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Implementation of Coding and Artificial Intelligence as an Additional Subject in an Indonesian Private Elementary School: A Qualitative Case Study

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Abstract

Coding and artificial intelligence (Coding-AI) are increasingly introduced in elementary schools to provide age-appropriate experiences in computational thinking, purposeful technology use, and responsible engagement with artificial intelligence. However, evidence on how Coding-AI is implemented as an additional subject in Indonesian private elementary schools remains limited. This qualitative case study examined the implementation of Coding-AI in one Grade-5 class at SD Muhammadiyah 1 Kesamben, Blitar, Indonesia, during the 2025/2026 academic year. Participants were one teacher and 15 students. Data were generated through classroom observations, semi-structured interviews, and documentation and analyzed using the interactive processes of data condensation, data display, and conclusion drawing/verification. The analysis used six sensitizing competence elements: computational thinking, digital literacy, algorithms and programming, data analysis, AI literacy and ethics, and AI use for learning. Case-specific coded evidence was documented for digital literacy among 15/15 students (100.0%), computational thinking among 14/15 (93.3%), AI literacy and ethics among 14/15 (93.3%), algorithms and programming among 13/15 (86.7%), AI use for learning among 13/15 (86.7%), and data analysis among 12/15 (80.0%). These frequencies summarize observed or reported behaviors within the case and do not represent standardized competency scores or changes over time. The teacher facilitated stepwise problem solving, purposeful and safe technology use, introductory programming, and ethical AI exploration, while students described systematic task completion, information seeking, and guided engagement with digital learning resources. The convergence of classroom, interview, and documentary evidence informed a contextual representation of Coding-AI implementation that emphasizes scaffolded participation rather than independent mastery. Because the findings derive from one teacher and 15 Grade-5 students in one private school, they should be interpreted as analytically, rather than statistically, transferable.

Keywords: Artificial Intelligence Literacy; Coding Education; Computational Thinking; Digital Literacy; Elementary School; Qualitative Case Study

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INTRODUCTION

Digital transformation has expanded the competencies that elementary schools are expected to cultivate. Contemporary learning increasingly requires children not only to use digital technologies but also to understand computational processes, engage critically with digital information, and develop an age-appropriate awareness of artificial intelligence. Within this context, computational thinking, digital literacy, and AI literacy represent related but distinct competencies that can support relevant, safe, and developmentally appropriate learning opportunities. Research on digital competence emphasizes purposeful, critical, and ethical participation in digital environments, while K-12 research identifies computational thinking and AI literacy as increasingly important dimensions of contemporary learning (Aliyyah et al., 2025; Chiu et al., 2024; Ogegbo & Ramnarain, 2022; Wang et al., 2026). In this study, these competencies are examined as dimensions of quality-oriented teaching and learning opportunities rather than as comprehensive indicators of educational quality. Educational quality itself is therefore treated as a contextual policy concept, not as a directly measured school-level outcome.

At the elementary level, Coding-AI learning must be interpreted developmentally. Children do not need to become professional programmers; they need guided opportunities to understand how instructions, data, automation, and intelligent systems function in everyday life. Age-appropriate coding activities can help students arrange steps, test ideas, identify errors, and explain why a digital output occurs (Cimino et al., 2025; Misirli & Komis, 2023; Su et al., 2023; Yim & Su, 2025). Introductory AI learning can also help students recognize that AI systems depend on data, may produce inaccurate or biased outputs, and require safe and ethical use. These dimensions are theoretically related but not identical: computational thinking concerns problem formulation and algorithmic solution processes; digital literacy concerns purposeful, critical, and safe use of digital resources; and AI literacy concerns understanding, evaluating, using, and ethically reflecting on AI systems (Chiu et al., 2024; Kong et al., 2024; Su & Zhong, 2022). This developmental perspective positions Coding-AI as an opportunity to cultivate structured reasoning, responsible technology use, and critical awareness rather than simply to introduce technical tools.

In Indonesia, policy attention to coding and artificial intelligence has increased, and schools are encouraged to adapt implementation to available resources, student readiness, and institutional context (Farchan, 2025; Rahmatullah & Azzahra, 2026; Sulasmono et al., 2026). For private elementary schools, adoption is shaped by school vision, teacher capacity, parental expectations, infrastructure, subject scheduling, and the developmental characteristics of young learners. Consequently, the implementation of Coding-AI is not determined by curriculum content alone but also by how schools organize instructional time, prepare teachers, provide learning resources, and respond to differences in student readiness. These contextual conditions make implementation-focused case studies useful because they show how a national or sectoral innovation is translated into actual classroom practice.

Previous studies indicate that coding activities can provide opportunities for computational thinking, logical reasoning, creativity, and problem-solving among young learners, especially when tasks are authentic, tools are age appropriate, and teacher scaffolding is sustained (Lye & Koh, 2014; Ogegbo & Ramnarain, 2022; Yeni et al., 2024; Yuana et al., 2025). K-12 AI education research similarly emphasizes concrete examples, project-based activity, ethical reflection, and guided interaction with AI concepts and tools (Akgun & Greenhow, 2022; Lee & Kwon, 2024; Su et al., 2023; Wu et al., 2024). Together, these studies demonstrate the educational relevance of coding, computational thinking, and AI literacy, but they provide less detail on how these dimensions are combined and sustained within a routine additional subject at the elementary-school level. The literature also varies in setting, participants, methodological emphasis, and the extent to which coding and AI literacy are examined together. Table 1 summarizes selected literature used to position the present study and to identify the contextual and methodological gap addressed by this case.

