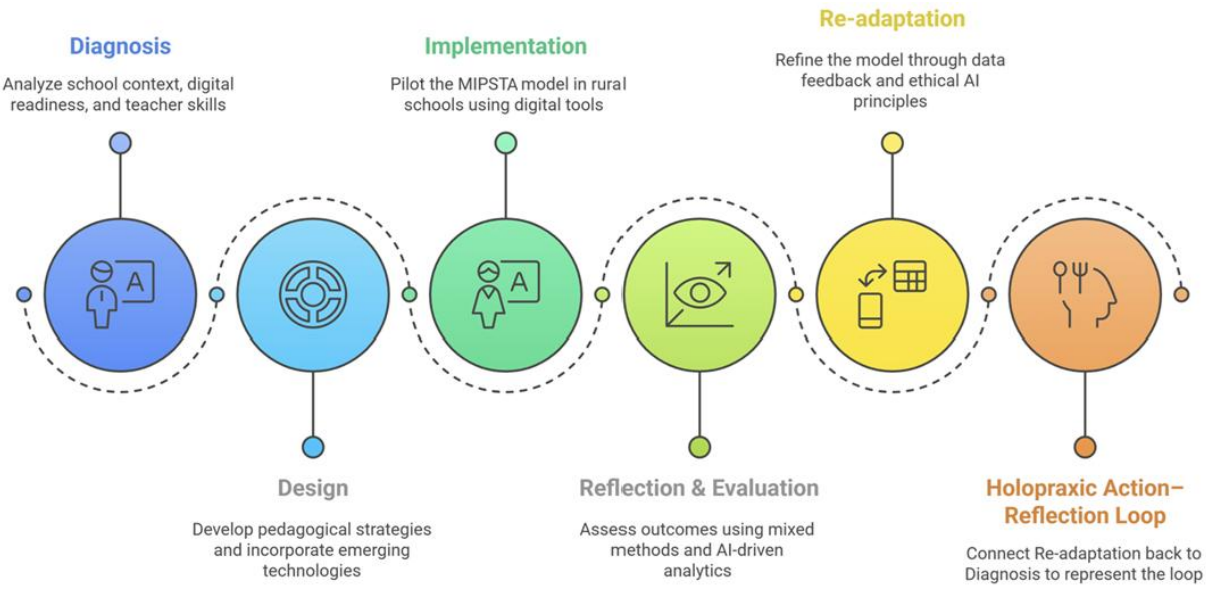


Fig. 12. MIPSTA Model Implementation Process
Note. The diagram illustrates the five iterative phases—Diagnosis, Design, Implementation, Reflection & Evaluation, and Re-adaptation—integrated within the Holopraxic Action–Reflection Loop.

5. Conclusion

The projective, holopraxic action-research design adopted in this study supports a conclusion that is best expressed in terms of *evidence-calibrated change under real rural constraints*, rather than as a one-shot "treatment effect". Across the semester-long cycle (Diagnosis → Design → Implementation → Reflection & Evaluation → Re-adaptation), the MIPSTA framework functioned as an iterative mechanism for aligning pedagogical support, analytics-informed guidance, and institutional feasibility conditions, allowing the intervention to be evaluated and refined without assuming that rural adoption follows linear or uniform trajectories.

Quantitatively, baseline digital competence was empirically comparable between groups, which strengthens the interpretability of post-intervention contrasts in a quasi-experimental setting. The main outcome, defined as absolute competence gain on the 0–100 scale (Δ = Post − Pre), showed a clear displacement in the experimental group relative to the control group. The experimental cohort achieved a median gain of 6.25 points (IQR = 6.78), whereas the control group remained centered near 0.00 (IQR = 3.12). The between-group contrast in Δ distributions was robust (Mann–Whitney $U = 2753.5$, $p < 0.001$), with a moderate-to-large rank-based separation ($r = 0.458$) and a probabilistic effect size indicating that an experimental participant exceeds a control participant in Δ about 76.5% of the time (Vargha–Delaney $A = 0.765$). Consistently, within-group inference supports a reliable pre–post improvement in the experimental cohort (Wilcoxon $W = 159.5$, $p < 0.001$; $r = 0.708$), while the control cohort does not show a statistically reliable shift at conventional thresholds ($W = 531.5$, $p = 0.216$). This pattern—stronger change signal concentrated in Δ rather than in raw post scores—also matches the logic of focusing inference on *change distributions* when baseline variability is substantial and assumptions of normality are not guaranteed.

