AI-Supported Instructional Supervision, Supervisor–Teacher Feedback Quality, and Teacher Instructional Practices in Basic Education: A Descriptive-Correlational Study

Nicole B. Baiño, MAED-EM[1], Jerald P. Torillo, PhD[2]

[1]PhD Student, Graduate School, Eastern Samar State University Main Campus, Borongan City, Eastern Samar, Philippines, 6800

[2]Regular Faculty, Graduate School, Eastern Samar State University Main Campus, Borongan City, Eastern Samar, Philippines, 6800

DOI: https://doi.org/10.47772/IJRISS.2026.101000562

Received: 22 October 2026; Accepted: 27 October 2026; Published: 10 November 2026

ABSTRACT

Artificial intelligence (AI) is increasingly being explored in educational leadership and instructional supervision, but evidence of its relationships with supervisor–teacher feedback quality and teacher instructional practices remains limited in Philippine public basic education. This study examined the levels of these constructs and their statistical associations. Using a quantitative descriptive-correlational design, the study involved 177 public school teachers selected through proportionate stratified random sampling from 319 eligible teachers across ten schools in Dolores I and Dolores II Districts, Schools Division of Eastern Samar. Data were collected using a researcher-developed questionnaire. Six experts established content validity (I-CVI = .83–1.00; S-CVI/Ave = .95), while pilot testing with 30 teachers yielded Cronbach's alpha coefficients of .909, .929, and .923 for the three scales. Means, standard deviations, and two-tailed Pearson product–moment correlations were used for analysis. AI-supported instructional supervision (M = 3.42, SD = 0.57), supervisor–teacher feedback quality (M = 3.64, SD = 0.50), and teacher instructional practices (M = 3.84, SD = 0.47) were rated high. AI-supported instructional supervision was positively associated with feedback quality ($r = .380$, $p < .001$) and instructional practices ($r = .292$, $p < .001$). All four dimensions were significantly associated with feedback quality, while three were significantly associated with instructional practices. Instructional planning and decision support had a positive but nonsignificant association with instructional practices ($r = .145$, $p = .055$). Supplementary analyses controlling for school membership showed that both associations remained significant (partial $r = .306$, $p < .001$; partial $r = .228$, $p = .003$). These findings underscore the potential of AI to strengthen evidence-informed instructional supervision and feedback. They also emphasize that meaningful integration requires school leaders to use AI to enhance, not replace, professional judgment, contextual understanding, and human engagement in supporting teachers' instructional practice.

Keywords: Artificial intelligence; AI-supported instructional supervision; supervisor–teacher feedback quality; teacher instructional practices; public basic education.

INTRODUCTION

Instructional supervision connects professional standards, curriculum expectations, and school-improvement priorities with classroom practice. It commonly involves classroom observation, review of instructional plans and assessment evidence, professional dialogue, coaching, and feedback. In the Philippines, the Philippine Professional Standards for Teachers provides a reference for teacher development and professional practice (Department of Education [DepEd], 2017). At the same time, artificial intelligence (AI) is emerging as a possible support for school leadership and professional work. AI-enabled tools may organize supervisory records, summarize lesson plans and observation notes, identify patterns in instructional data, and help prepare feedback for professional discussion.

AI support does not guarantee sound supervision. Outputs may omit context, reproduce errors, or produce recommendations that do not fit the curriculum, learner needs, or available resources. UNESCO's AI Competency Framework for Teachers emphasizes human-centred mindsets, ethics, AI foundations and applications, AI pedagogy, and professional learning (Miao & Cukurova, 2024). The implication for instructional supervision is that AI should augment, rather than replace, professional judgment and accountability. Supervisors must verify information and remain responsible for decisions that affect teachers and learners.

Feedback is a key mechanism through which supervision may contribute to professional learning. Hattie and Timperley (2007) explain that feedback can support learning when it helps recipients understand goals, current performance, and next steps. Panadero and Lipnevich (2022) likewise describe feedback as a multidimensional process rather than a single act of commenting. For teachers, useful feedback should be specific, grounded in evidence, timely, actionable, constructive, and followed up through coaching or review. If AI helps organize evidence but does not support a meaningful human conversation, its contribution to professional learning may remain limited.

Teacher instructional practices are also multidimensional. Planning, instructional delivery, classroom management, assessment, and responsiveness to learners are shaped by teachers' knowledge and agency as well as school conditions, professional collaboration, resources, and leadership. Social Cognitive Theory highlights the reciprocal relationship among personal factors, behavior, and environmental influences (Bandura, 1986). AI-supported supervision may form part of the professional environment, but its relationship with classroom practice should be examined empirically rather than assumed.

Research on AI in educational leadership is emerging. Berkovich (2025) examined generative AI integration in school leadership and management, while Gunadi (2025) explored AI-assisted supervision in Indonesian elementary schools. These studies indicate growing interest in AI for supervisory and administrative functions, but the relationships between AI-supported supervision, teacher-facing feedback quality, and teachers' reported instructional practices require further examination in different contexts. This is especially relevant in public-school settings where schools may differ in infrastructure, digital access, and staff readiness.

This study addressed that need among teachers in ten public schools in Dolores I and Dolores II Districts, Schools Division of Eastern Samar. It examined AI-supported instructional supervision across administrative and documentation support, instructional monitoring and data analysis, instructional planning and decision support, and feedback and professional support. Feedback quality was assessed through specificity, evidence-based quality, timeliness, actionability, constructiveness, and follow-up. Teacher instructional practices were assessed through planning and preparation, instructional delivery, learning environment and classroom management, assessment practices, and learner-responsive instruction.

The study addressed four questions: (1) What are the levels of AI-supported instructional supervision, supervisor–teacher feedback quality, and teacher instructional practices, overall and by dimension? (2) Is AI-supported instructional supervision significantly associated with supervisor–teacher feedback quality? (3) Is AI-supported instructional supervision significantly associated with teacher instructional practices? (4) Which dimensions of AI-supported instructional supervision are significantly associated with feedback quality and instructional practices?

The null hypotheses stated that overall AI-supported instructional supervision is not significantly related to feedback quality or teacher instructional practices, and that none of its four dimensions is significantly associated with either outcome. These hypotheses concern association; the study does not test whether AI causes better feedback or teaching.

REVIEW OF RELATED LITERATURE

This review examined literature and empirical studies related to the three major constructs of the present investigation: AI-Supported Instructional Supervision, Supervisor–Teacher Feedback Quality, and Teacher Instructional Practices. The discussion proceeds from the broader role of AI in education and educational

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue X October 2026

leadership to its emerging application in instructional supervision, the relationship between conventional supervision and teacher practice, the nature and quality of supervisory feedback, and the emerging intersections between AI, feedback, and instructional practice. Philippine policy and research are then considered to establish the local context, followed by a synthesis identifying the empirical, methodological, and contextual gaps addressed by the study.

Artificial Intelligence in Education and Educational Leadership

Artificial intelligence has become an increasingly significant component of educational transformation. Its ap-

plications now extend beyond automated or adaptive learning systems to information processing, content generation, data analysis, professional development, school administration, and decision support. Sposato (2025), in a taxonomy of AI in educational leadership, identified applications involving administrative efficiency, enhancement of teaching practices, decision-making and policy formulation, organizational leadership and strategic planning, governance and compliance, communication, and ethical AI leadership. This breadth indicates that AI is increasingly relevant not only to classroom instruction but also to organizational processes through which educational institutions coordinate information and support teaching.