Table 1. Positioning of selected previous studies relevant to the present study

Authors / year	**Educational setting / context**	**Coding/CT focus**	**AI-literacy focus**	**Limitation / gap relevant to the present study**
Lye & Koh (2014)	K-12 educational contexts	Strong focus on computational thinking through programming	Not a primary focus	Provides foundational evidence for programming and CT but predates the current integration of coding with AI literacy
Ogegbo & Ramnarain (2022)	School-based learning	Computational thinking/problem-solving	Limited/not central	Supports CT-oriented learning but does not specifically document Coding-AI as an additional subject in an Indonesian private elementary school
Su et al. (2023)	Early/K-12 AI education	Related computational processes	Strong AI-learning focus	Emphasizes age-appropriate AI learning but does not examine the bounded implementation context investigated in the present study
Akgun & Greenhow (2022)	K-12 AI education	Not primarily coding-focused	Strong focus on AI ethics	Provides an ethical framework for AI education rather than an empirical account of integrated Coding-AI classroom implementation
Lee & Kwon (2024)	K-12/young learner AI education	Limited/related	Strong AI-learning focus	Focuses on AI learning but does not integrate teacher experience, student accounts, observation, and documentation in the present Indonesian context
Wu et al. (2024)	K-12 AI education	Related	Strong	Provides evidence on guided AI learning but offers limited evidence regarding implementation as a routine additional elementary-school subject

Authors / year	Educational setting / context	Coding/CT focus	AI-literacy focus	Limitation / gap relevant to the present study
Yuana et al. (2025)	Educational programming context	Programming / computational thinking	Limited / not primary	Supports programming-based learning but does not examine the combined Coding-AI implementation and ethical dimensions addressed here
Present study	Private Indonesian elementary school; one Grade-5 class	Computational thinking, algorithms, programming, and data analysis	AI literacy and ethics; AI use for learning	Examines Coding-AI as a routine additional subject through an integrated qualitative account of classroom implementation, teacher facilitation, student experiences, observations, documentation, contextual challenges, and contradictory evidence within one bounded case

As Table 1 indicates, the present study addresses four related gaps in the existing literature. First, much of the literature examines interventions, learning products, or outcomes, whereas fewer studies document how a newly introduced Coding-AI subject is organized, facilitated, and experienced as part of routine elementary-school practice. Second, computational thinking and AI literacy are often examined separately even though schools may implement them within one subject. Third, detailed qualitative evidence from Indonesian private elementary schools remains limited. Fourth, teacher and student accounts are not always integrated with observations and learning documentation to explain implementation conditions, challenges, and contradictory evidence. Taken together, these gaps indicate a need for context-rich evidence on how integrated Coding-AI learning is enacted in actual classroom practice. The present study addresses this need without seeking to establish a general theory, demonstrate causal improvement, or validate a school-quality model.

This study examines the implementation of Coding-AI as an additional subject in one Grade-5 class at SD Muhammadiyah 1 Kesamben, Blitar, Indonesia. The case was bounded by one school, one class, one teacher, the 2025/2026 academic year, and the scheduled Coding-AI learning activities observed by the researchers. The study uses computational thinking, digital literacy, algorithms and programming, data analysis, AI literacy and ethics, and AI use for learning as sensitizing categories for organizing the evidence. Rather than treating these categories as standardized measures, the study uses them to examine how Coding-AI was enacted through teacher facilitation, student participation, learning activities, and contextual conditions. Its contribution is primarily contextual and practical: it provides a transparent account of implementation, participant experiences, challenges, and a proposed case-derived conceptual representation. More specifically, the study contributes classroom-level evidence of how coding, introductory data practices, digital-resource use, and responsible AI exploration were integrated within one additional elementary-school subject. The study was guided by three research questions: (1) How was Coding-AI implemented as an additional subject in the Grade-5 class? (2) What teacher and student experiences and coded behavioral evidence characterized the implementation? and (3) What challenges and contextual conditions affected the implementation?

Accordingly, this study developed an air-pressure-based projectile-motion teaching aid using a modified Define–Design–Develop process and conducted a limited evaluation of the product. Specifically, the study examined (1) technical performance through measurements of horizontal range and maximum height at different elevation angles and pressure conditions, (2) content and media validity based on expert judgment, (3) teacher and student responses during limited classroom implementation, and (4) students' post-instruction mastery of projectile-motion concepts. By integrating technical evaluation with expert and classroom-based evidence, the study sought to establish the preliminary feasibility of the apparatus without attributing causal improvements in learning outcomes beyond the scope of the research design.

METHOD

Research Design

This study used a qualitative case study design. The bounded case was the implementation of Coding-AI as an additional subject in one Grade-5 class at SD Muhammadiyah 1 Kesamben during the 2025/2026 academic year. The unit of analysis was the classroom-level implementation process, including the teacher's facilitation, students' participation, learning resources, and contextual challenges. The school served as the institutional context, whereas the empirical unit was the implementation process within the selected Grade-5 class rather than the school or all grade levels as a whole. The design was selected to develop a context-rich account of how the subject was implemented and experienced, rather than to estimate causal effects, measure improvement, or generalize statistically.

Research Context and Participants

The study was conducted at SD Muhammadiyah 1 Kesamben, Blitar, Indonesia, during the 2025/2026 academic year. The school offered Coding-AI to Grades 5 and 6. Grade 5 was purposively selected because its Coding-AI lessons followed a regular schedule during the data-collection period and covered the sequence of topics relevant to the study. This continuity allowed the researchers to collect observation, interview, and documentary evidence from the same bounded class across the designated research period. Grade 6 was not included because its instructional schedule did not provide the same continuity of observation during that period.

The participating class consisted of all 15 enrolled Grade-5 students who met the inclusion criterion of direct participation in the observed Coding-AI lessons; no participating student was excluded from the descriptive coding. Students were approximately 10-12 years old. Gender-disaggregated information was not collected because gender comparison was not part of the study design or analytical objectives. Regarding prior technology access and coding experience, most students had previously used smartphones or tablets at home for communication, entertainment, and internet searches. However, only four students reported prior experience with block-based coding, and none had received formal AI instruction.

The participating teacher had eight years of elementary-school teaching experience and was responsible for the observed Coding-AI subject. The teacher had completed a 32-hour professional-development program covering introductory coding, computational thinking, and responsible AI use. The program was delivered through a school-supported accredited teacher-training provider, and the teacher received a certificate of completion.

The school enrolled approximately 180 students across Grades 1-6. Its computer room contained 20 internet-connected laptops, and classroom facilities included Wi-Fi access and a projector. Coding-AI was scheduled as a weekly 70-minute additional subject. The school adopted the subject to support its digital-learning program and to introduce computational thinking and responsible technology use before students entered secondary education.

