

ARTIFICIAL INTELLIGENCE EDUCATION POLICY IN ELEMENTARY SCHOOLS FOR K12

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ABSTRACT

As governments increasingly promote coding and artificial intelligence (AI) in primary education, attention has shifted from policy adoption to the realities of implementation at the school level. This study investigates how elementary schools in Grobogan District, Indonesia, translate national expectations for coding and AI education into everyday teaching practices under the Merdeka Curriculum. Using a qualitative collective case study design, the research combines policy enactment theory, the TPACK framework, and computational thinking as complementary analytical perspectives. Data were generated through interviews with eight teachers, four principals, and twelve students, supported by observations of six classroom sessions and analysis of relevant school and policy documents. The findings show that implementation does not follow a single model. Instead, schools adopt different approaches according to their available resources, teacher competence, and organizational capacity. These approaches include project-based activities using digital coding tools, combinations of unplugged and plugged tasks, integration of unplugged coding concepts into existing subjects, and introductory teacher-led demonstrations. The extent to which the policy was enacted also depended strongly on school leadership and on individual teachers who assumed a leading role in introducing new practices. Differences in teachers' technological, pedagogical, and content knowledge were evident, with technological competence emerging as the weakest area. Although limited infrastructure restricted the scope of implementation, schools were able to adapt activities to local conditions rather than abandoning the policy altogether. Students showed initial signs of computational thinking, particularly when they decomposed problems, tested alternative solutions, corrected errors collaboratively, and refined their approaches through repeated attempts.

Keywords: AI, Education, K12, Elementary, Schools

Received: 10 September 2026

Accepted: 30 September 2026

Published: 1 October 2026

Cite: Susanto, E., & Arifin, M. (2026). Artificial Intelligence Education Policy in Elementary Schools for K12. *AI-Driven Journal of Interdisciplinary Social Research*, 1(1), 1-15. <https://doi.org/10.5281/zenodo.23197675>

DOI: <https://doi.org/10.5281/zenodo.23197675>

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INTRODUCTION The rapid advancement of artificial intelligence (AI) has fundamentally transformed educational paradigms globally, shifting from technological discourse to an integral component of policy architectures and pedagogical practices (Crompton et al., 2022; Yeter et al., 2024). Within this context, the integration of coding and AI education in elementary schools has emerged as a critical policy priority across diverse national contexts, from Singapore's systematic curriculum integration to Japan's generative AI guidelines for primary education (Seow et al., 2019). The U.S. Department of Education's report on Artificial Intelligence and the Future of Teaching and Learning emphasizes that AI holds substantial potential for enhancing educational equity, learning effectiveness, and operational efficiency, while simultaneously presenting novel challenges concerning ethics, privacy, and social

justice. This dual nature of AI as both opportunity and challenge underscores the urgency of understanding how educational institutions translate policy aspirations into classroom realities, particularly in resource-constrained contexts (Karan & Angadi, 2023; UNESCO, 2023). International scholarship has documented the expanding corpus of AI in Education (AIED) research, encompassing diverse applications ranging from intelligent tutoring systems and learning analytics to adaptive learning environments (Holmes et al., 2019; Lee & Kwon, 2024; Zhai et al., 2021). Systematic reviews indicate that AI implementation in elementary schools can enhance teaching effectiveness, facilitate personalized learning pathways, and increase student engagement (Chen et al., 2020; Moreno-Guerrero et al., 2022; Yeter et al., 2024). Concurrently, the global impetus to integrate computational thinking from early childhood has intensified, with Wing (2006) positing that computational thinking constitutes a fundamental competency equivalent to literacy and numeracy. Nations such as Estonia, Singapore, Finland, and Korea have operationalized this vision through national policies incorporating coding and computational thinking as curricular components at the elementary level, reflecting a paradigm shift from basic digital literacy toward AI literacy and computational thinking as prerequisites for societal participation (Bocconi et al., 2016; Grover & Pea, 2013; Seow et al., 2019). Indonesia has responded to these global dynamics through the Merdeka Curriculum, which prioritizes digital literacy strengthening, character development, and 21st-century skill acquisition. The specific policy concerning coding and artificial intelligence learning in elementary schools represents a strategic initiative to prepare younger generations for increasingly digitalized ecosystems. Research confirms that coding and AI integration contributes to digital literacy enhancement, computational thinking development, and learning relevance to future workforce demands (Su & Zhong, 2023). However, despite policy proliferation, substantial gaps persist between policy design and school-level implementation. International literature cautions that AI implementation without adequate governance frameworks risks widening digital divides, generating algorithmic bias, and threatening student data privacy (Akgun & Greenhow, 2022; Baker & Hawn, 2022; UNESCO, 2023). Moreover, UNESCO's Global Education Monitoring Report (2023) documents significant implementation challenges in low- and middle-income countries, where infrastructure limitations and inadequate teacher preparation create formidable barriers to effective technology integration. Critical knowledge gaps remain in understanding policy enactment processes, particularly in developing country contexts. First, geographically, most