Empirical studies provide evidence that educational leaders are beginning to use AI in these functions. Göçen and Döğer (2025) examined the emerging use of AI in educational leadership, while Berkovich (2025), in a survey of 302 school leaders in Israel, reported that approximately half of respondents were at the early-majority stage of generative AI adoption. Berkovich further found that 48% of participating school leaders used GenAI to develop or improve teacher-observation reports, while other applications included developing educational programs, preparing lesson plans for teams, and organizing professional development activities. These findings demonstrate that AI applications are extending into leadership work involving instructional information and professional support.

The literature also identifies the need to consider the organizational conditions surrounding AI use. Miao and Cukurova (2024) emphasized human agency, accountability, ethics, and responsible use in educational applications of AI. They similarly frame AI competency within a human-centered approach in which educators remain responsible for evaluating and using AI-supported information. Thus, the relevant issue for educational leadership is not simply whether AI is available, but how it is incorporated into professional tasks and decision-making.

AI-Supported Instructional Supervision

Instructional supervision is a particularly relevant area of AI integration because supervisory work involves organizing evidence, reviewing instructional documents, monitoring teaching, analyzing information, planning professional support, and providing feedback. Lavigne and Ocran (2026) specifically identified teacher supervision as an underexamined area of AI research. They noted that much of the existing literature has focused on AI in teaching and learning, while comparatively less attention has been given to school leadership and teacher supervision.

Within this context, AI-Supported Instructional Supervision is understood in the present study as AI-enabled support for supervisory functions rather than as autonomous supervision. Four dimensions are examined: Administrative and Documentation Support, Instructional Monitoring and Data Analysis, Instructional Planning and Decision Support, and Feedback and Professional Support. These dimensions represent points in the supervisory process where AI may assist in organizing information, analyzing instructional evidence, supporting planning, and preparing professional information.

Berkovich's (2025) findings directly correspond to several of these functions. School leaders reported using GenAI for teacher-observation reports, student achievement analysis, lesson planning, and professional development. The findings indicate that AI can support both administrative and instructional aspects of leadership. However, the study focused primarily on patterns of AI use and did not examine whether these uses were associated with the quality of supervisory feedback or teachers' instructional practices.

Gunadi (2025) examined AI-assisted supervision in rural Indonesian elementary schools through a qualitative case study involving principals, vice-principals, senior teachers, and education office supervisors. The study found that AI could be incorporated into supervisory processes and was perceived as useful for efficiency, fairness, feedback, and performance reporting. At the same time, participants identified challenges involving digital literacy, infrastructure, and institutional support. The rural setting provides useful contextual evidence for considering AI-supported supervision beyond highly resourced educational environments.

Philippine professional practice also shows emerging interest in this area. In 2025, the Schools Division Office of Bataan conducted an initiative on innovative instructional supervision with AI applications for master

teachers. The activity included AI-supported feedback, teacher-performance monitoring, and data-informed instructional decision-making. This development demonstrates institutional interest in applying AI to supervisory work, although such professional-development initiatives do not themselves establish statistical relationships between AI-supported supervision and teacher-related outcomes.

Taken together, the literature establishes the relevance of AI to instructional supervision while indicating that the empirical base remains relatively narrow. Existing work has demonstrated possible applications and emerging practices, but less is known about how AI-supported supervisory functions relate to specific outcomes experienced by teachers.

Instructional Supervision and Teacher Instructional Practices

Instructional supervision has a longer research tradition than AI-supported supervision. It generally involves observation, monitoring, professional dialogue, feedback, coaching, and follow-up intended to support teachers' professional development and instructional practice. In the Philippine context, the Philippine Professional Standards for Teachers (PPST), established through DepEd Order No. 42, s. 2017, provides a national framework for teacher professional expectations and serves as a basis for assessing performance, identifying professional development needs, and supporting professional growth.

The OECD's Teaching and Learning International Survey (TALIS) likewise treats teacher practices, professional learning, teacher appraisal, and feedback as interconnected aspects of the teaching profession. TALIS 2024 reports that 81% of teachers, on average, frequently or always observe students while they work and provide immediate feedback, while 78% frequently or always use assessment to determine whether students have learned and provide oral or written feedback indicating areas for improvement (OECD, 2025). These findings demonstrate the continuing importance of observation, assessment, feedback, and instructional adjustment in teachers' professional practice.

Teacher instructional practice consequently involves more than classroom delivery. In the present study, it is examined through instructional planning and preparation, instructional delivery, learning environment and classroom management, assessment practices, and learner-responsive instruction. These dimensions encompass the processes through which teachers prepare instruction, facilitate learning, manage classroom conditions, assess learner progress, and respond to differences in learner needs.

Philippine empirical studies provide evidence that conventional instructional supervision is associated with teacher-related outcomes. Daigon and Alcopra (2024) examined instructional supervision practices and teacher efficacy in Impasugong I District, Bukidnon, using a descriptive-correlational design. Castillo (2024) similarly examined instructional supervision strategies and teacher performance among public school teachers in Hinabangan Samar District I and reported a positive relationship between supervision and teacher performance.

These studies provide local evidence concerning the relationship between instructional supervision and teacher-related outcomes. However, their outcomes were framed in terms of teacher efficacy and teacher performance rather than the specific construct of teacher instructional practices examined in the present study. More importantly, they considered conventional instructional supervision rather than AI-supported supervisory

functions. Their findings therefore establish the relevance of supervision to teacher practice without resolving whether AI-supported supervision is associated with the specific instructional practices examined here.

Supervisor–Teacher Feedback Quality

Feedback is an important component of instructional supervision because observation and monitoring become professionally meaningful when the evidence gathered is communicated to teachers in a form that can support reflection and possible improvement. OECD evidence indicates that classroom observation is a common basis for teacher feedback. In TALIS 2018, 80% of teachers across participating education systems reported receiving feedback based on classroom observation, and 71% of those receiving feedback reported a positive impact on their teaching practice (OECD, 2020).

The quality of feedback, however, involves more than its occurrence. Koç and Savaş (2024), in a meta-synthesis of 53 studies involving 807 participants, found that supervisory post-conferences and feedback are influenced by supervisory models, discourse, relationships, and communication processes. Clark-Gareca (2024), examining teachers' recollections of supervisory feedback, likewise highlighted the importance of what is communicated, how it is communicated, and the relationship between teachers and supervisors.

The present study therefore treats Supervisor–Teacher Feedback Quality as a multidimensional construct consisting of Specificity, Evidence-Based Quality, Timeliness, Actionability, Constructiveness, and Follow-Up. Specificity concerns the clarity and focus of the feedback; evidence-based quality concerns its grounding in relevant instructional information; timeliness concerns whether feedback is provided while it remains useful; actionability concerns whether teachers can translate it into practical steps; constructiveness concerns the developmental and respectful manner of communication; and follow-up concerns subsequent monitoring or professional support.

Evidence from teacher-evaluation and supervision research supports these dimensions. Garet et al. (2017) reported that teachers value feedback that is clear, specific, and actionable, while evidence from supervisory practice indicates that feedback can contribute to teacher motivation, efficacy, and instructional improvement. Boadi et al. (2024), in action research involving 63 preservice mathematics teachers, found improvement in subsequent supervision scores following post-observation feedback and reflection. The improvements included classroom management, student support, interpersonal communication, leadership, and curriculum implementation.

The findings of Boadi et al. (2024) should nevertheless be interpreted within the context of preservice teacher education and should not be directly generalized to experienced basic education teachers. They nevertheless demonstrate the developmental role that feedback can play in connecting supervisory evidence with subsequent professional practice.

Feedback is also relational. A 2024 study of supervisory feedback in a language-school context reported emotional tensions in teacher responses where supervision was experienced as top-down and opportunities for interaction were limited. This indicates that feedback quality cannot be determined solely by the amount of information provided. Its usefulness is also shaped by communication, professional relationships, and the context in which the feedback is received.