The empirical record covered six classroom lessons conducted, with each lesson lasting approximately 70 minutes. The observed topics included unplugged algorithms, decomposition and sequencing, introductory block-based programming, debugging, simple data classification and pattern interpretation, everyday AI applications, and privacy, verification, and academic honesty in AI use. Students used Scratch for block-based programming, selected demonstrations using Google Teachable Machine and a teacher-mediated generative-AI interface, school laptops, a projector, and printed cards or worksheets for unplugged sequencing activities. These details delimit the duration, instructional content, and technological conditions represented in the empirical record and clarify the context in which the case-specific coded evidence was generated.

Data Sources and Instruments

Three sources of data were used: classroom observation, semi-structured interviews, and documentation. Classroom observations captured teacher-student interaction, task sequencing, device and media use, problem-solving attempts, AI-related discussion, and student participation. Interviews explored participants' experiences, perceived usefulness, difficulties, and understanding of responsible technology use.

Representative teacher interview questions included: “How do you introduce students to solving Coding-AI tasks step by step?”, “What difficulties do students commonly experience during coding and data-related activities?”, “How do you explain responsible and ethical AI use to Grade-5 students?”, and “What school or classroom conditions support or constrain the implementation of Coding-AI?” Representative student prompts included: “What do you usually do when you cannot complete a coding task?”, “How do you use digital devices or internet resources during Coding-AI lessons?”, “Why are ordered steps important when making a program?”, “What do you do when you need to interpret information or patterns?”, “What should students consider when using AI?”, and “How can AI be used to support learning?” These questions served as flexible prompts; follow-up questions were used to clarify participants’ examples and experiences.

Documentation included lesson materials, classroom photographs, school documents, and anonymized samples of students' flow-sequence worksheets, Scratch project screenshots, debugging notes, and simple pattern-classification worksheets. The six competence elements were selected deductively as sensitizing concepts from computational-thinking, digital-literacy, and AI-literacy literature and relevant Indonesian implementation guidance. Inductive coding was then used to identify contextual practices, implementation challenges, and contradictory or negative cases that were not adequately captured by the initial categories. Thus, the six elements were used as sensitizing categories rather than validated competency scales.

Interviews were conducted through one preliminary teacher interview, one follow-up teacher interview, and three student focus-group interviews consisting of five students each. The teacher interview lasted approximately 45 minutes, and student interviews lasted 25-30 minutes per group. Interviews were conducted in Bahasa Indonesia, audio-recorded with participant permission, transcribed verbatim, and checked against the audio recordings. The two authors translated the transcripts into English: the first author prepared the initial translation, and the second author checked the translation for conceptual equivalence.

Student interviews were conducted in three small groups in a quiet classroom after the scheduled lessons by the first author, who was not the students' classroom teacher and had no role in assigning their grades. Because student interviews were conducted in focus groups rather than as individual interviews, responses may have been influenced by peer interaction, agreement, or the willingness of some students to speak more frequently than others. Accordingly, focus-group statements were interpreted as contextual qualitative evidence and were not treated as independent individual competency measurements unless supported by student-specific observational or documentary evidence.

To ensure transparency in the interpretation of the qualitative evidence, the six competence elements were operationalized into observable indicators, participant experiences, documentary sources, and case-specific coding criteria. These elements were not treated as standardized competency scales but as sensitizing categories derived from the literature on computational thinking, digital literacy, programming, data analysis, and AI literacy. Table 2 presents the operational framework used to guide data collection and analysis, including teacher facilitation, student experience, representative evidence, documentary sources, and the criteria used to identify case-specific qualifying evidence for each element.

Table 2. Operationalization of data sources and coding criteria

Element	Teacher facilitation	Student experience	Representative excerpt	Documentary source	Case-specific coding rule	Representative interview question
Computational thinking	Prompted task decomposition, sequencing, testing, and revision.	Students attempted a task and sought support when blocked.	T1: “I ask students to think about the steps first, not only the final answer.” S04: “When I do not understand, I try again	Task notes / worksheets	Qualifying evidence was identified when at least one corroborated observation or artifact showed task-	“What do you do when a Coding-AI task seems difficult or cannot be completed immediately?”

Element	Teacher facilitation	Student experience	Representative excerpt	Documentary source	Case-specific coding rule	Representative interview question
			and ask my friend or teacher."		relevant stepwise problem solving and contradictory evidence did not outweigh the qualifying evidence.	
Digital literacy	Guided purposeful use of devices, internet resources, and applications.	Students searched for examples and completed assigned digital activities.	T1: "Technology is useful when students know what they are looking for." S07: "I use the internet to find examples for the task."	Photographs, task records	Qualifying evidence was identified when purposeful digital-resource use was observed or documented and supported by interview evidence.	"How do you use a laptop, internet resource, or digital application to complete the learning task?"
Algorithms and programming	Required ordered instructions before a simple coding task.	Students explained that sequence supported task completion.	S09: "If the steps are arranged, the work becomes easier because I know what to do first."	Algorithm / coding artifact	Qualifying evidence was identified when a student produced or explained an ordered sequence that was relevant to the task.	"Why is it important to arrange the steps before making or running a program?"
Data analysis	Used observation, comparison, and prompts for conclusion drawing.	Students located information, but interpretation often required support.	T1: "The most difficult part is helping students explain what the data means, not only read it."	Worksheet / simple dataset	Qualifying evidence was identified when a student moved beyond locating information to making a relevant	"After finding information or observing a pattern, how do you decide what it means?"

Element	Teacher facilitation	Student experience	Representative excerpt	Documentary source	Case-specific coding rule	Representative interview question
					comparison or simple interpretation.	
AI literacy and ethics	Discussed privacy, honesty, verification, and safe use.	Students stated that AI should support rather than replace thinking.	S12: "AI can help us learn, but we still have to think and not copy everything."	Reflection notes / interview	Qualifying evidence was identified when a student articulated at least one relevant ethical, safety, or evaluation principle.	"What should you consider before using or trusting information produced by AI?"
AI use for learning	Connected AI examples to daily life and guided learning tasks.	Students used or discussed AI for ideas and information.	T1: "I introduce AI through examples close to their daily life so they are not afraid of it."	Task / reflection record	Qualifying evidence was identified when guided AI use was connected to a learning purpose and the need for independent judgment was acknowledged.	"How can AI help you learn without replacing your own thinking?"

