RESEARCH ARTICLE

JENER Journal of Empirical and Non-Empirical Research
Volume 2, Issue 8, Page 736-745 | Article No. 80
DOI: 10.4898/jener.v2i8.a80
ISSN: 7895-9216
Journal homepage: https://jenerjournal.com
Journal email: editor@jenerjournal.com

JENER Journal
JENER Journal of Empirical and Non-Empirical Research

Responsible Artificial Intelligence Adoption in Public Basic Education: Opportunities, Risks, and Readiness in the Schools Division of Quirino, Philippines

Jeanvie C. Bueza[1] & Angelica A. Bahag[2]

[1,2]Northeastern College

ARTICLE INFORMATION

Article history:
Published: August 2026

Keywords:
Artificial Intelligence in Education
Teacher Readiness
Responsible AI
Digital Equity
Educational Governance
Quirino Province

ABSTRACT

Artificial intelligence (AI) entered public basic education faster than school-level rules, teacher preparation, and infrastructure could develop. This study examined the opportunities, risks, readiness conditions, and responsible-use practices associated with AI in the Schools Division of Quirino, Philippines. A convergent mixed-methods design combined a survey of 298 teachers from 36 public schools with interviews involving 18 teachers and six school leaders. The instrument measured opportunity, challenge, AI literacy, infrastructure readiness, policy clarity, and responsible adoption. Content validation involved nine experts, and a separate 52-teacher pilot supported reliability. Descriptive statistics summarized perceptions and use patterns. Multilevel linear models accounted for teachers nested within schools, municipality fixed effects, and selected professional characteristics. Thematic analysis examined interview accounts, and joint displays integrated both strands. Teachers rated AI opportunities highly ($M = 3.87$, $SD = 0.54$) while rating challenges slightly higher ($M = 4.02$, $SD = 0.55$). Lesson planning and resource creation were the most common uses; student-facing tutoring remained least common. Privacy and security, output accuracy and bias, and academic integrity received the highest concern ratings. Teachers in less accessible schools reported lower infrastructure readiness (adjusted mean difference = -0.66, 95% CI [-0.85, -0.47]) and responsible adoption (adjusted mean difference = -0.22, 95% CI [-0.37, -0.07]). In the multilevel model, AI literacy, infrastructure readiness, policy clarity, perceived opportunity, prior training, and weekly use were independently associated with responsible adoption. Interviews clarified that teachers valued time savings but required verification routines, locally relevant examples, privacy safeguards, assessment redesign, and practical division-level guidance. The findings indicated that responsible AI adoption depended less on unrestricted access to tools than on coordinated investment in teacher capability, equitable infrastructure, clear governance, and human review.

1. Introduction

Artificial intelligence became an immediate school-governance concern when systems capable of producing fluent text, images, feedback, lesson materials, and data summaries became widely accessible. In education, the same tool could reduce routine workload, expand access to explanations, and help teachers adapt materials, yet it could also generate inaccurate content, reproduce bias, expose personal information, and weaken the validity of conventional assessment. UNESCO therefore framed AI adoption as a human-centred governance problem rather than a simple technology-purchase decision.[4,7,9]

The Philippine basic education system had begun to position AI as an instrument for empowerment, administrative efficiency, and improved decision-making. DepEd publicly called for responsible and ethical use, stressed that AI should amplify rather than replace human agency, and expanded national work through the Education Center for AI Research.[1,2] More recent initiatives applied AI to infrastructure visibility, administrative data, leadership systems, learner screening, and instructional support.[2,3] These directions created a strong policy signal, but local implementation still depended on connectivity, devices, staff capability, privacy safeguards, and rules that translated broad principles into daily classroom decisions.

The Schools Division of Quirino offered a particularly useful setting for examining those implementation conditions. DepEd listed the division among the field offices of Region II, with its headquarters in Cabarroguis.[12] The national school inventory dashboard listed 186 public schools in the division when the sampling frame was prepared.[13] Schools were distributed across Aglipay, Cabarroguis, Diffun, Maddela, Nagtipunan, and Saguday, creating variation in travel time, connectivity, and access to technical support. Such variation mattered because AI tools were often delivered through cloud services that required stable internet access, updated devices, and accounts governed by external terms of service.

National connectivity gains did not eliminate local inequalities. The Philippine Statistics Authority reported that 48.8% of households had internet access at home in 2024, while individual internet use was more widespread.[14] Household access, however, did not indicate whether a connection was stable, affordable, sufficiently fast, or available during school hours. In geographically dispersed divisions, the relevant question was not only whether teachers could open an AI service, but whether they could use it consistently, verify outputs, protect learner data, and redesign instruction without increasing inequity.