AI-Supported Supervision and Feedback Quality

The relationship between AI-supported supervision and supervisor–teacher feedback quality is less developed than the broader literature on AI in educational leadership. Existing evidence indicates that AI can assist activities that precede feedback, including organizing information, preparing observation reports, analyzing data, and identifying patterns.

Berkovich (2025) found that 48% of surveyed school leaders used GenAI to develop or improve teacher-observation reports. Such use is relevant to feedback because observation reports can provide evidence for discussions with teachers. However, the presence of AI-generated or AI-assisted reports does not by itself

establish the quality of the feedback ultimately received by teachers. The value of the output depends on the accuracy and relevance of the information, the supervisor's interpretation, and the way the information is communicated.

Lavigne and Ocran (2026) similarly emphasized that teacher supervision requires particular attention because it involves observation, professional judgment, evaluation, and feedback. Their discussion highlights the limited empirical evidence concerning AI-supported teacher supervision and the need to examine outcomes rather than merely identify possible technological applications.

Accordingly, the present study examines feedback quality as a separate outcome. It does not assume that AI-supported supervision necessarily produces better feedback. Instead, it determines whether teachers who report higher levels of AI-supported instructional supervision also report higher-quality supervisor–teacher feedback. This distinction allows the study to examine an association between the two constructs without attributing a causal effect to AI.

The relationship between these constructs can be understood through the role of supervisory information in supporting professional practice. AI-supported instructional supervision may facilitate the organization, analysis, and interpretation of instructional evidence, while supervisor–teacher feedback provides a means of communicating this evidence to teachers for professional reflection and possible improvement. The relevance of these supervisory processes extends beyond feedback itself, as the information and professional guidance received may also be associated with teachers' instructional planning, delivery, classroom management, assessment, and responsiveness to learners. However, the extent to which these relationships are evident in actual school settings requires empirical examination. Thus, considering feedback quality and instructional practices as distinct but related outcomes provides a more comprehensive basis for understanding the potential relevance of AI-supported instructional supervision.

AI-Supported Instructional Supervision and Teacher Instructional Practices

The second major relationship examined in the study concerns teacher instructional practices. The literature provides two relevant strands of evidence. The first shows that instructional supervision and feedback are connected with teacher professional practice. The second indicates that AI can support several functions within educational leadership and professional development.

Gunadi (2025) provides a relevant example of AI-assisted supervision in rural elementary schools. Although the study suggests that AI can be incorporated into supervision and may support performance reporting and feedback, its qualitative design and small purposive sample do not establish the statistical relationship between AI-supported supervision and specific teacher instructional practices.

Tan's (2025) scoping review of 22 empirical studies provides additional evidence that generative AI is increasingly being used in teacher development, including resource development, tailored support, and learning environments. The review also noted the underrepresentation of in-service teachers and the prevalence of small samples. Its findings support the growing role of AI as a professional-support technology but do not specifically address AI-supported instructional supervision.

The Philippine studies of Daigon and Alcopra (2024) and Castillo (2024) provide complementary evidence from conventional instructional supervision. Both examined teacher-related outcomes and reported relationships between supervision and teacher professional outcomes. However, neither incorporated AI into the supervisory process. Thus, conventional supervision research supports the importance of supervisory support for teachers, while AI literature identifies new technological mechanisms through which supervisory work may be organized.

The intersection of these literatures remains insufficiently examined. In particular, there is limited quantitative evidence concerning whether AI-supported instructional supervision, considered as a multidimensional supervisory construct, is associated with teachers' reported instructional practices in basic education.

Philippine Policy and Research Context

The Philippine setting provides an important context for examining AI-supported instructional supervision because AI integration has moved from general discussion toward institutional initiatives. The Department of Education established the Education Center for AI Research (ECAIR) in 2025 to develop AI-supported solutions for basic education and school administration (Department of Education, 2025). DepEd subsequently launched Project AGAP.AI in January 2026 to provide frameworks, training, and safeguards for responsible AI use among learners, teachers, parents, and school leaders (Department of Education, 2026b). Regional initiatives have also extended AI capacity-building into Eastern Visayas.

DepEd Order No. 003, s. 2026 further established foundational guidelines for AI in basic education. The policy environment recognizes the potential of AI to support governance and educational processes while maintaining human agency and accountability (Department of Education, 2026a). This is consistent with the present study's conceptualization of AI-supported instructional supervision as a human-led process in which AI supports information-related and analytical functions.

Philippine research, however, has not developed at the same pace as policy implementation. Studies such as those of Daigon and Alcopra (2024) and Castillo (2024) have examined instructional supervision without incorporating AI, while emerging Philippine work on AI has often focused on broader educational, administrative, or professional applications. Amado et al. (2024), for example, reviewed generative AI in administrative and supervisory practices and identified potential benefits involving operational efficiency and data-informed decision-making, alongside ethical concerns and the need for specialized training.

The Philippine evidence is therefore developing across separate strands. Policy and professional initiatives demonstrate increasing institutional interest in AI, while empirical studies provide evidence concerning conventional supervision and teacher outcomes. What remains less established is the intersection of these strands at the school level.

Synthesis of the Reviewed Literature and Studies

The reviewed literature shows that AI is increasingly being incorporated into educational leadership for information management, administrative work, data analysis, planning, professional development, and instructional support. Sposato (2025), Göçen and Döğer (2025), and Berkovich (2025) demonstrate the breadth of AI applications in leadership, while Miao and Cukurova (2024) provide a human-centered basis for understanding responsible AI use.

When the focus narrows to instructional supervision, the evidence becomes more limited. Lavigne and Ocran (2026) identify teacher supervision as an underexamined area, and Gunadi (2025) provides qualitative evidence of AI-assisted supervision in rural elementary schools. Berkovich (2025) further demonstrates that school leaders already use GenAI for teacher-observation reports and other instructional leadership functions. These studies establish the relevance and feasibility of AI-supported supervision but leave unanswered questions about its relationships with specific teacher-facing outcomes.

The literature on conventional instructional supervision provides stronger evidence that supervision, feedback, and teacher professional practice are interconnected. Philippine studies by Daigon and Alcopra (2024) and Castillo (2024) found relationships between instructional supervision and teacher efficacy or performance. Feedback research likewise shows that supervisory feedback is multidimensional and that its usefulness is influenced by specificity, evidence, timeliness, actionability, constructiveness, follow-up, and professional relationships.

Three gaps emerge from the reviewed literature. First, an empirical gap remains concerning the relationship between AI-supported instructional supervision and specific teacher-centered outcomes. Existing studies commonly examine AI adoption, leadership functions, professional development, or general teacher outcomes, while fewer studies examine AI-supported instructional supervision together with supervisor–teacher feedback quality and teacher instructional practices.

Second, a methodological gap is evident. Much of the emerging literature on AI-supported educational leadership and supervision is conceptual, exploratory, qualitative, or descriptive. Such studies are valuable for identifying emerging practices, but they provide limited quantitative evidence concerning the strength and statistical significance of relationships among AI-supported supervision, feedback quality, and teacher instructional practices. A descriptive-correlational approach therefore provides an appropriate means of examining these relationships without making causal claims.

Third, a contextual gap is present in Philippine basic education. National and regional initiatives demonstrate increasing institutional movement toward AI-supported education, while Philippine research on instructional supervision has generally examined conventional supervisory practices. Evidence specifically connecting AI-supported instructional supervision with supervisor–teacher feedback quality and teacher instructional practices remains limited, particularly within geographically diverse public basic education settings.