Data Analysis and Trustworthiness

Data were analyzed using the interactive model of Miles et al. (2014): data condensation, data display, and conclusion drawing/verification. The analysis combined deductive and inductive coding. First, the first author coded observation notes, transcripts, and documents using the six sensitizing elements and open codes for implementation conditions, challenges, and negative cases. Second, the second author reviewed all observation records, interview transcripts, and documentary samples of the coded material. Disagreements were resolved through discussion and comparison with the raw evidence. Because this review process was interpretive and consensus-based, a numerical intercoder-reliability coefficient was not calculated. Third, matrices were developed to compare teacher evidence, student evidence, artifacts, and contradictory instances.

A student was classified as having case-specific qualifying evidence for an element only when the relevant coding criterion in Table 2 was met through at least one sufficiently specific item, with triangulation used where supporting evidence was available. Classification as qualifying evidence indicated only that the specified behavior, statement, or artifact occurred within the observed case. It did not indicate persistence across lessons, proficiency, mastery, or independent performance. Frequencies were calculated as n/15 and converted to percentages solely to summarize the distribution of coded evidence within this class; these descriptive frequencies were not interpreted as test scores, effect sizes, or measures of change over time.

Trustworthiness was addressed through source triangulation, method triangulation, maintenance of an evidence matrix, attention to negative or contradictory cases, and member checking. For member checking, a two-page summary of the preliminary categories and interpretations was returned to the teacher. The teacher confirmed the general accuracy and clarified the scheduling and device-use descriptions. A child-friendly oral summary was discussed with the three student groups; students confirmed the main descriptions and suggested minor wording changes. These clarifications were documented in the audit trail before preparation of the final coding matrix. The audit trail linked analytical codes with interview excerpts, observation notes, documentary evidence, and subsequent clarifications.

Ethical safeguards were implemented because the participants were children. The study received written research authorization from the school principal before data collection. As this classroom-based study involved minimal risk and was conducted within the school setting, no separate institutional ethical-clearance number was issued for the study. Accordingly, participant protection was implemented through documented school authorization, written informed consent from parents or guardians, age-appropriate student assent, confidentiality and anonymity procedures, voluntary participation, and separate permission for publication of classroom photographs. These procedures are reported as participant-protection measures and are not presented as equivalent to independent institutional ethical review. Participants were informed that participation was voluntary and would not affect school assessment. Teacher and student identities were replaced with codes (T1 and S01-S15). Classroom photographs were used only with explicit publication permission; where identifiable publication permission was not available, identifying visual information was removed or obscured before publication.

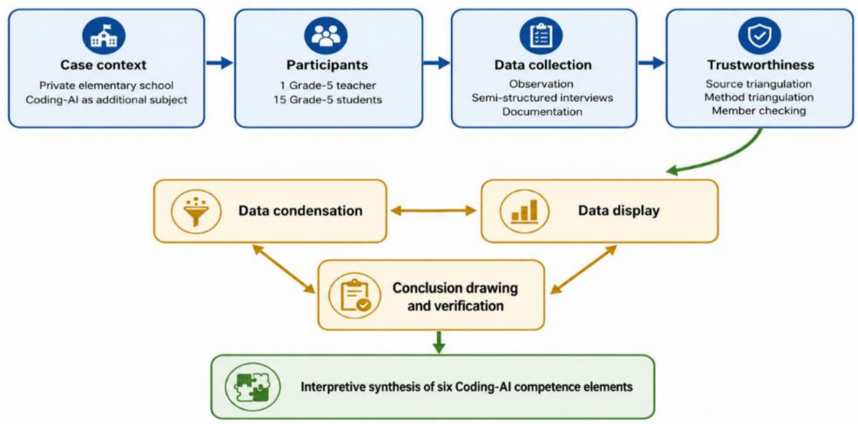


Figure 1. Sequence of case delimitation, data collection, transcription, coding, category development, interpretation, triangulation, and member checking (Source: Authors' own elaboration)

RESULTS AND DISCUSSION

Coding-AI implementation was examined through the sequence of classroom activities, teacher facilitation, student participation, and the distribution of case-specific coded evidence across the six sensitizing elements. Coding-AI learning activities are illustrated in Figure 2. The Results section reports evidence generated within the bounded case and does not interpret the coded frequencies as demonstrated competence, mastery, or improvement. The six elements functioned as organizing categories, while implementation conditions and challenges were also coded inductively. Percentages are presented together with frequencies and should be read as the proportion of the 15 students who met the relevant case-specific coding criterion during the observed implementation.

Figure 2. Student participation during a Coding-AI learning activity; the photograph documents classroom engagement but does not independently demonstrate competence (Source: Research documentation; publication consent)

Implementation of Coding-AI as an Additional Subject

Across the six observed lessons, Coding-AI was implemented through a progression from unplugged activities to guided digital, programming, data-related, and AI-focused activities. Early activities emphasized algorithms, decomposition, and sequencing through printed cards and worksheets before students moved to introductory block-based programming and debugging using Scratch. Subsequent activities introduced simple data classification and pattern interpretation, followed by exploration of everyday AI applications and discussion of privacy, verification, and academic honesty in AI use. Selected demonstrations using Google Teachable Machine and a teacher-mediated generative-AI interface were used to make AI concepts more concrete and accessible to the students.

The teacher combined direct explanation, questioning, guided practice, peer interaction, and ethical reminders throughout the lessons. Students were encouraged to arrange steps before completing tasks, test and revise their work, seek help when necessary, use digital resources for specific learning purposes, and discuss responsible ways of engaging with AI-generated information. Thus, Coding-AI was enacted not as programming instruction alone but as an integrated set of activities involving sequential reasoning, digital-resource use, introductory programming, simple data interpretation, guided AI exploration, and ethical reflection.