1.1 Educational opportunities associated with AI

Research described AI as a family of systems that could support planning, instruction, assessment, learner support, and administration. Systematic reviews found potential value in identifying learning needs, generating instructional alternatives, automating selected tasks, supplying rapid feedback, and supporting teacher reflection.[15,16] Generative systems extended those possibilities by producing examples, questions, summaries, rubrics, differentiated passages, and draft communications through natural-language interaction.[17,18] These functions were especially attractive where teachers carried heavy preparation and reporting responsibilities. Efficiency alone did not establish educational value. Generated material still had to be aligned with competencies, learner age, language, local context, and sound pedagogy. The technological-pedagogical-content knowledge tradition emphasized that tools became useful only when teachers connected their affordances with disciplinary knowledge and instructional design.[23] AI could therefore assist a competent teacher, but it could not determine by itself what learners should understand, what evidence would demonstrate learning, or which errors required human intervention.

AI literacy was another opportunity. Ng and colleagues described AI literacy as the capacity to understand, use, evaluate, and consider ethical issues in AI.[19] Long and Magerko likewise treated literacy as involving recognition of AI, understanding of strengths and weaknesses, interpretation of data and outputs, and responsible human interaction with intelligent systems.[20] UNESCO later organized teacher competency around a human-centred mindset, ethics, foundations and applications, AI pedagogy, and professional learning.[5] In this view, the school did not merely consume AI; it prepared teachers and learners to question how outputs were produced, whose data were used, and when human judgment had to prevail.

1.2 Risks and governance challenges

The most immediate risk was epistemic. Large language systems produced plausible responses without guaranteeing truth, source quality, curricular alignment, or freedom from bias. Reviews and case analyses documented inaccurate references, inconsistent answers, oversimplified assessment items, and responses that changed with prompt wording.[17,18] When teachers used such output without verification, speed could magnify error. When learners treated fluency as authority, the tool could displace the productive struggle needed for explanation, writing, and critical thinking.

Academic integrity presented a related but distinct problem. AI-generated work challenged assignments that inferred learning from a polished final product. Prohibition alone was difficult to enforce and could encourage surveillance practices with their own validity and fairness problems. A stronger response redesigned assessment around drafts, oral explanation, local data, process evidence, classroom performance, and explicit disclosure of permitted assistance.[4,18] This approach protected the inferential meaning of assessment rather than relying on uncertain detection.

Privacy and child protection imposed non-negotiable limits. The Data Privacy Act of 2012 required transparency, legitimate purpose, proportionality, security, and protection against unauthorized processing.[11] Educational records could include sensitive personal information, and teachers could inadvertently transfer learner names, performance histories, disability information, family circumstances, or identifiable work to an external service. UNESCO and UNICEF guidance therefore stressed age appropriateness, human oversight, data governance, safety, fairness, inclusion, and protection of children's rights.[4,10]

Equity also shaped risk. Technology could expand access to support, but it could deepen differences when some schools had stable connectivity, newer devices, paid services, and local technical assistance while others relied on intermittent mobile data. The Southeast Asian technology report emphasized that appropriate, equitable, scalable, and sustainable use required infrastructure, governance, evidence, and sustained teacher preparation.[7] For Quirino, an adoption strategy that ignored accessibility differences could inadvertently concentrate benefits in already better-served schools.

1.3 Readiness, trust, and adoption

Technology-adoption research consistently linked use with perceived usefulness, ease, facilitating conditions, and social influence.[22] For AI, however, adoption had to include calibrated trust. Teachers needed enough confidence to test useful functions, enough skepticism to verify outputs, and enough institutional support to reject unsafe uses. Research on teacher trust in AI-powered educational technology showed that professional learning could improve understanding of system capabilities and foster more appropriate reliance.[21]

This study therefore distinguished access from responsible adoption. Responsible adoption referred to purposeful use in which the teacher retained instructional authority, verified important content, protected personal data, disclosed material AI assistance when appropriate, preserved meaningful learner work, and selected a tool only when it improved a defined educational task. Readiness comprised AI literacy, infrastructure, policy clarity, and training. Perceived opportunity and perceived challenge were treated as simultaneous appraisals rather than opposite ends of one continuum.

1.4 Research gap and contribution

Much of the published evidence on AI in education came from higher education, early-adopter settings, or international surveys. Reviews noted uneven attention to K-12 practice, teacher roles, local infrastructure, and governance.[15,16] Philippine policy discourse advanced quickly, but division-level evidence on what teachers actually valued, feared, understood, and needed remained limited. A provincial public-school system required an analysis that joined instructional opportunities with digital equity, privacy, assessment validity, and organizational readiness.

The present study addressed that gap in three ways. First, it examined opportunities, risks, and readiness in one coherent design rather than treating adoption as simple willingness to use a tool. Second, it used multilevel analysis to account for teachers nested within schools. Third, it integrated survey patterns with teacher and school-leader explanations, producing implementation priorities that could be acted upon at division and school levels.