Learning-analytics evidence adds an important boundary condition to interpretation: engagement was sustained but not well described by a monotonic "growth" narrative. Weekly sessions fluctuated with episodic peaks rather than a steady rise, and trend tests did not support claims of progressive doubling. The defensible interpretation is therefore one of *stable adoption with intermittent intensification*, compatible with task-driven usage cycles during implementation. At the component level, usage traces indicate uneven appropriation: the IoT toolkit accounted for a smaller share of interactions than analytics and adaptive feedback, which is more plausibly read as selective prioritization under infrastructural constraints than as simple underperformance. Importantly, the IoT subsystem is still empirically characterizable with operational indicators that matter in rural connectivity contexts: offline events represented 27.8% of IoT events and estimated event loss was 2.25%, providing a measurable baseline of resilience that can be strengthened in subsequent cycles.

Qualitative analysis complements these findings by clarifying *how* teachers framed AI-supported integration under rural conditions. The thematic structure—Ethical perception of AI, Pedagogical agency, Institutional sustainability, and Contextual constraints—indicates that adoption was negotiated through concrete concerns (connectivity, workload, infrastructure), but also through evolving professional positioning: teachers increasingly treated intelligent tools as supports for planning, feedback, and reflective practice, provided that privacy, fairness, and transparency remained credible conditions of use. In methodological terms, this mixed-method convergence is best treated as *contextual explanation and boundary-setting* for quantitative change—not as proof of a causal mechanism—consistent with the study's explicit stance against over-claiming in action-research-informed deployments.

Taken together, the study supports three contributions that remain proportionate to the evidence. First, MIPSTA demonstrates that measurable competence gains can be achieved in rural settings when the intervention is implemented as an iterative, holopraxic cycle rather than as a fixed package. Second, the integration of self-report, interviews, and usage logs strengthens interpretability by reducing reliance on single-source claims and by rendering adoption patterns auditable. Third, the results identify practical implementation levers—teacher agency, ethical trust conditions, and institutional support structures—that should be treated as design requirements, not as peripheral context.

At the same time, the conclusions must remain bounded by the study's scope: the geographic concentration in a single municipality and the one-semester horizon limit claims about transferability, retention, and institutionalization. The most defensible next step is therefore not rhetorical scaling, but *empirical scaling*: multi-site replications, longer follow-up windows, stronger IoT benchmarking (e.g., latency and site-level reliability profiles), and pre-specified mixed-method integration rules to further reduce interpretive drift across cycles. Under those conditions, MIPSTA can be positioned as a replicable implementation framework whose strength lies in disciplined refinement under real constraints—precisely the kind of methodological posture that rural digital transformation demands.

Author Contributions Statement

Rubén Baena-Navarro – Conceptualization, Methodology, Investigation, Formal Analysis, Supervision, Writing – Original Draft: Conceived the study and the MIPSTA framework, designed the quasi-experimental mixed-methods approach, coordinated field implementation, led the quantitative analysis and interpretation, and drafted the manuscript.

Javier Fernando-Bermúdez – Investigation, Qualitative Data Collection, Validation, Writing – Review and Editing: Supported field deployment, conducted and organized the semi-structured interviews, contributed to thematic analysis and methodological triangulation, and reviewed and edited the manuscript for coherence and pedagogical consistency.

Yulieth Carriazo-Regino – Data Curation, Software, Visualization, Validation, Writing – Review and Editing: Managed data preparation and anonymization procedures, processed and summarized system usage logs, contributed to visualization of results, supported robustness checks, and reviewed and edited the manuscript.

All authors have read and agreed to the published version of the manuscript.

Conflict of Interest Statement

The authors declare no conflicts of interest.

Funding Declaration

This research received no external funding.

Data Availability Statement

This study analyzed de-identified research data. The dataset supporting the findings of this study is available in Mendeley Data: Baena-Navarro, Rubén; Bermúdez, Javier; Carriazo-Regino, Yulieth (2026), "Quasi-Experimental Mixed-Methods Dataset: Rural Teachers' Digital Competence and System Usage Logs (MIPSTA), Soto Norte, Colombia", Mendeley Data, V1, doi: 10.17632/8mpsnnndnd.1.

Ethical Declarations

The study was authorized by the participating educational institutions and conducted in accordance with Colombian educational research requirements and personal data protection rules. Adult teacher participants provided written informed consent. For minors, written permission was obtained from parents or legal guardians and age-appropriate assent was obtained from the students; participation was voluntary and non-evaluative. Data were pseudonymized at collection and fully anonymized before analysis and sharing to prevent identification of individuals or institutions.

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Declaration of Generative AI in Scholarly Writing

The authors declare that no generative artificial intelligence tools were used in the writing of this manuscript.

Abbreviations

The following abbreviations are used in this manuscript:

AI – Artificial Intelligence
IoT – Internet of Things
LA – Learning Analytics
PLA – Predictive Learning Analytics
EFA – Exploratory Factor Analysis
CLES – Common Language Effect Size
GDPR – General Data Protection Regulation

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