Distribution of Case-Specific Coded Evidence Across Coding-AI Elements

Qualifying evidence was identified across all six organizing elements, although its distribution varied among the 15 students. Purposeful device and online-resource use was documented for 15 of 15 students. Stepwise problem solving and statements about responsible AI use were documented for 14 of 15 students. Ordered instructions or introductory programming evidence and guided AI use for learning were documented for 13 of 15 students, while simple data interpretation was documented for 12 of 15 students. These frequencies summarize the occurrence of behaviors, statements, or artifacts that met the case-specific coding criteria within the six observed lessons. They do not indicate stable competence, mastery, or improvement from a baseline. Table 3 reports both frequencies and percentages.

Table 3. Distribution of case-specific coded evidence among Grade-5 students

Competence element	Students meeting the case-specific coding criterion	Pedagogical interpretation
Computational thinking	14/15 (93.3%)	Students attempted stepwise solutions, identified problems, and sought support when needed.
Digital literacy	15/15 (100.0%)	Students used devices and internet resources for learning with teacher guidance.
Algorithms and programming	13/15 (86.7%)	Most students arranged sequential steps before completing coding tasks.
Data analysis	12/15 (80.0%)	Students began to identify information and patterns, but interpretation frequently required teacher support.
AI literacy and ethics	14/15 (93.3%)	Most students articulated at least one relevant idea indicating that AI should support learning and be used responsibly.
AI use for learning	13/15 (86.7%)	Most students described or demonstrated guided use of AI for information seeking and learning support.

Variation and Non-qualifying Evidence

The distribution also revealed non-qualifying and partially contradictory evidence that tempered the overall pattern. One student did not meet the case-specific criterion for computational thinking, two did not meet the criterion for algorithms and programming, three did not meet the criterion for data analysis, one did not meet the criterion for AI literacy and ethics, and two did not meet the criterion for AI use for learning. All students met the case-specific criterion for digital literacy.

These cases should not be interpreted as deficits or failure; rather, they indicate that qualifying evidence was not sufficiently documented for every student within the six observed lessons. The largest concentration of non-qualifying evidence occurred in data analysis, where three students did not meet the criterion and classroom observations indicated that interpreting patterns or explaining what information meant often required teacher prompting. These negative, incomplete, or partially contradictory cases were retained in the analytical matrix rather than removed from the descriptive frequencies. Their inclusion highlights variation within the class and prevents the overall frequency pattern from being interpreted as uniform performance.

Evidence Matrix: Teacher Facilitation, Student Experience, and Interview Excerpts

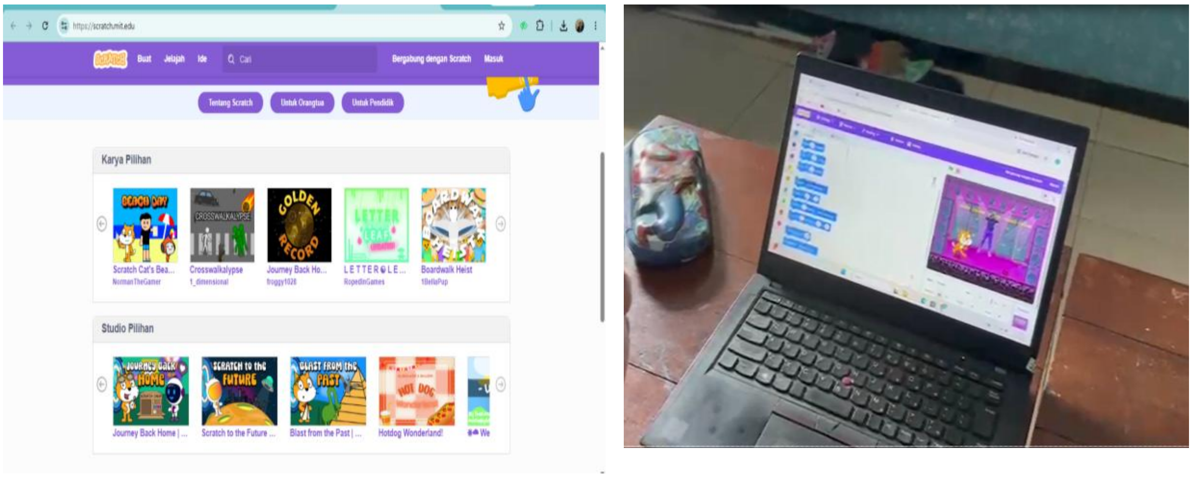
The teacher combined direct guidance, practice, discussion, and ethical reminders. Students described independent attempts, requests for peer or teacher support, and guided use of digital resources. Across the six elements, the evidence consistently showed interaction between student participation and teacher scaffolding rather than uniformly independent performance. Table 4 presents representative excerpts with participant codes. The quotations were translated into English and lightly edited for grammar and readability without intentionally changing their substantive meaning.

Table 4. Evidence matrix and representative participant excerpts

Element	Teacher facilitation	Student experience	Representative interview excerpt
Computational thinking	Guided students to break tasks into smaller steps, discuss problems, and test solutions.	Students attempted tasks independently and asked for support when stuck.	T1: "I ask students to think about the steps first, not only the final answer." S04: "When I do not understand, I try again and ask my friend or teacher."
Digital literacy	Used laptops, mobile phones, internet, projector, and digital applications while emphasizing purposeful use.	Students used devices to search for learning materials and complete activities.	T1: "Technology is useful when students know what they are looking for." S07: "I use the internet to find examples for the task."
Algorithms and programming	Asked students to arrange ordered instructions before making a simple program.	Students recognized that ordered steps made coding tasks easier.	S09: "If the steps are arranged, the work becomes easier because I know what to do first."
Data analysis	Encouraged observation, comparison, and simple conclusion drawing.	Students identified information but still needed guidance to interpret patterns.	T1: "The most difficult part is helping students explain what the data means, not only read it."
AI literacy and ethics	Introduced responsible AI use, privacy, honesty, and safe internet behavior.	Students described AI as a tool that should support learning without replacing their own thinking and should be used responsibly.	S12: "AI can help us learn, but we still have to think and not copy everything."
AI use for learning	Connected AI examples to daily life and encouraged AI as a learning aid.	Students described interest in using AI for ideas, information, and coding-related support within guided learning activities.	T1: "I introduce AI through examples close to their daily life so they are not afraid of it."