1.5 Purpose, research questions, and hypotheses

The study examined responsible AI adoption among public-school educators in the Schools Division of Quirino and identified the institutional conditions required for equitable and educationally sound implementation.

RQ1. What AI tools and educational uses were reported by teachers?

RQ2. How did teachers assess AI-related opportunities, challenges, AI literacy, infrastructure readiness, policy clarity, and responsible adoption?

RQ3. Did opportunity, challenge, readiness, and adoption differ between more accessible and less accessible school settings after adjustment for teacher and school characteristics?

RQ4. Which teacher- and school-level factors were associated with responsible AI adoption?

RQ5. How did teachers and school leaders explain the conditions under which AI supported or threatened teaching, assessment, equity, and professional responsibility?

The primary hypothesis stated that AI literacy, infrastructure readiness, policy clarity, perceived opportunity, and prior training would be positively associated with responsible adoption after adjustment for experience, school level, accessibility, and municipality. A second hypothesis stated that infrastructure readiness and responsible adoption would be lower in less accessible schools. Challenge awareness was examined without a directional hypothesis because greater awareness could either discourage use or indicate more reflective practice.

2. Methods

2.1 Research design

The study used a convergent mixed-methods design. Quantitative and qualitative data were collected during the same implementation period, analyzed separately, and integrated through side-by-side comparison and joint displays. This design was appropriate because numerical ratings described prevalence and association, while interviews explained why the same technology was experienced as useful, risky, or inaccessible. Integration focused on convergence, complementarity, and divergence rather than using one strand merely to validate the other.[30]

2.2 Setting and sampling frame

The setting was the Schools Division of Quirino in Region II. The division office was located in Cabarroguis, and the sampling frame was organized across the province's six municipalities.[12] The public inventory listed 186 schools when sampling preparation was completed.[13] Schools varied in grade coverage, enrollment, road access, travel time to municipal centers, availability of wired or mobile internet, and proximity to technical assistance.

Schools were classified into two analytic accessibility strata using a pre-specified combination of typical travel time to the municipal center, stability of school internet service, and availability of an on-site computer coordinator. The classification was used only for sampling and analysis; it did not replace any official DepEd geographic classification. Thirty-six schools were selected, with six schools represented from each municipality and balance sought across elementary and secondary levels and accessibility strata.

2.3 Participants and sample-size basis

The quantitative participants were public-school teachers and teaching school leaders who had completed at least one school year in their current station. Within selected schools, eligible personnel were listed and sampled systematically. The target of approximately 300 respondents was set to support stable estimation of descriptive domain means and a multilevel model with 36 school clusters and a limited number of pre-specified predictors. With an average of about eight respondents per school and a planning intraclass correlation of .10, the design effect was approximately 1.7, leaving an effective sample near 175 for fixed-effect estimation. Of 312 invited personnel, 298 returned complete questionnaires, yielding a 95.5% response rate.

The qualitative sample used maximum-variation selection after the survey. Eighteen teachers and six school leaders were selected to represent all municipalities, both school levels, both accessibility strata, different experience levels, prior AI training, and contrasting adoption scores. Selection sought information richness rather than numerical representation. Interviews continued until the coding team judged that later accounts clarified existing categories without materially changing the thematic structure.

2.4 Conceptual and measurement framework

The instrument was developed from UNESCO guidance, AI competency frameworks, technology-adoption research, teacher-focused systematic reviews, and Philippine data-protection requirements.[4,5,11,15,19,22] It separated favorable appraisals from safeguards so a respondent could recognize both high opportunity and high risk. All multi-item scales used a five-point response format from 1 (strongly disagree or very low) to 5 (strongly agree or very high). Domain scores were computed only when at least 80% of items were answered; person-mean substitution within the same domain was used for the small number of isolated missing responses.

Table 1. Measurement framework and scoring

Construct	Operational emphasis	Items	Score
Perceived opportunity	Planning, assessment, differentiation, learner support, and administration	20	Mean, 1-5
Perceived challenge	Accuracy, privacy, integrity, infrastructure, equity, policy, and training	20	Mean, 1-5
AI literacy	Understanding, use, evaluation, prompting, limits, and ethical judgment	10	Mean, 1-5
Infrastructure readiness	Connectivity, devices, accounts, technical support, and continuity	6	Mean, 1-5
Policy clarity	Permitted use, disclosure, verification, privacy, assessment, and accountability	6	Mean, 1-5
Responsible adoption	Purposeful use, human review, disclosure, privacy protection, and assessment validity	10	Mean, 1-5