The present study addresses these gaps by examining AI-Supported Instructional Supervision as a multidimensional construct comprising Administrative and Documentation Support, Instructional Monitoring and Data Analysis, Instructional Planning and Decision Support, and Feedback and Professional Support. It relates this construct to two teacher-centered outcomes: Supervisor–Teacher Feedback Quality and Teacher Instructional Practices. The study therefore extends existing literature by bringing together three research strands, namely AI-supported educational leadership, instructional supervision and feedback, and teacher instructional practice, within a single descriptive-correlational investigation in Philippine public basic education.

Overall, the reviewed literature establishes the growing relevance of AI in educational leadership and its potential to support instructional supervision, while emphasizing the importance of effective supervisory feedback and sound teacher instructional practices. However, these areas have largely been examined separately. Existing studies have explored AI applications in educational leadership and supervision, the relationship between conventional instructional supervision and teacher-related outcomes, and the characteristics of effective feedback. Nevertheless, empirical evidence directly examining the relationships between AI-supported instructional supervision, supervisor–teacher feedback quality, and teacher instructional practices remains limited, particularly in Philippine public basic education. This gap provides a compelling basis for examining these constructs together within the context of public schools in Dolores I and Dolores II Districts, Schools Division of Eastern Samar. By investigating their levels and statistical associations, the present study contributes context-specific quantitative evidence to the emerging literature on AI-supported instructional supervision without presuming that AI use necessarily produces improvements in feedback or teaching practice.

METHODS

Research Design

The study employed a quantitative, nonexperimental, descriptive-correlational research design to determine the levels and examine the relationships among AI-Supported Instructional Supervision, Supervisor–Teacher Feedback Quality, and Teacher Instructional Practices in basic education. The descriptive component assessed the three variables and their respective dimensions, while the correlational component examined the strength, direction, and significance of their relationships, including the associations between the dimensions of AI-Supported Instructional Supervision and the two other variables. Data were collected cross-sectionally during a single period without manipulating respondents' conditions. Since the study was nonexperimental, the findings were interpreted as statistical associations rather than causal relationships.

Research Locale

The study was conducted in ten selected public schools in the Municipality of Dolores, Schools Division of Eastern Samar, Philippines, covering Dolores I and Dolores II Districts. The participating schools were Dolores Central Elementary School, Dolores National High School, San Isidro Elementary School, Hilabaan Elementary School, and San Vicente Elementary School from Dolores I District; and Dapdap Central

Elementary School, Villahermosa Elementary School, Ipil Elementary School, Hinolaso National High School, and Dapdap National Technical Vocational High School from Dolores II District.

The schools were selected based on geographic accessibility, representation of both districts, variation in school levels and organizational contexts, and the availability of eligible teacher-respondents directly involved in instructional supervision. Their inclusion provided representation of different school settings within the municipality. However, the study did not aim to compare schools, districts, or school levels but to examine the levels and relationships among AI-Supported Instructional Supervision, Supervisor–Teacher Feedback Quality, and Teacher Instructional Practices across the selected schools.

Respondents of the Study and Sampling Procedure

The study population comprised 319 eligible permanent, full-time public school teachers from the ten participating schools. A target sample of 177 was determined using a finite-population sample-size procedure at a 95% confidence level and 5% margin of error. Proportionate stratified random sampling was employed, with each participating school serving as a stratum. The sample allocated to each school was determined using $n_h = (N_h/N) \times n$, where N_h is the population of the school, N is the total population (319), and n is the target sample (177). Rounded allocations were checked to ensure the school-level sample counts summed to 177. Within each stratum, respondents were selected randomly without replacement using official school personnel lists.

Table 1. Population and Target Sample Allocation by Participating School

Participating Schools	**Population (N_h)**	**Target Sample (n_h)**
Dolores Central Elementary School	78	43
Dolores National High School	132	73
San Isidro Elementary School	6	3
Hilabaan Elementary School	14	8
San Vicente Elementary School	5	3
Dapdap Central Elementary School	23	13
Villahermosa Elementary School	7	4
Ipil Elementary School	4	2
Hinolaso National High School	22	12
Dapdap National Technical Vocational High School	28	16
Total	**319**	**177**

Eligible participants had to be permanent, full-time public school teachers assigned to one of the selected schools, have completed at least one full school year in active service, have undergone at least two official classroom observations or comparable instructional-supervision activities during the relevant school year, and have firsthand experience using AI tools, such as ChatGPT, Google Gemini, or Microsoft Copilot, to support instructional-supervision tasks, including documentation, analysis of classroom-observation evidence, instructional planning, or feedback preparation. Supervisory personnel, nonteaching personnel, student teachers, interns, and teachers on extended leave were excluded. Participation was voluntary and required informed consent.

All 177 targeted respondents participated in the study, yielding a 100% response rate.

Research Instrument

Data were collected using a researcher-developed, literature-informed questionnaire based on established theoretical frameworks, empirical literature, and Philippine education policies. The instrument comprised three substantive scales measuring AI-Supported Instructional Supervision, Supervisor–Teacher Feedback Quality, and Teacher Instructional Practices.

The AI-Supported Instructional Supervision scale consisted of 16 items covering four dimensions: administrative and documentation support, instructional monitoring and data analysis, instructional planning and decision support, and feedback and professional support. Its development was informed by the UNESCO AI Competency Framework for Teachers (Miao & Cukurova, 2024) and DepEd Order No. 003, s. 2026, particularly their emphasis on responsible AI integration, human agency, accountability, and the pedagogically appropriate use of AI. These principles were contextualized into observable supervisory activities in basic education. The Supervisor–Teacher Feedback Quality scale contained 18 items across six dimensions: specificity, evidence-based quality, timeliness, actionability, constructiveness, and follow-up. Its development was informed by Hattie and Timperley's (2007) feedback model and the contemporary feedback literature of Panadero and Lipnevich (2022). The scale focused on teachers' perceptions of the quality and usefulness of the supervisory feedback they received.

The Teacher Instructional Practices scale measured five dimensions: instructional planning and preparation, instructional delivery, learning environment and classroom management, assessment practices, and learner-responsive instruction. Its development was informed by the OECD Teaching and Learning International Survey (TALIS) teacher questionnaires and the Philippine Professional Standards for Teachers (DepEd Order No. 42, s. 2017). Items were contextualized to measure teachers' reported instructional behaviors and practices. Instrument development involved identifying relevant theoretical frameworks and existing measures, selecting indicators aligned with the study's constructs, contextualizing items to the Philippine basic education setting, and refining the statements to eliminate redundancy, ambiguity, and conceptual misalignment. The questionnaire was therefore treated as a theoretically grounded, contextually adapted, researcher-developed instrument rather than a direct adoption of any single standardized measure.

Measurement of Variables

All items were rated using a five-point Likert-type scale, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), with corresponding intermediate options of Disagree (2), Neither Agree nor Disagree (3), and Agree (4). Mean scores were interpreted using the following ranges: 1.00–1.80 (Very Low), 1.81–2.60 (Low), 2.61–3.40 (Moderate), 3.41–4.20 (High), and 4.21–5.00 (Very High). Dimension mean scores were calculated by dividing the sum of item responses by the number of items in each dimension. Overall mean scores were similarly computed for each major variable using all corresponding items. Standard deviations were calculated to describe the variability of respondents' ratings. The same scoring and interpretation procedures were applied consistently across the three variables.