The evidence matrix further shows that teacher facilitation differed according to the demands of each element. Stepwise questioning and task decomposition supported computational-thinking activities; ordered instructions supported introductory programming; observation and comparison prompts were particularly important for data interpretation; and explicit discussion of privacy, verification, honesty, and independent thinking accompanied AI-related activities. Student accounts similarly indicated a combination of independent attempts and reliance on peer or teacher assistance. Taken together, the evidence suggests that participation across the six elements was primarily scaffolded, with the degree of required support varying by task.

To complement the interview and observational evidence, Figure 3 presents documentary evidence of the digital environment and Scratch-based programming activities used during the Coding-AI lessons. The images illustrate students' exposure to the Scratch platform and their direct engagement with block-based programming during classroom activities. The photographs provide contextual documentation of the instructional environment and student participation; they are not treated as independent evidence of programming proficiency, mastery, or sustained performance.



(a) (b)

Figure 3. Documentary evidence of Scratch-based programming activities during Grade-5 Coding-AI lessons: (a) the Scratch online learning environment used during the instructional activities and examples of Scratch projects available through the platform; and (b) students engaging with block-based programming on a classroom laptop (Source: Research documentation).

Discussion

Computational Thinking as Emerging Stepwise Problem Solving

The case provided evidence of emerging stepwise problem solving, but it did not measure change in computational thinking. Observation and interview data showed that students were prompted to identify a task, arrange solution steps, test a result, and revise an error. These practices are consistent with computational-thinking processes described in previous literature (Lye & Koh, 2014; Ogegbo & Ramnarain, 2022; Palop et al., 2025). The findings suggest that teacher questioning and structured task sequencing helped make abstract problem-solving processes more accessible within the observed lessons. At the same time, the frequent use of prompting indicates that the documented behaviors reflected scaffolded participation rather than uniformly independent performance. Thus, the contribution of the case lies in showing how computational-thinking practices were enacted through guided classroom activity, rather than in demonstrating gains in computational-thinking competence.

Digital Literacy as Guided and Purposeful Technology Use

Purposeful digital-resource use was the most widely documented behavior, occurring for all 15 students. This pattern likely reflects the combination of students' prior familiarity with phones or internet resources, the relative accessibility of device-use tasks, and sustained teacher guidance during classroom activities. At the elementary level, digital literacy also includes evaluation, safety, and responsible participation (Aliyyah et al., 2025; Li et al., 2025; Sari et al., 2024), dimensions that were only partially represented in this case. Accordingly, the finding is best interpreted as evidence of broad participation in purposeful, teacher-guided digital activity rather than as evidence of comprehensive digital literacy. This distinction is important because operational familiarity with devices does not necessarily imply the ability to evaluate information critically or act independently in more complex digital environments.

Algorithms and Programming as Evidence of Sequential Thinking

Ordered-step evidence was documented for 13 students. Students commonly explained that arranging instructions made tasks easier, and classroom evidence showed introductory sequencing and testing. This is consistent with research arguing that programming can make computational processes visible through hands-on activity (Gardeli & Vosinakis, 2025; Lye & Koh, 2014; Misirli & Komis, 2023; Yuana et al., 2025). In this case, the combination of ordered instructions, block-based programming, testing, and debugging provided students with concrete opportunities to connect sequential reasoning with visible program behavior. Nevertheless, the available documentation does not establish the complexity, independence, or persistence of students' programming performance. The evidence therefore supports a bounded interpretation: introductory programming served as a practical context for making sequential and algorithmic reasoning observable during the lessons.

Data Analysis as the Most Challenging Element

Data interpretation had the lowest coded frequency among the six organizing elements (12/15, 80.0%). Students could often locate information or notice a simple pattern, but explaining meaning and drawing a relevant conclusion frequently required teacher prompts. This contrast with the more widely documented digital-resource use suggests that locating or accessing information was less demanding for students than interpreting what the information represented. Several explanations are possible: the tasks may have been more cognitively demanding, students may have had limited prior experience, the instructional time may have been insufficient, or the operational criterion may have been stricter than for device use. Because the study did not compare task difficulty experimentally, these explanations remain interpretive possibilities rather than tested causes.

Pedagogically, the finding identifies data interpretation as an area requiring more explicit scaffolding within future Coding-AI lessons. Future lessons could use simple tables, visual patterns, and structured questions such as 'What changed?', 'What pattern do you see?', and 'What conclusion is supported?' (Lai & Lin, 2025; Liu & Zhong, 2025; Wang et al., 2026). Such activities would extend students' participation beyond identifying information toward explaining relationships and supporting conclusions with evidence.

AI Literacy and Ethics as Early Critical Awareness

Fourteen students articulated at least one relevant idea about responsible AI use, such as not copying everything, protecting information, or continuing to think independently. These statements indicate emerging critical and ethical awareness within the instructional context, particularly around verification, privacy, academic honesty, and the continued role of human judgment. K-12 AI-literacy frameworks similarly emphasize conceptual understanding, critical evaluation, ethics, safety, and practical use (Akgun & Greenhow, 2022; Chiu et al., 2024; Kong et al., 2024). The alignment between these frameworks and the classroom evidence suggests that ethical reflection can be introduced alongside practical AI use rather than treated as a separate or advanced topic.

However, the pattern also reflects the teacher's explicit reminders during the observed lessons. The next pedagogical challenge is therefore not simply whether students can state an ethical principle, but whether they can apply that principle when evaluating unfamiliar AI-generated content or making independent decisions about AI use.

AI Use for Learning as Guided Educational Support

Thirteen students described or demonstrated guided AI use for learning purposes. Students commonly viewed AI as a source of ideas or information, and the teacher used familiar examples to reduce abstraction. These observations are consistent with K-12 literature on concrete, guided AI learning (Lee & Kwon, 2024; Wu et al., 2024; Yim & Su, 2025). The case therefore illustrates an introductory approach in which AI was positioned as a learning support rather than as a replacement for students' own reasoning. Students' expressed interest in AI should nevertheless be interpreted as part of their experience during the observed implementation rather than as evidence of increased motivation. The study did not measure motivation before and after implementation; consequently, it cannot attribute changes in motivation or engagement to participation in the subject.