2.5 Instrument validation and pilot testing

Nine validators examined item relevance, clarity, coherence, cultural appropriateness, and feasibility. The panel included specialists in educational technology, curriculum and instruction, measurement, school leadership, data privacy, and language review. Item-level content validity indices (I-CVI), scale-level average content validity indices (S-CVI/Ave), and Aiken's V were calculated. For nine raters, I-CVI values of .78 or higher were retained as acceptable, while scale averages at or above .90 supported strong content validity.[26,27]

A separate group of 52 teachers completed the pilot form. Cognitive debriefing identified ambiguous references to specific commercial products, leading the instrument to use function-based descriptions instead. Internal consistency was summarized with McDonald's omega because it did not require equal item loadings.[28] Items with corrected item-total correlations below .30, redundant wording, or unclear school applicability were revised or removed. The final questionnaire contained 72 scaled items plus demographic and use-pattern questions.

2.6 Data-collection procedures

Division and school coordination preceded recruitment. Survey packets explained the study purpose, voluntary participation, confidentiality, and the distinction between AI use for professional tasks and disclosure of any identifiable learner information. Respondents completed the questionnaire individually through a secured online form or an equivalent paper form where connectivity was unreliable. Paper responses were double-entered and reconciled. No learner names, student work, account credentials, or prompts from commercial AI services were collected.

Semi-structured interviews lasted approximately 40 to 60 minutes. Questions addressed actual functions for which AI was used, verification practices, examples of useful and problematic output, assessment decisions, privacy concerns, access barriers, school-level guidance, and preferred training. Interviewers avoided requesting confidential records or demonstrations using learner data. Field summaries were completed immediately after each session, and transcripts were de-identified before coding.

2.7 Quantitative analysis

Frequencies and percentages summarized tool exposure, use patterns, training, and policy awareness. Means, standard deviations, and 95% confidence intervals summarized multi-item scale scores. Because the constructs were represented by multiple approximately continuous items, domain means were used for estimation; interpretation emphasized confidence intervals and practical magnitude rather than labels alone. Reliability was reported with omega and 95% bootstrap confidence intervals.

Teachers were nested within schools, so ordinary regression would have understated uncertainty if responses were correlated within schools. Random-intercept linear models were therefore estimated with restricted maximum likelihood. Municipality was entered as a fixed effect, while school received a random intercept. Accessibility comparisons adjusted for school level, teacher experience, role, and municipality. Five planned comparisons were corrected with the Holm procedure. Standardized mean differences accompanied adjusted group contrasts.

The primary multilevel model predicted the standardized responsible-adoption score from standardized AI literacy, infrastructure readiness, policy clarity, perceived opportunity, perceived challenge, and years of experience, together with indicators for formal AI training, weekly AI use, school accessibility, school level, and role. Variance inflation factors were examined for the fixed predictors. Model residuals were inspected for linearity, normality, and constant variance. Marginal R squared summarized variance explained by fixed effects, while conditional R squared incorporated the school random effect.[31] Two-sided statistical significance was set at .05, but the interpretation prioritized effect direction, interval width, and implementation relevance.

2.8 Qualitative analysis and mixed-methods integration

Thematic analysis followed familiarization, initial coding, focused category development, theme construction, review, and analytic naming.[29] A deductive starting frame covered opportunity, risk, readiness, governance, and equity; inductive coding captured mechanisms not anticipated by the survey. Two analysts independently coded 25% of transcripts, discussed disagreements, refined definitions, and then divided the remaining material with periodic cross-checks. Agreement after the first coding round was substantial (Cohen's kappa = .82).

Integration occurred after separate results were finalized. A joint display aligned quantitative results with qualitative explanations and identified confirmation, expansion, or tension. A meta-inference was accepted only when it remained consistent with the measurement definition and did not convert an interview explanation into a prevalence estimate. Qualitative findings were reported as patterns without invented verbatim quotations.

2.9 Ethical and data-protection safeguards

The protocol treated AI-related information as potentially sensitive because teachers could describe school systems, learner-data practices, or assessment concerns. Participation was voluntary, identifiers were separated from responses, results were aggregated, and small cells were suppressed when necessary. The data plan followed transparency, legitimate purpose, proportionality, confidentiality, and security principles under the Data Privacy Act.[11] The interview guide explicitly prohibited the transfer of identifiable learner information into any AI service for demonstration.

3. Results

3.1 Participant profile

The analytic sample included 298 respondents from 36 schools. Participants represented all six municipalities, elementary and secondary levels, and both accessibility strata. The mean age was 39.1 years (SD = 8.5), and mean teaching experience was 11.4 years (SD = 7.3). Women comprised 72.5% of the sample. Most participants held Teacher I-III positions, while master teachers and teaching school leaders provided smaller but analytically useful groups.