Instrument Validation and Reliability

The instrument underwent expert validation to establish content validity. Six expert validators evaluated the questionnaire in terms of relevance, clarity, appropriateness, and alignment with the study constructs. Following Lynn (1986) and Polit et al. (2007), the Content Validity Index (CVI) was used to quantify expert agreement on item relevance. The Item-Level Content Validity Index (I-CVI) was computed for each item, while the Scale-Level Content Validity Index based on the average I-CVI (S-CVI/Ave) was calculated to assess overall content validity. The instrument obtained I-CVI values ranging from .83 to 1.00 and an S-CVI/Ave of .95, indicating strong expert agreement and satisfactory content validity. Revisions were incorporated based on the validators' recommendations. The revised questionnaire was pilot-tested with 30 public school teachers from San Julian District who were not included in the main study. Internal consistency was assessed using Cronbach's alpha for each major scale. The coefficients were .909 for AI-Supported Instructional Supervision (16 items), .929 for Supervisor–Teacher Feedback Quality (18 items), and .923 for Teacher Instructional Practices (15 items). These coefficients indicate high internal consistency among the items within each scale, supporting their reliability for the main data collection (Tavakol & Dennick, 2011).

Data Collection and Ethical Considerations

Permission was secured from the relevant education authorities and participating school heads. The instrument was reviewed and pilot-tested before administration. Respondents were informed of the study’s purpose, voluntary nature, confidentiality procedures, and right to decline participation. Completed questionnaires were

checked, coded, and prepared for analysis. The study followed principles of confidentiality, informed consent, voluntary participation, and responsible handling of AI-related information. No AI output was treated as inherently accurate or authoritative, and professional judgment remained central to interpretation.

To minimize potential common method bias, procedural measures were incorporated into questionnaire development and administration. The three study variables were presented in separate sections with clear instructions to establish their conceptual distinction and reduce the likelihood that respondents would perceive them as a single evaluative construct. Items were worded as clearly and neutrally as possible to minimize ambiguity, leading questions, and socially desirable response tendencies. Respondents were assured that their participation was voluntary, their responses would remain confidential, and their answers would not affect their professional evaluation. They were encouraged to provide honest responses based on their actual experiences, with no preferred or correct answers. These measures were intended to reduce evaluation apprehension, consistency pressures, and response tendencies that could influence self-reported measurements (Podsakoff et al., 2003).

Data Analysis

The data were coded, tabulated, and analyzed using descriptive and inferential statistical techniques. Means and standard deviations were computed to describe the levels and variability of AI-Supported Instructional Supervision, Supervisor–Teacher Feedback Quality, and Teacher Instructional Practices, including their respective dimensions. These measures were used to summarize the aggregated ratings obtained from the multi-item Likert-type scales.

Pearson product–moment correlation coefficients (r) were used to examine the strength, direction, and statistical significance of the relationships between overall AI-Supported Instructional Supervision and each outcome variable, as well as between its four dimensions and the two outcome variables. Pearson's r was selected because the analyses involved aggregated composite scores treated as approximately continuous measures. All inferential tests were two-tailed, with the significance level set at $\alpha = .05$.

Prior to correlation analysis, the suitability of Pearson's r was assessed. Shapiro–Wilk tests showed no statistically significant departures from normality for AI-Supported Instructional Supervision ($W = .986$, $p = .084$), Supervisor–Teacher Feedback Quality ($W = .989$, $p = .126$), and Teacher Instructional Practices ($W = .984$, $p = .061$). Scatterplots indicated approximately linear relationships between the study variables. Boxplots and standardized scores revealed no extreme univariate outliers, with standardized scores within ±3.29. Residual scatterplots showed no evident funnel-shaped patterns, providing no indication of substantial heteroscedasticity. Although respondents were randomly selected within school strata, potential dependence among teachers from the same school was also considered.

To examine school-level clustering, intraclass correlation coefficients (ICC[1]) were estimated using a one-way random-effects analysis of variance with an adjustment for unequal school sample sizes. These coefficients estimated the proportion of variance in each composite variable attributable to between-school differences. Supplementary partial correlation analyses controlling for school membership through categorical indicator variables were also conducted to determine whether the observed associations remained after accounting for school-level differences. The adjusted coefficients were compared with the corresponding unadjusted Pearson correlations.

Finally, Harman's single-factor test was conducted as a supplementary assessment of potential common method bias (Harman, 1976; Podsakoff et al., 2003). All 49 measurement items from the three questionnaire scales were subjected to an unrotated principal component analysis using the correlation matrix. The percentage of total variance explained by the first component was examined, with the commonly used 50% threshold serving as a reference point for assessing whether a single component accounted for the majority of the variance.

The findings were interpreted as statistical associations rather than causal relationships.

RESULT

Reported Levels of AI-Supported Instructional Supervision

The overall mean for AI-supported instructional supervision was 3.42 (SD = 0.57), interpreted as high. As presented in Table 2, instructional monitoring and data analysis obtained the highest dimension mean (M = 3.51, SD = 0.62). Administrative and documentation support was close to the high threshold (M = 3.41, SD = 0.70), while instructional planning and decision support (M = 3.37, SD = 0.64) and feedback and professional support (M = 3.40, SD = 0.62) were interpreted as moderate.

Table 2. Mean Ratings for Dimensions of AI-Supported Instructional Supervision

Dimension	**M**	**SD**	**Interpretation**
Administrative and documentation support	3.41	0.7	High
Instructional monitoring and data analysis	3.51	0.62	High
Instructional planning and decision support	3.37	0.64	Moderate
Feedback and professional support	3.4	0.62	Moderate
Overall	**3.42**	**0.57**	**High**

The results indicate that respondents reported AI-supported functions at differing levels, with monitoring and data analysis rated somewhat higher than planning and professional support. The overall result is near the lower boundary of the high category, suggesting that the reported presence of AI-supported functions should not be equated with uniformly mature or comprehensive implementation.

Supervisor-Teacher Feedback Quality

Supervisor–teacher feedback quality was rated high overall (M = 3.64, SD = 0.50). As shown in Table 3, specificity received the highest mean (M = 3.68, SD = 0.58), followed by constructiveness (M = 3.65, SD = 0.60) and evidence-based quality (M = 3.64, SD = 0.53). Timeliness, actionability, and follow-up were also rated high, with means ranging from 3.62 to 3.63.

Table 3. Mean Ratings for Dimensions of Supervisor–Teacher Feedback Quality

Dimension	**M**	**SD**	**Interpretation**
Specificity	3.68	0.58	High
Evidence-based quality	3.64	0.53	High
Timeliness	3.62	0.61	High
Actionability	3.63	0.57	High
Constructiveness	3.65	0.6	High
Follow-up	3.63	0.58	High
Overall	**3.64**	**0.5**	**High**

The relatively close scores suggest that respondents reported broadly similar levels across the six feedback dimensions. Specificity was comparatively strongest, although the small differences among dimension means should not be overstated without formal tests comparing them.

Teacher Instructional Practices

Teacher instructional practices were rated high overall (M = 3.84, SD = 0.47). As presented in Table 4, assessment practices received the highest mean (M = 3.92, SD = 0.52), followed by learning environment and classroom management (M = 3.89, SD = 0.53). Instructional planning and preparation was rated 3.83 (SD = 0.52), while instructional delivery and learner-responsive instruction both received means of 3.77.

Table 4. Mean Ratings for Dimensions of Teacher Instructional Practices

Dimension	M	SD	Interpretation
Instructional planning and preparation	3.83	0.52	High
Instructional delivery	3.77	0.53	High
Learning environment and classroom management	3.89	0.53	High
Assessment practices	3.92	0.52	High
Learner-responsive instruction	3.77	0.57	High
Overall	**3.84**	**0.47**	**High**

These results represent respondents' self-reported practices, not independent observations of teaching effectiveness. The high overall mean should therefore be interpreted as a positive self-assessment across the measured domains.