Cross-Cutting Pattern: Scaffolded Participation Across Uneven Levels of Independence

Across the six organizing elements, a common pattern was the interaction between student participation and teacher scaffolding. Students engaged with stepwise problem solving, digital resources, programming, data interpretation, and AI-related tasks, but the level of support required varied according to the activity. Purposeful digital-resource use was documented most broadly, whereas data interpretation generated the greatest number of non-qualifying cases and more frequent teacher prompting. Programming, computational thinking, and AI-related activities occupied an intermediate position in which most students produced qualifying evidence but continued to rely on structured guidance.

This cross-cutting pattern suggests that the defining characteristic of the observed implementation was not independent mastery but scaffolded participation across progressively different forms of digital and computational reasoning. The distinction is substantively important because it shifts interpretation away from whether students had already “acquired” the six competencies and toward how classroom activities created opportunities for those competencies to emerge, be practiced, and become visible. In this sense, the case contributes an implementation-level account of how integrated Coding-AI learning can be organized for elementary students while still accommodating uneven readiness and differing levels of teacher support.

Coding-AI as a Context-Dependent, Quality-Oriented School Innovation

Within the limited scope of this case, Coding-AI functioned as a school innovation that created opportunities for guided digital activity, stepwise problem solving, introductory programming, simple data interpretation, and discussion of responsible AI use. These classroom opportunities are relevant to quality-oriented educational practice because they address contemporary forms of digital, computational, and ethical participation; however, educational quality itself was not measured as an outcome.

At the institutional level, implementation also required teacher preparation, scheduling, device management, internet access, and ethical guidance. The case therefore indicates that implementation depended on the interaction between pedagogy and institutional conditions rather than on the availability of digital tools alone. The evidence supports a cautious claim: Coding-AI may support quality-oriented educational practices when it is embedded in developmentally appropriate pedagogy and sustained institutional support. Its value in this case lies in the opportunities it created for guided learning and responsible technology engagement, not in evidence of school-wide quality improvement.

Proposed Contextual Representation

Figure 4 is presented as a proposed conceptual representation rather than a validated model. The representation integrates two analytically distinct layers. The first consists of components grounded directly in the empirical case: teacher facilitation, guided classroom practice, student participation, uneven readiness, infrastructure dependence, and the six organizing elements. The second consists of broader enabling conditions and implications informed jointly by the case evidence and relevant literature, including school policy, sustained professional learning, progressive assessment, continuous improvement, and quality-oriented school innovation. The arrows indicate hypothesized relationships for future investigation; they were not statistically or longitudinally tested in this study.

This distinction is important because broader concepts represented in Figure 4 should not be interpreted as separately measured student or school outcomes. Rather, they extend the empirical findings into a hypothesis-generating representation of the conditions through which Coding-AI might be sustained and developed. Alternative explanations for the generally widespread qualifying evidence include the teacher's enthusiasm, novelty effects, students' prior technology exposure, and the resource environment of a private school.

At the institutional level, Coding-AI implementation may support quality-oriented practices by creating a need for teacher professional learning and context-responsive school innovation. The observed implementation illustrates why teachers need to combine technological knowledge with task design, inquiry facilitation, ethical guidance, and progressive attention to students' learning processes. This demand may create opportunities for continuous teacher development, especially when supported by training, mentoring, and collaborative reflection.

At the same time, the school demonstrates innovation by introducing an additional subject that responds to current educational needs while still adapting to available resources, schedules, and student readiness. However, the sustainability of this quality-oriented innovation depends on consistent institutional support, including adequate infrastructure, internet access, teacher mentoring, ethical guidelines for AI use, and assessment models that capture students' thinking processes rather than only final products. Accordingly, Figure 4 conceptualizes sustainable Coding-AI implementation as the alignment of learning resources, teacher readiness, school support, classroom practice, responsible AI guidance, and continuous improvement rather than as a linear pathway to predetermined outcomes.

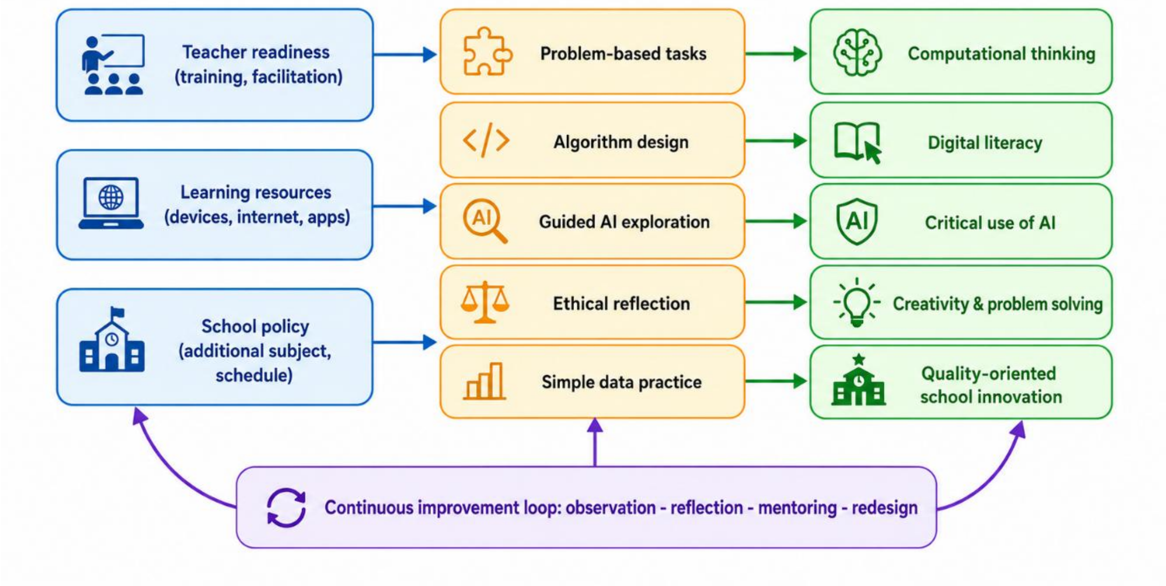


Figure 4. Proposed contextual representation of Coding-AI implementation derived from case evidence and literature (Source: Authors' own elaboration)

Challenges and Practical Improvement Directions

The case also contained implementation constraints and uneven evidence. These challenges contextualize the generally widespread qualifying evidence and reinforce the interpretation of the findings as implementation patterns rather than demonstrated improvement. Table 5 distinguishes challenges identified from the empirical record from improvement directions proposed by the authors.