Table 2. Characteristics of survey participants (N = 298)

Characteristic	n	% or M (SD)
Age, years		39.1 (8.5)
Teaching experience, years		11.4 (7.3)
Female	216	72.5
Male	82	27.5
Elementary level	181	60.7
Secondary level	117	39.3
Teacher I-III	229	76.8
Master teacher	33	11.1
Teaching school leader/TIC	36	12.1
More accessible school stratum	166	55.7
Less accessible school stratum	132	44.3
Completed formal AI-related training	82	27.5
Reported school-level AI guidance	65	21.8

3.2 AI exposure and use patterns

AI use was present but unevenly institutionalized. One hundred eighty-two respondents (61.1%) reported using at least one AI-enabled tool weekly, 59 (19.8%) used one monthly, 29 (9.7%) had tried a tool only once or rarely, and 28 (9.4%) had not used one. Only 27.5% had completed formal AI-related training, and 21.8% reported written or consistently communicated school-level guidance. Thus, practice had spread faster than structured preparation and governance.

Teachers most often used AI for work performed before or after direct instruction. Lesson planning, resource drafting, editing, translation, and assessment-item generation were common. Student-facing tutoring remained least common, indicating that teachers were more willing to use AI as a professional assistant than to place it in direct interaction with learners.

Table 3. Reported educational uses of AI (N = 298)

Use during the current school year	n	%
Lesson-plan outlining or activity ideation	217	72.8
Worksheet, example, or resource drafting	200	67.1
Language editing or translation support	164	55.0
Assessment-item or rubric drafting	145	48.7
Differentiated or leveled material preparation	115	38.6
Drafting formative feedback	102	34.2
Administrative reports or communications	94	31.5
Student-facing tutoring or chatbot activity	54	18.1

3.3 Instrument quality

Expert review supported the relevance and clarity of the instrument. Across scales, S-CVI/Ave values ranged from .93 to .97, and Aiken's V ranged from .86 to .98. Pilot omega values ranged from .84 to .91. Reliability in the analytic sample remained strong, with omega values from .87 to .93. These results supported domain-level interpretation while recognizing that reliability did not by itself establish validity.

Table 4. Content validity and reliability evidence

Scale	S-CVI/Ave	Aiken's V	Pilot omega	Study omega
Perceived opportunity	.96	.88-.98	.91	.93
Perceived challenge	.95	.87-.98	.90	.92
AI literacy	.94	.86-.97	.86	.89
Infrastructure readiness	.93	.86-.96	.84	.87
Policy clarity	.97	.89-.98	.88	.91
Responsible adoption	.96	.88-.98	.89	.91

3.4 Perceived opportunities

Overall perceived opportunity was high (M = 3.87, SD = 0.54, 95% CI [3.81, 3.93]). Planning and resource creation received the highest rating, followed by administrative efficiency. Differentiation and accessibility were viewed favorably but less strongly, reflecting the additional requirement for dependable learner information, language sensitivity, and teacher review. Learner support and engagement received the lowest opportunity rating, although it remained above the scale midpoint.

Table 5. Perceived AI opportunities

Opportunity domain	M	SD	95% CI
Planning and resource creation	4.19	0.58	[4.12, 4.26]
Administrative efficiency	3.96	0.61	[3.89, 4.03]

Opportunity domain	M	SD	95% CI
Assessment and feedback	3.81	0.67	[3.73, 3.89]
Differentiation and accessibility	3.74	0.64	[3.67, 3.81]
Learner support and engagement	3.66	0.70	[3.58, 3.74]
Overall opportunity	3.87	0.54	[3.81, 3.93]

Note. Scores ranged from 1 to 5. Confidence intervals were calculated for the sample means.

3.5 Perceived challenges and readiness

Overall challenge was also high (M = 4.02, SD = 0.55). Privacy and security received the highest mean, narrowly followed by accuracy and bias and by academic integrity and learner dependency. Infrastructure and equity remained substantial concerns. Policy and training gaps received a somewhat lower mean but were directly linked to uncertainty about what teachers were permitted to upload, how AI assistance should be disclosed, and who was accountable for inaccurate material.

Table 6. Perceived AI challenges

Challenge domain	M	SD	95% CI
Privacy and security	4.22	0.63	[4.15, 4.29]
Accuracy, fabrication, and bias	4.14	0.61	[4.07, 4.21]
Academic integrity and learner dependency	4.09	0.66	[4.02, 4.17]
Infrastructure and access equity	3.88	0.75	[3.80, 3.97]
Policy clarity and professional learning gaps	3.76	0.70	[3.68, 3.84]
Overall challenge	4.02	0.55	[3.96, 4.08]

AI literacy averaged 3.31 (SD = 0.66), infrastructure readiness averaged 3.14 (SD = 0.74), and policy clarity averaged 2.73 (SD = 0.78). Responsible adoption averaged 3.43 (SD = 0.61). The combination suggested that teachers had already developed practices for cautious use, but enabling conditions remained incomplete. Policy clarity was the weakest readiness domain and the only mean below 3.00.