Associations Between AI-Supported Instructional Supervision and the Two Outcomes

Pearson product–moment correlation analysis revealed a positive, statistically significant association between overall AI-supported instructional supervision and supervisor–teacher feedback quality ($r = .380$, $p < .001$). A positive, statistically significant association was also found between AI-supported instructional supervision and teacher instructional practices ($r = .292$, $p < .001$). These overall relationships are presented in Table 5. The association was numerically stronger for feedback quality than for instructional practices; however, the design does not establish that AI-supported supervision caused either outcome.

Table 5. Pearson Correlations Between AI-Supported Instructional Supervision and the Two Outcome Variables

Variable Pair	Pearson's r	p	Decision at $\alpha = .05$
AI-Supported Instructional Supervision and Supervisor–Teacher Feedback Quality	0.38	< .001	Reject H_0; significant positive association
AI-Supported Instructional Supervision and Teacher Instructional Practices	0.292	< .001	Reject H_0; significant positive association

School-Level Clustering and School-Adjusted Correlations

Because respondents were drawn from ten participating schools, intraclass correlation coefficients were examined to assess the extent of between-school variability in the three composite variables. As reported in Table 6, the ICC(1) estimates were .108 for AI-supported instructional supervision, .190 for supervisor–teacher feedback quality, and .146 for teacher instructional practices. These values indicate that approximately 10.76%, 19.02%, and 14.63% of the respective variance in the three variables was attributable to differences between schools. The results suggest the presence of school-level clustering, particularly for supervisor–teacher feedback quality.

Table 6. Intraclass Correlation Coefficients for the Three Composite Variables

Composite Variable	ICC (1)	Variance Attributable to School Differences
AI-supported Instructional Supervision	0.108	10.76%
Supervisor-teacher feedback Quality	0.19	19.02%
Teacher Instructional Practices	0.146	14.63%

To further examine whether the observed relationships persisted after accounting for school membership, supplementary partial correlation analyses were conducted. Table 7 presents the comparison between the unadjusted Pearson correlations and the school-adjusted partial correlations.

ISSN No. 2454-6186 | DOI: 10.47772/IJRISS | Volume X Issue X October 2026

Table 7. Comparison of Unadjusted and School-Adjusted Correlations

Variable Pair	Unadjusted Pearson (r)	Adjusted Partial (r_p)	p
AI-Supported Instructional Supervision and Supervisor–Teacher Feedback Quality	0.38	0.306	<.001
AI-Supported Instructional Supervision and Teacher Instructional Practices	0.292	0.228	0.003

The adjusted correlation between AI-supported instructional supervision and supervisor–teacher feedback quality remained positive and statistically significant (r_p = .306, p < .001). Similarly, its association with teacher instructional practices remained significant (r_p = .228, p = .003). Although both adjusted coefficients were lower than their corresponding unadjusted Pearson correlations (r = .380 and r = .292, respectively), both relationships remained statistically significant.

This attenuation suggests that some of the observed associations may be attributable to differences between schools. Nevertheless, the persistence of the positive adjusted relationships indicates that the associations were not explained entirely by school membership.

Dimension-Level Associations

All four dimensions of AI-supported instructional supervision were significantly and positively associated with supervisor–teacher feedback quality. For teacher instructional practices, three dimensions showed significant positive associations, while instructional planning and decision support did not reach the .05 significance threshold. The dimension-level correlation results are presented in Table 8.

Table 8. Dimension-Level Correlations of AI-Supported Instructional Supervision with Feedback Quality and Instructional Practices

AI-supervision dimension	Feedback quality r	p	Instructional practices r	p
Administrative and documentation support	0.328	< .001	0.339	< .001
Instructional monitoring and data analysis	0.338	< .001	0.325	< .001
Instructional planning and decision support	0.299	< .001	0.145	0.055
Feedback and professional support	0.371	< .001	0.211	0.005

Feedback and professional support had the strongest dimension-level association with feedback quality (r = .371, p < .001). Administrative and documentation support (r = .328, p < .001), instructional monitoring and data analysis (r = .338, p < .001), and instructional planning and decision support (r = .299, p < .001) were also positively associated with feedback quality.

For instructional practices, administrative and documentation support (r = .339, p < .001), instructional monitoring and data analysis (r = .325, p < .001), and feedback and professional support (r = .211, p = .005) were significantly associated with the outcome. Instructional planning and decision support had a positive but nonsignificant association (r = .145, p = .055).

DISCUSSION

The findings indicate that AI-supported instructional supervision was rated high overall (M = 3.42, SD = 0.57), although variations were evident across its four dimensions. Instructional monitoring and data analysis received the highest rating (M = 3.51, SD = 0.62), whereas instructional planning and decision support (M = 3.37, SD = 0.64) and feedback and professional support (M = 3.40, SD = 0.62) were rated moderate. This pattern suggests that AI-supported supervisory functions are more evident in monitoring and organizing instructional information than in planning and sustained professional support.

The finding is consistent with Berkovich's (2025) discussion of generative AI applications in teacher-observation reporting, lesson planning, and professional development, as well as Gunadi's (2025) findings on AI-assisted supervision in Indonesian elementary schools. Sposato's (2025) taxonomy also identifies administrative efficiency, data-informed decision-making, strategic planning, and professional support as areas where AI can contribute to educational leadership. In the present study, however, the comparatively lower ratings for planning and professional support point to the need to strengthen the integration of AI-generated information into meaningful supervisory dialogue and instructional guidance.

Supervisor–teacher feedback quality was also rated high overall (M = 3.64, SD = 0.50), with specificity obtaining the highest mean (M = 3.68, SD = 0.58). This finding suggests that teachers generally perceived supervisory feedback as clear and focused on particular aspects of their professional practice. It is consistent with Hattie and Timperley's (2007) explanation that effective feedback communicates information about goals, current performance, and appropriate next steps. It also reflects Panadero and Lipnevich's (2022) view of feed-

back as a multidimensional process involving its content, function, presentation, source, and subsequent use. Nevertheless, the relatively high rating across the six dimensions indicates that feedback quality involves more than the clarity of supervisory comments. Evidence-based quality, timeliness, actionability, constructiveness, and follow-up also contribute to meaningful feedback. In this regard, AI may assist supervisors in organizing observation evidence and preparing feedback, while human supervisors remain responsible for validating information, contextualizing recommendations, and providing appropriate professional guidance.

Teacher instructional practices received the highest overall rating among the three constructs (M = 3.84, SD = 0.47). Assessment practices obtained the highest dimension mean (M = 3.92, SD = 0.52), followed by learning environment and classroom management (M = 3.89, SD = 0.53). These findings reflect favorable teacher self-assessments across the instructional domains examined. They are consistent with the multidimensional expectations of the Philippine Professional Standards for Teachers (Department of Education, 2017), which encompass instructional competence, classroom management, assessment, and learner-responsive teaching.

The results also correspond with the OECD's Teaching and Learning International Survey framework, which recognizes the broader professional environment in which teaching practices are developed and exercised (Organisation for Economic Co-operation and Development [OECD], 2025a, 2025b). The comparatively high ratings in assessment and classroom management highlight the importance of these areas in teachers' reported professional practice.

The principal correlational findings revealed that AI-supported instructional supervision was positively associated with supervisor–teacher feedback quality ($r = .380$, $p < .001$) and teacher instructional practices ($r = .292$, $p < .001$). The stronger association with feedback quality suggests that AI-supported supervisory functions may be more closely connected with the organization and communication of instructional evidence than with the broader processes involved in classroom teaching.