Table 5. Empirically identified challenges and proposed improvement directions

Challenge identified	Meaning for implementation	Suggested improvement
Uneven student readiness	Students differ in prior digital experience and confidence.	Use tiered tasks, peer support, and gradual progression from unplugged to plugged activities.
Limited depth in data analysis	Students can identify information but need help interpreting patterns and conclusions.	Use simple datasets, visual prompts, and guided questions for evidence-based reasoning.
Risk of AI dependence	Students may rely on AI answers without verification.	Teach prompt literacy, fact-checking, source comparison, and reflection on independent thinking.
Teacher workload	Coding-AI requires preparation of devices, tasks, and ethical guidance.	Provide lesson banks, mentoring, collaborative planning, and school-level technical support.

Infrastructure dependence	Implementation opportunities and constraints were associated with device availability, internet access, and classroom management.	Plan blended activities, rotating stations, and backup unplugged coding tasks.

The challenges presented in Table 5 show that implementation was shaped by differences in prior experience, task difficulty, teacher workload, infrastructure, and the risk of uncritical AI dependence. Uneven readiness suggests a need for differentiated support, but tiered tasks and peer support are recommendations rather than interventions evaluated in this study. Similarly, the lower frequency for data interpretation indicates a need for more scaffolding, although the precise cause cannot be determined from the available evidence.

The risk of AI dependence was reflected in participants' emphasis on avoiding uncritical copying and maintaining independent thinking. This pattern supports the inclusion of verification, source comparison, and reflection within future AI-related learning activities. Lesson banks, collaborative planning, rotating stations, and backup unplugged tasks are therefore offered as practical possibilities grounded in the challenges and literature, not as proven solutions.

Implementation should also be interpreted in relation to possible novelty and context effects. Students may have participated enthusiastically because the subject and tools were new; the teacher's training and enthusiasm may have generated unusually intensive scaffolding; and access conditions in a private school may differ from those in other schools. These contextual influences offer plausible alternative explanations for the generally widespread qualifying evidence and limit the extent to which the observed pattern can be transferred to other settings without attention to contextual similarity. These factors reinforce the need for multi-site and longitudinal research.

The negative and non-qualifying cases identified in this study reinforce the need for future research to examine variation among students more intensively, particularly differences associated with prior digital exposure, the level of teacher prompting required, and performance across multiple instructional units. Future studies should also compare authentic student work longitudinally to determine whether qualifying evidence becomes more independent, persistent, and transferable over time. Such research would help distinguish initial participation under structured support from the development of more autonomous and sustained computational, digital, and AI-related practices.

CONCLUSIONS

This qualitative case study described the implementation of coding and artificial intelligence as an additional subject in one Grade-5 class at a private Indonesian elementary school. Case-specific coded evidence was found across six organizing elements, with purposeful digital-resource use most widely documented and data interpretation least widely documented. Across these elements, the dominant pattern was scaffolded participation: students engaged in sequential problem solving, guided digital-resource use, introductory programming, simple data interpretation, and responsible AI-related activities with varying levels of teacher support.

The teacher facilitated sequencing, problem solving, safe technology use, and ethical discussion, while students described systematic task completion, information seeking, and interest in technology. The variation across the six elements indicates that participation was not uniform and that some forms of reasoning, particularly data interpretation, required more explicit scaffolding than others. The uneven distribution of qualifying evidence, including non-qualifying cases across several elements, indicates that the observed implementation should not be interpreted as uniform student mastery.

The study therefore contributes a context-rich account of how Coding-AI can be enacted as an integrated additional subject in elementary-school practice, combining computational thinking, digital-resource use, introductory programming, data-related activities, and responsible AI exploration within a single classroom context. These findings indicate implementation patterns and participant experiences; they do not demonstrate causal improvement in competence or educational quality because the study had no baseline, comparison group, standardized measure, or longitudinal follow-up.

The proposed contextual representation should be understood as a hypothesis-generating synthesis of the case rather than as a validated implementation model. Its transferability is limited and depends on similarities in school context, teacher readiness, infrastructure, student experience, and the degree of instructional support available. Within these boundaries, the case highlights the importance of aligning teacher facilitation, developmentally appropriate tasks, ethical guidance, and institutional support when introducing Coding-AI at the elementary-school level.

RECOMMENDATIONS

Based directly on the observed challenges, schools should clarify the subject's learning objectives, provide age-appropriate ethical guidance, plan for uneven student readiness, and ensure feasible access to devices and internet resources. Implementation should also include deliberate scaffolding for activities that require interpretation and judgment, particularly data-analysis and AI-related tasks, rather than focusing primarily on access to digital tools.

Additional proposals—such as teacher-readiness mapping, lesson banks, rotating stations, and structured mentoring—are reasonable implementation options but were not evaluated in this study. These options should therefore be treated as context-sensitive strategies to be adapted and evaluated rather than as proven interventions.

Future research should include multiple schools and grades, incorporate longitudinal analysis of authentic student work, investigate negative and contradictory cases, and compare evidence across students with different levels of prior digital experience. Multi-site studies would help determine which implementation patterns are context-specific and which may be transferable across different school settings, while longitudinal research could examine whether initially scaffolded participation becomes more independent and persistent over time. Longitudinal or mixed-method designs are particularly needed to examine whether participation in Coding-AI is associated with subsequent changes in computational thinking, digital literacy, AI literacy, and broader indicators of educational quality.

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Ethical Approval
This research was conducted in accordance with principles of research ethics and academic integrity. All research procedures complied with applicable institutional policies. Participants’ privacy and data confidentiality were protected, and research data were used solely for scientific purposes.

Data Availability
The data that support the findings of this study are available from the corresponding author upon reasonable request, subject to the confidentiality and consent conditions applicable to data collected from child participants.

Author Contributions Statement

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Dian Fitri Nur Aini	✓	✓		✓	✓	✓		✓	✓	✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

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