AIED research originates from high-income countries with established digital infrastructure, leaving developing country contexts, including Indonesia, significantly underrepresented, particularly at the elementary school level (Santos et al., 2018; Pedro et al., 2019; Yeter et al., 2024). Second, methodologically, while numerous studies focus on effectiveness testing of specific AI platforms, qualitative research examining how coding and AI policies are enacted in schools—with all their constraints and adaptive practices—remains limited (Ball et al., 2012; Braun et al., 2011; Roll & Wylie, 2016). Third, contextually, understanding of how infrastructure limitations, teacher capacity, and local sociocultural norms influence coding and AI learning practices requires deeper empirical investigation (So et al., 2020; Mason & Rich, 2019). Moreover, research reveals critical gaps in teachers' Technological Pedagogical Content Knowledge (TPACK) readiness for AI integration, with technological knowledge and AI-specific competencies representing primary constraints (Oved & Alt, 2025; Ning et al., 2024; Radloff et al., 2025). This study addresses these gaps by examining how elementary schools in Grobogan District, Central Java—a region characterized by mixed urban-rural contexts with distinct variations in resources, digital infrastructure, and teacher capacity—enact the national coding and AI education policy. Drawing upon Ball, Maguire, and Braun's (2012) policy enactment framework, which conceptualizes policy implementation as an interpretive process involving translation and negotiation by local actors within specific contexts (Braun et al., 2011), combined with the Technological Pedagogical Content Knowledge (TPACK) framework (Koehler & Mishra, 2009) extended to include AI-specific competencies through Intelligent-TPACK (Celik et al., 2023; Radloff et al., 2025), and

computational thinking concept (Wing, 2006), this research investigates the complex dynamics between policy aspirations and classroom realities. The study's novelty lies in its integrated theoretical approach, district-level empirical focus representing Indonesia's heterogeneous educational landscape, and potential to generate evidence-based recommendations for narrowing the policy-practice gap in resource-constrained contexts. The research is guided by the following question: How do elementary schools in Grobogan District enact the coding and artificial intelligence learning policy in relation to its effectiveness and urgency for student competency development? This inquiry is elaborated through four sub-focuses examining: (1) teachers' and principals' interpretations and perceived urgency of coding and AI integration; (2) contextual factors influencing policy implementation; (3) adaptation strategies developed by schools and teachers; and (4) student experiences and perceived impacts on learning engagement and 21st-century skill development. By documenting implementation models, TPACK readiness variations, and emergent computational thinking practices, this study contributes empirical insights essential for policy refinement, teacher professional development design, and governance strengthening in coding and AI education across similar educational contexts.

METHODS This study employed a qualitative collective case study design to develop in-depth understanding of how coding and artificial intelligence learning policy is enacted within elementary school contexts. The case study approach was deemed appropriate as the research examines complex policy phenomena situated within real-world settings with clearly defined contextual boundaries, enabling exploration of the "how" and "why" questions central to policy enactment processes. Four public elementary schools in Grobogan District, Central

Java, were purposively selected based on criteria including: (a) evidence of initiating or preparing to implement coding and AI learning activities, and (b) representation of diverse contexts including sub-district centers and peripheral areas with varying facility access. This purposive sampling strategy facilitated maximum variation sampling, capturing implementation dynamics across heterogeneous school environments while maintaining coherence within a single district policy framework. Research participants comprised 24 individuals selected through criterion-based purposive sampling: eight upper-grade teachers (grades 5-6) serving as coding or AI learning coordinators, four school principals or vice-principals functioning as policy decision-makers, and twelve students (grades 5-6) who had participated in coding or AI-related learning activities. Participant selection continued until data saturation was achieved, evidenced when additional interviews yielded no substantially new insights regarding policy interpretation, implementation strategies, or student experiences. Data collection employed methodological triangulation through four primary techniques. Semi-structured in-depth interviews were conducted using protocol guides developed from the study's theoretical frameworks—policy enactment (Ball et al., 2012), TPACK (Koehler & Mishra, 2009), and computational thinking (Wing, 2006)—with each protocol tailored to participant roles. Interview protocols underwent expert validation by two educational management professors and pilot testing with three teachers from non-participating schools, resulting in refinements to question clarity and sequencing. Classroom observations were conducted across six learning sessions using structured observation sheets documenting pedagogical approaches, technology integration patterns, student-teacher interactions, and evidence of computational thinking elements. Field notes were systematically recorded and, where permitted, supplemented with photographic documentation following ethical protocols. Document analysis examined curricular materials, policy documents, lesson plans, teaching modules, and activity reports to trace policy trajectories from national to school levels and compare written plans with actual implementation. Additionally, two focus group discussions with teachers were conducted to validate preliminary findings and observe collective sense-making processes regarding policies and practices.