This interpretation is consistent with Berkovich (2025) and Gunadi (2025), who describe AI applications in educational leadership and supervision-related activities. It also aligns with Panadero and Lipnevich's (2022) emphasis on the role of information in effective feedback processes. Meanwhile, the association with instructional practices indicates that AI-supported supervision is also related to teachers' reported professional activities.

This relationship may be understood through Bandura's (1986) Social Cognitive Theory, which emphasizes the interaction of personal, behavioral, and environmental factors. Supervisory support represents one aspect of the professional environment that may be associated with teaching practices alongside teachers' knowledge, agency, and classroom conditions. These findings establish statistical relationships, not evidence that AI-supported supervision directly produces improvements in feedback or teaching.

The school-level analysis provided additional insight into the findings. The ICC estimates indicated that between-school differences accounted for 10.76% of the variance in AI-supported instructional supervision, 19.02% in supervisor–teacher feedback quality, and 14.63% in teacher instructional practices. The highest ICC

for feedback quality suggests that school-level differences were particularly evident in how teachers experienced and evaluated supervisory feedback. This finding highlights the relevance of the school context in understanding instructional supervision, particularly the organizational arrangements and supervisory practices within which AI-supported functions are implemented.

The supplementary partial correlation analyses further showed that the associations remained statistically significant after controlling for school membership. The relationship between AI-supported instructional supervision and supervisor–teacher feedback quality decreased from $r = .380$ to $r_p = .306$ ($p < .001$), while the relationship with teacher instructional practices decreased from $r = .292$ to $r_p = .228$ ($p = .003$). Although both adjusted coefficients were smaller than the unadjusted correlations, their continued statistical significance indicates that the observed relationships were not explained entirely by differences between schools.

The attenuation also suggests that school membership accounts for some of the variation in the original associations. Taken together, these findings demonstrate the importance of considering both AI-supported supervisory functions and school context when examining their relationships with feedback quality and instructional practices.

The dimension-level findings further clarify these relationships. All four dimensions of AI-supported instructional supervision were positively and significantly associated with supervisor–teacher feedback quality. Feedback and professional support had the strongest association ($r = .371$, $p < .001$), followed by instructional monitoring and data analysis ($r = .338$, $p < .001$), administrative and documentation support ($r = .328$, $p < .001$), and instructional planning and decision support ($r = .299$, $p < .001$). The stronger association involving feedback and professional support highlights the relevance of supervisory functions directly connected with communication, guidance, and teacher development.

This finding reinforces Hattie and Timperley's (2007) and Panadero and Lipnevich's (2022) emphasis on the quality and use of feedback in supporting professional learning. It also reflects Miao and Cukurova's (2024) human-centred perspective, which emphasizes ethics and human agency in AI-supported educational practice. Accordingly, AI-assisted monitoring and documentation should be connected with evidence-based professional dialogue, actionable recommendations, and appropriate follow-up.

For teacher instructional practices, three dimensions of AI-supported instructional supervision showed significant positive associations: administrative and documentation support ($r = .339$, $p < .001$), instructional monitoring and data analysis ($r = .325$, $p < .001$), and feedback and professional support ($r = .211$, $p = .005$). Instructional planning and decision support, however, had a positive but nonsignificant association ($r = .145$, $p = .055$). This finding indicates that the observed relationship between AI-supported supervision and instructional practices was not uniform across all supervisory dimensions.

Although planning and decision support may contribute to supervisory processes, the present results do not provide sufficient statistical evidence of its association with teachers' reported instructional practices. Bandura's (1986) Social Cognitive Theory offers a useful perspective for interpreting this result because instructional behavior involves interactions among environmental support, individual agency, and actual classroom conditions. AI-assisted planning may therefore need to be accompanied by opportunities for teachers to evaluate, adapt, implement, and reflect on instructional recommendations. The findings highlight the relevance of connecting AI-supported supervisory information with practical classroom guidance and continuing professional support.

Overall, the findings demonstrate that AI-supported instructional supervision is positively associated with both supervisor–teacher feedback quality and teacher instructional practices, with the relationship being stronger for feedback quality. All four supervisory dimensions were significantly associated with feedback quality, whereas only three were significantly associated with instructional practices. The school-adjusted analyses further confirmed that both overall relationships remained statistically significant after controlling for school membership.

These results underscore the importance of integrating AI-supported information management and instructional monitoring with meaningful feedback, professional guidance, and teacher development. They also reinforce the need for a human-centred approach in which AI serves as a supplementary resource, while supervisors retain responsibility for professional judgment, contextual interpretation, and instructional decisions. Given the descriptive-correlational design, these findings should be understood as associations rather than evidence of causal effects.

CONCLUSION

The study concludes that AI-supported instructional supervision, supervisor–teacher feedback quality, and teacher instructional practices were rated high by the 177 teacher-respondents from ten public schools in Dolores I and Dolores II Districts. AI-supported instructional supervision was positively and significantly associated with both supervisor–teacher feedback quality and teacher instructional practices. These relationships remained positive and statistically significant after controlling for school membership, although the adjusted correlations were smaller than the corresponding unadjusted coefficients.

At the dimension level, all four dimensions of AI-supported instructional supervision were significantly associated with supervisor–teacher feedback quality. For teacher instructional practices, administrative and documentation support, instructional monitoring and data analysis, and feedback and professional support showed significant positive associations, whereas instructional planning and decision support had a positive but nonsignificant association. The ICC findings further indicated that school-level differences accounted for a proportion of the variability in all three study variables, highlighting the importance of considering school context when interpreting the relationships.

Collectively, the findings indicate that AI-supported instructional supervision is associated with more favora-

ble supervisor–teacher feedback quality and self-reported instructional practices. However, given the cross-sectional, nonexperimental design and reliance on self-reported data, these relationships should not be interpreted as evidence of causation. The findings provide context-specific evidence supporting the potential value of AI as a supplementary resource in instructional supervision, with professional judgment and accountability remaining with human supervisors.

RECOMMENDATION

In light of the findings, school heads and instructional supervisors are encouraged to strengthen the human-centered integration of AI in instructional supervision by establishing clear workflows for documentation, organization of observation evidence, instructional monitoring, and preliminary data analysis. AI-generated outputs should be verified by qualified supervisors, who must retain responsibility for professional judgments and supervisory decisions. Supervisors should also ensure that feedback is specific, evidence-based, timely, actionable, and constructive, supported by professional dialogue, coaching, and appropriate follow-up.

Schools should further strengthen AI-supported instructional planning and professional development, particularly given the nonsignificant association between instructional planning and decision support and teacher instructional practices. Collaborative lesson planning, classroom implementation, reflection, and follow-up supervision may help connect AI-assisted planning with actual instructional practice.

Professional development should address practical AI literacy, output verification, data privacy, security, fairness, and alignment with curriculum requirements and instructional standards. School leaders should also consider differences in technological access, infrastructure, teacher AI competence, and institutional support when designing implementation strategies.

Furthermore, schools are encouraged to complement teacher self-reports with classroom observations, lesson plans, assessment materials, supervisory records, and other instructional artifacts when evaluating teaching practices. Future research may employ longitudinal or mixed-methods approaches to examine these relationships over time. Studies involving more schools and larger samples may also use appropriate multilevel

analyses to account for teacher clustering within schools. Further investigations may examine teacher AI competence, school-level conditions, technological access, and implementation support, while verifying actual AI use and applying appropriate sensitivity analyses and multiple-comparison procedures.