3.6 Accessibility-stratum comparisons

Perceived opportunity did not differ materially between accessibility strata after covariate adjustment. Teachers in less accessible schools nevertheless reported higher challenge, lower AI literacy, substantially lower infrastructure readiness, and lower responsible adoption. The infrastructure difference was the largest standardized contrast. All conclusions except perceived opportunity remained statistically significant after Holm correction across the five planned comparisons.

Table 7. Adjusted comparisons by school accessibility

Outcome	More accessible M	Less accessible M	Adjusted difference	95% CI	Holm p
Perceived opportunity	3.91	3.82	-0.05	[-0.17, 0.07]	.393
Perceived challenge	3.89	4.18	0.27	[0.14, 0.40]	<.001
AI literacy	3.45	3.14	-0.26	[-0.42, -0.10]	.006
Infrastructure readiness	3.45	2.75	-0.66	[-0.85, -0.47]	<.001
Responsible adoption	3.56	3.27	-0.22	[-0.37, -0.07]	.008

3.7 Multilevel predictors of responsible adoption

The null model produced an intraclass correlation of .14, confirming meaningful school-level clustering. In the final model, AI literacy, infrastructure readiness, policy clarity, perceived opportunity, formal training, and weekly use were positively associated with responsible adoption. Challenge awareness was not independently negative after readiness and opportunity were controlled, suggesting that reflective users could recognize risk while still applying safeguards. Accessibility was no longer statistically distinct after infrastructure, training, and policy clarity entered the model, indicating that these modifiable conditions accounted for much of the raw geographic difference.

Table 8. Random-intercept model predicting responsible AI adoption (N = 298; 36 schools)

Predictor	Standardized b	95% CI	p
AI literacy	0.28	[0.17, 0.39]	<.001
Infrastructure readiness	0.19	[0.08, 0.30]	.001
Policy clarity	0.16	[0.06, 0.26]	.002
Perceived opportunity	0.22	[0.11, 0.33]	<.001
Perceived challenge	0.07	[-0.03, 0.17]	.168
Formal AI training (yes)	0.24	[0.08, 0.40]	.004
Weekly AI use (yes)	0.20	[0.05, 0.35]	.009
Less accessible school	-0.11	[-0.26, 0.04]	.151
Teaching experience	0.03	[-0.06, 0.12]	.512
Secondary school level	0.06	[-0.08, 0.20]	.401

Note. Continuous predictors and the outcome were standardized. Municipality and role fixed effects were included but omitted for space. Marginal R squared = .46; conditional R squared = .54; final school-level ICC = .08. Variance inflation factors ranged from 1.18 to 2.04. Residual inspection did not show consequential nonlinearity or heteroscedasticity. The conditional model explained 54% of variance when fixed predictors and the school random effect were considered together. Sensitivity analysis using cluster-robust standard errors yielded the same substantive conclusions. Removing respondents who had never used AI reduced the sample but did not change coefficient directions or the set of statistically supported predictors.

3.8 Qualitative themes

Six themes organized the interview findings. They showed that teachers did not divide neatly into enthusiasts and opponents. Most participants held conditional positions: they valued functions that reduced low-level workload, but they insisted that teachers remain responsible for accuracy, context, privacy, and evidence of student learning.

Table 9. Themes from teacher and school-leader interviews

Theme	Analytic description	Implementation implication
Efficiency became valuable only after verification	AI accelerated first drafts, examples, and routine communication, but checking facts, difficulty, and competency alignment remained teacher work.	Training had to include verification protocols, not prompt techniques alone.
Local context was a recurring quality test	Outputs often lacked provincial examples, local language sensitivity, school resource realism, or appropriate learner reading level.	Teachers needed adaptation checklists and locally reviewed prompt-and-resource banks.
Access shaped who could experiment and improve	Stable connectivity and personal devices enabled repeated practice; intermittent access made use episodic and discouraged experimentation.	Offline alternatives, shared devices, and differentiated rollout were required.
Assessment validity mattered more than detection	Participants doubted that AI detectors could settle authorship and preferred process evidence, oral checks, drafts, and classroom performance.	Assessment policy had to specify permitted assistance and authentic evidence of learning.
Policy ambiguity shifted risk to individual teachers	Unclear rules produced inconsistent practices regarding accounts, disclosure, learner data, and acceptable student use.	The division needed minimum safeguards with room for subject-specific application.
Human judgment remained the governing principle	Teachers accepted AI as an assistant but rejected substitution for care, disciplinary judgment, feedback conversations, and final decisions.	Adoption criteria had to protect teacher authority and learner agency.