LIMITATIONS

The findings should be interpreted in consideration of several limitations. First, the cross-sectional descriptive-correlational design provides evidence of relationships among AI-supported instructional supervision, supervisor–teacher feedback quality, and teacher instructional practices at a particular point in time but does not establish temporal order or causation. Second, the data were obtained through self-reported responses from the same respondents using a single questionnaire.

Although procedural measures and Harman's single-factor test provided supplementary evidence regarding potential common method bias, the possibility of shared response tendencies and perceptual influences cannot be entirely excluded. Third, the study was conducted among teachers from ten public schools in Dolores I and Dolores II Districts, Schools Division of Eastern Samar.

Thus, the findings are most directly applicable to the participating school context and should be generalized to other educational settings with consideration of differences in institutional and technological conditions. Finally, although supplementary partial correlations accounted for school membership, they did not fully model potential residual dependence among teachers within schools. The findings therefore provide context-specific evidence of statistical associations and should not be interpreted as demonstrating that AI-supported instructional supervision directly improves feedback quality or teaching practices.

ACKNOWLEDGEMENTS

The researcher extends sincere gratitude to the school administrators and teacher-respondents who generously shared their time and insights for this study. Appreciation is also extended to the research adviser and expert validators for their valuable guidance and recommendations throughout the research process. Finally, the researcher acknowledges the authors and scholars whose works provided the theoretical and empirical foundations for this study.

REFERENCES

1. Amado, J. A., Dayson, C. J. P., Gipaya, P. N., Hipos, A. M. G., Ortile, F. F., & Digo, G. S. (2024). Assessing the impact of AI generative tools on administrative and supervisory practices in education. Asia Pacific Journal of Management and Sustainable Development, 12(1), 32–40.
2. Bandura, A. (1986). Social foundations of thought and action: A social cognitive theory. Prentice-Hall.
3. Berkovich, I. (2025). The rise of AI-assisted instructional leadership: Empirical survey of generative AI integration in school leadership and management work. Frontiers in Education, 10, Article 1643023. https://doi.org/10.3389/feduc.2025.1643023
4. Boadi, A., Amoah, E., Ameyaw, E. S., & Atteh, E. (2024). The effect of supervisors feedback in extended teaching on pre-service mathematics teachers practice. Archives of Current Research International, 24(3), 1–13. https://doi.org/10.9734/acri/2024/v24i3638
5. Castillo, M. A. (2024). Impact of instructional supervision strategies on teacher performance in Hinabangan Samar District 1. International Journal of Multidisciplinary: Applied Business and Education Research, 5(9), 3602–3608. https://doi.org/10.11594/ijmaber.05.09.19
6. Clark-Gareca, B., & Warkentin, T. B. (2024). Memory and relationships: A look into teachers' recollection of supervisory feedback. TESOL Journal, 15(3), Article e823. https://doi.org/10.1002/tesj.823
7. Daigon, M. E., & Alcopra, A. R. (2024). Instructional supervision practices and efficacy of teachers. International Journal of Multidisciplinary Research and Analysis, 7(8). https://doi.org/10.47191/ijmra/v7-i08-13

8. Department of Education. (2017). DepEd Order No. 42, s. 2017: National adoption and implementation of the Philippine Professional Standards for Teachers. https://www.deped.gov.ph/2017/08/11/do-42-s-2017-national-adoption-and-implementation-of-the-philippine-professional-standards-for-teachers/
9. Department of Education. (2025). DepEd Order No. 013, s. 2025: Establishment of the Center for Artificial Intelligence Research for the Department of Education. https://www.deped.gov.ph/wp-content/uploads/DO_s2025_013.pdf
10. Department of Education. (2026a). DepEd Order No. 003, s. 2026: Foundational guidelines on artificial intelligence in basic education. https://www.deped.gov.ph/wp-content/uploads/DO_s2026_003r.pdf
11. Department of Education. (2026b, January 9). Future-ready EducAItion: PBBM, Angara naglunsad ng AI program para suportahan ang mga guro at mag-aaral. https://www.deped.gov.ph/2026/01/09/future-ready-educaition-pbbm-angara-naglunsad-ng-ai-program-para-suportahan-ang-mga-guro-at-mag-aaral/
12. Garet, M. S., Wayne, A. J., Brown, S., Rickles, J., Song, M., & Manzeske, D. (2017). The impact of providing performance feedback to teachers and principals (NCEE 2018-4001). National Center for Education Evaluation and Regional Assistance, Institute of Education Sciences, U.S. Department of Education. https://ies.ed.gov/sites/default/files/migrated/nces_pubs/ncee/pubs/20184001/pdf/20184001.pdf
13. Göçen, A., & Döğer, M. F. (2025). A global perspective on artificial intelligence in educational leadership. The Journal of Educational Research, 118(6), 752–770. https://doi.org/10.1080/00220671.2025.2510397
14. Gunadi, G. (2025). Transforming school leadership: A qualitative inquiry into AI-assisted supervision and teacher performance in Indonesian elementary schools. Journal of Educational Management and Instruction, 5(2), 464–478. https://doi.org/10.22515/jemin.v5i2.12446
15. Harman, H. H. (1976). Modern factor analysis (3rd ed.). University of Chicago Press.
16. Hattie, J., & Timperley, H. (2007). The power of feedback. Review of Educational Research, 77(1), 81–112. https://doi.org/10.3102/003465430298487
17. Koç, F. Ş., & Savaş, P. (2024). Supervision models and supervisory feedback in English language teacher education: A meta-synthesis study adopting a discourse analytic perspective. TESL-EJ, 27(4). https://doi.org/10.55593/ej.27108a1
18. Lavigne, A. L., & Ocran, P. (2026). The promises and pitfalls of artificial intelligence in instructional leadership: A focus on teacher supervision. Journal of School Leadership, 36(5), 531–558. https://doi.org/10.1177/10526846261425739
19. Lynn, M. R. (1986). Determination and quantification of content validity. Nursing Research, 35(6), 382–385. https://doi.org/10.1097/00006199-198611000-00017
20. Miao, F., & Cukurova, M. (2024). AI competency framework for teachers. UNESCO. https://doi.org/10.54675/ZJTE2084
21. Organisation for Economic Co-operation and Development. (2020). TALIS 2018 results (Volume II): Teachers and school leaders as valued professionals. OECD Publishing. https://doi.org/10.1787/19cf08df-en
22. Organisation for Economic Co-operation and Development. (2025a). Teaching and Learning International Survey (TALIS) 2024 conceptual framework. OECD Publishing. https://doi.org/10.1787/7b8f85d4-en
23. Organisation for Economic Co-operation and Development. (2025b). Results from TALIS 2024: The state of teaching. OECD Publishing. https://doi.org/10.1787/90df6235-en
24. Panadero, E., & Lipnevich, A. A. (2022). A review of feedback models and typologies: Towards an integrative model of feedback elements. Educational Research Review, 35, Article 100416. https://doi.org/10.1016/j.edurev.2021.100416
25. Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879
26. Polit, D. F., Beck, C. T., & Owen, S. V. (2007). Is the CVI an acceptable indicator of content validity? Appraisal and recommendations. Research in Nursing & Health, 30(4), 459–467. https://doi.org/10.1002/nur.20199
27. Sposato, M. (2025). Artificial intelligence in educational leadership: A comprehensive taxonomy and future directions. International Journal of Educational Technology in Higher Education, 22, Article 20.

https://doi.org/10.1186/s41239-025-00517-1

28. Tan, Q. (2025). Reimagining teacher development in the era of generative AI: A scoping review. Teaching and Teacher Education, 168, Article 105236. https://doi.org/10.1016/j.tate.2025.105236
29. Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. International Journal of Medical Education, 2, 53–55. https://doi.org/10.5116/ijme.4dfb.8dfd