3.9 Mixed-methods integration

The two strands converged on a conditional-adoption explanation. High opportunity ratings were not evidence of uncritical acceptance; the same respondents also reported high risk. Quantitative associations showed that literacy, infrastructure, policy, and training predicted responsible adoption, while interviews explained the mechanisms: repeated practice improved judgment, stable access allowed experimentation, and clear rules reduced unsafe improvisation. The strands also clarified why perceived challenge did not predict lower adoption after adjustment. Risk awareness functioned as part of responsible practice when teachers had the capacity and rules needed to act on it.

Table 10. Joint display of integrated findings

Quantitative result	Qualitative explanation	Meta-inference
Planning/resource opportunity was highest (M = 4.19).	Teachers valued faster first drafts but continued to verify content and level.	AI was most acceptable as a teacher-controlled drafting assistant.
Privacy was the highest challenge (M = 4.22).	Participants were uncertain about entering learner work and records into external services.	A no-identifiable-data rule was a prerequisite for routine use.
Infrastructure gap was -0.66 points in less accessible schools.	Intermittent connectivity reduced experimentation and continuity.	Equitable adoption required infrastructure-sensitive implementation, not uniform deadlines.
Training and policy clarity predicted responsible adoption.	Teachers requested scenarios, verification routines, and clear boundaries.	Professional learning and governance had to be developed together.
Student-facing tutoring was least common (18.1%).	Participants protected the relational and supervisory role of teachers.	Early rollout should prioritize teacher-facing functions before direct learner deployment.

4. Discussion

The study found neither a simple readiness to embrace AI nor a general resistance to it. Teachers reported high opportunity and high challenge simultaneously. This dual appraisal was educationally rational. AI could reduce preparation time and broaden the range of instructional options, but it could also produce credible-looking error, transfer sensitive data, and weaken assessment validity. The results therefore supported human-centred approaches that judged technology by educational purpose, equity, evidence, and sustainability.[4,7]

4.1 Opportunity was strongest in teacher-facing work

Planning and resource creation received the highest opportunity rating and the highest reported use. This pattern was consistent with teacher-focused reviews that identified planning, implementation, and assessment support as recurring AI functions.[15] It was also

practically understandable: a teacher could ask for alternative examples, a first draft of a worksheet, or a revised reading passage while retaining control over the final material. The cost of error remained manageable when the teacher reviewed the output before learners encountered it.
Lower use of student-facing tutoring showed that adoption followed a risk gradient. Direct interaction raised questions about age appropriateness, supervision, data transfer, dependency, and whether the system's response aligned with curriculum and learner needs. A staged implementation should therefore begin with lower-risk teacher-facing tasks, build review competence, and require stronger evidence before enabling autonomous or semi-autonomous learner interactions. This sequence reflected UNESCO's emphasis on preserving human agency and validating pedagogical suitability.[4,5]
The opportunity findings did not justify measuring success by the number of tools used. A teacher who employed one approved service carefully could demonstrate stronger adoption than a frequent user who copied unverified material. The responsible-adoption construct accordingly emphasized purpose, review, privacy, and assessment validity. This distinction helped prevent innovation discourse from rewarding activity without educational value.

4.2 Privacy, accuracy, and integrity formed a connected risk system
Privacy and security received the highest challenge rating. This finding carried particular weight in basic education because school records concerned minors and could contain sensitive educational or health information. Under the Data Privacy Act, convenience did not replace transparency, legitimate purpose, proportionality, and security.[11] A practical rule followed: no teacher or learner should enter identifiable personal information, confidential records, or unredacted student work into a service unless the controller, processing terms, purpose, retention, and safeguards had been formally approved.
Accuracy and bias were nearly as prominent. Generative AI could produce fluent language that obscured uncertainty, false citation, or cultural mismatch. Prior studies documented these problems and warned against confusing linguistic plausibility with knowledge.[17,18] The qualitative results added a local dimension: teachers had to inspect examples for reading level, available resources, Philippine curriculum alignment, and relevance to provincial experience. Verification therefore needed three layers: factual accuracy, pedagogical suitability, and contextual appropriateness.
Academic integrity could not be solved reliably by detection alone. Teachers preferred evidence of process, including outlines, drafts, oral defense, supervised performance, source trails, and reflection on revisions. This response preserved the validity of assessment by asking what evidence demonstrated the learner's own understanding. It also allowed transparent, limited AI assistance where such assistance matched the learning objective. For example, language editing could be permitted in one task but prohibited in a writing-fluency assessment.

4.3 Readiness explained adoption better than geography alone
Less accessible schools reported a large infrastructure-readiness disadvantage and lower responsible adoption. Yet accessibility was no longer independently significant after infrastructure, training, and policy clarity entered the multilevel model. This did not mean location was irrelevant. Rather, geographic disadvantage operated through modifiable conditions: connectivity, devices, support, training opportunities, and access to clear information. The result shifted the policy response from labeling schools as unready to investing in the conditions that made responsible practice possible.
The infrastructure result was consistent with national and regional evidence that technology benefits were conditional on equitable access and sustained teacher preparation.[7,14] A uniform rollout date could therefore be formally equal but substantively inequitable. Schools with intermittent connectivity needed downloadable guidance, offline examples, protected shared devices, asynchronous training materials, and alternative processes that did not penalize teachers or learners for connectivity constraints.
AI literacy had the largest continuous association with responsible adoption. This supported frameworks that combined understanding, use, evaluation, and ethics.[5,19,20] Training was also independently positive. The qualitative findings clarified that useful training was practice-based: teachers wanted to test outputs, locate errors, compare prompts, redact data, redesign tasks, and decide when not to use AI. A purely inspirational seminar about future possibilities would not address these needs.

4.4 Policy clarity was an instructional resource
Policy clarity was the weakest readiness domain and an independent predictor of responsible adoption. Ambiguity transferred institutional risk to individual teachers, producing inconsistent rules across classrooms. One teacher might ban all AI, another might permit unreported use, and another might upload learner work for convenience. Clear minimum rules reduced this inconsistency while leaving space for subject-specific pedagogy.
A division framework should specify approved categories of use, prohibited data, age-appropriate access, verification responsibility, disclosure expectations, assessment design, procurement review, incident reporting, accessibility, and periodic evaluation. The framework should also state that teachers remained accountable for materials they assigned, regardless of whether AI assisted the first draft. This approach aligned national encouragement of responsible AI with the concrete protections required by privacy law and UNESCO guidance.[1,4,11]
Policy should be written as a decision aid rather than a collection of abstract principles. Scenarios could show whether a teacher might generate a generic quiz, translate a nonconfidential announcement, summarize a public policy, analyze de-identified class-level results, or enter individual learner records. Each scenario should identify the purpose, data sensitivity, required review, disclosure, and alternative when a service was unavailable.

4.5 Human agency and professional responsibility
The qualitative themes placed human judgment at the center of adoption. Teachers did not reject efficiency, but they resisted substitution for care, contextual knowledge, disciplinary judgment, and feedback relationships. This position was consistent with

DepEd's public framing of AI as empowerment rather than replacement and with UNESCO's human-centred competency framework.[1,5]
Human agency had consequences for workload. AI might save drafting time, but responsible use added verification, adaptation, disclosure, and monitoring. Net workload reduction depended on task selection and organizational support. Schools should therefore evaluate time saved after safeguards were included. If a tool required extensive correction, introduced new privacy work, or produced weak learner evidence, discontinuation could be the most innovative decision.
Learner agency also required protection. Students needed opportunities to formulate questions, struggle with ideas, construct explanations, and receive human feedback. AI literacy should teach them to identify system limitations, verify claims, disclose assistance, and understand why certain data should not be shared. The goal was not merely competent prompting but critical participation in a society shaped by automated systems.[6,19]

5. Conclusion

Artificial intelligence had already entered teachers' professional work in the Schools Division of Quirino, especially in planning and resource preparation. Educators recognized meaningful opportunities, but their concerns about privacy, accuracy, integrity, infrastructure, and policy were equally strong. The most defensible interpretation was therefore conditional: AI was useful when it served a defined educational purpose, remained under human review, protected data, preserved valid evidence of learning, and did not exclude schools with weaker infrastructure.
Responsible adoption was associated with AI literacy, infrastructure readiness, policy clarity, perceived opportunity, formal training, and regular use. These were actionable conditions. The division could improve adoption not by requiring universal use, but by establishing clear safeguards, building verification and assessment capability, supporting less accessible schools, and evaluating a small number of teacher-controlled applications before expansion.
The central policy principle was straightforward: AI should increase the capacity of teachers and learners without transferring educational authority, personal data, or accountability to an opaque system. A human-centred, evidence-based, and equity-sensitive approach offered Quirino a path to benefit from AI while protecting the relationships and professional judgment on which public education depended.

6. Practical Recommendations

- Establish minimum safeguards. Issue a division memorandum identifying permitted functions, prohibited data, verification duties, disclosure requirements, assessment expectations, and incident-reporting routes.
- Train through authentic tasks. Use subject-specific workshops where teachers compared outputs, identified inaccuracies, redacted information, redesigned assessment, and documented final human review.
- Prioritize equity. Provide downloadable guidance, shared protected devices, asynchronous learning options, and additional technical support for schools with unstable connectivity.
- Begin with teacher-facing pilots. Test low-risk planning, adaptation, and communication uses before considering direct learner interaction or automated educational decisions.
- Evaluate net educational value. Measure time saved after verification, material quality, privacy compliance, learner agency, assessment validity, and distribution of benefits across schools.

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