Data analysis followed Braun and Clarke's thematic analysis procedures conducted iteratively throughout data collection. The analytical process encompassed: (a) data familiarization through repeated reading and preliminary noting; (b) systematic coding of meaningful data segments using both deductive codes derived from theoretical frameworks and inductive codes emerging from data; (c) categorization of codes into potential themes; (d) theme review and refinement through peer debriefing; (e) theme definition and naming; and (f) integration of themes with theoretical constructs in report writing. Trustworthiness was established through multiple strategies including data source triangulation (interviews, observations, documents), investigator triangulation during coding and theme development, member checking whereby preliminary findings were validated with participants, and maintenance of detailed audit trails documenting analytical decisions. The researcher maintained reflexivity through journaling to acknowledge positionality and potential biases throughout the research process, ensuring interpretive rigor consistent with qualitative inquiry standards.

RESULTS AND DISCUSSION Results This section presents empirical research findings based on data collected through in-depth interviews, learning observations, and document analysis at several elementary schools in Grobogan District. Results presentation is structured according to research focuses and sub-focuses, connected with the policy enactment, TPACK, and computational thinking theoretical frameworks previously discussed.

General Description of Research Location and Informants This research was conducted at four public elementary schools in Grobogan District purposively selected based on criteria: (1) having begun introducing coding and/or AI learning, or (2) being at the preparation stage for coding and AI learning policy implementation. The four schools are designated with codes SD-A, SD-B, SD-C, and SD-D, each representing combinations of sub-district center areas and peripheral areas with limited facilities. Research informants consisted of teachers, principals/vice-principals, and students. Informant details are presented in Table 1.

Summary Informant	Code	Position/Role	Unit/Institution	Primary	Notes
Grade 5 and 6 teachers			SD-A, SD-B, SD-C, SD-D	Teaching	G1–G8 upper grades;
coding/AI coordinators	KS1–KS4	School principals	SD-A, SD-B, SD-C, SD-D		
School-level policy makers	S1–S12	Grade V and VI students	SD-A, SD-B, SD-C, SD-D		

Coding and/or AI learning participants Beyond interviews, researchers conducted observations of six learning sessions related to coding and/or AI utilization and analyzed policy and learning documents including School Operational Curricula (KOS), school work programs, teaching modules, and project activity reports.

Understanding and Sense-Making of Coding and AI Learning Policy Generally, teachers and principals were aware of the coding and artificial intelligence learning policy, primarily through district socialization, principal forums, and teacher WhatsApp groups. However, depth of understanding regarding policy content, implementation scope, and school-level consequences varied considerably. Some teachers made sense of this policy as an "additional innovation program" requiring accommodation amid dense teaching schedules. G1, for instance, stated: "We knew about the coding and AI program from district socialization and central materials, but honestly we're still figuring it out. What's clear is it's considered a digital literacy strengthening program, so schools are asked to start trying." (G1, SD-A) Principals tended to view this policy as both opportunity and challenge. KS2 emphasized:

"The direction is good because children must be prepared for technology. But in the field, we must consider which teachers are ready, how the equipment is, and not all parents understand why this is important." (KS2, SD-B) Regarding urgency, nearly all school-level informants acknowledged that coding abilities and AI understanding are important for students' futures. However, doubts existed concerning material depth appropriateness for elementary student characteristics and teacher readiness. This demonstrates that at the enactment level, policy is understood not merely as formal mandate but also positioned within realistic considerations of school and student capacities. From document analysis, only two schools (SD-A and SD-B) had explicitly incorporated coding and/or AI learning into their School Operational Curricula, though still in general formulations not yet elaborated into detailed learning objective structures.

Policy Implementation Strategies at School Level Implementation strategies for coding and AI learning policy at the four elementary schools in Grobogan District showed significant variation, influenced by IT infrastructure readiness, teacher training, and

adaptation to the national curriculum. Based on interviews with principals and teachers, classroom activity observations, and document analysis including lesson plans (RPP) and activity reports, at least four main enactment models emerged at the school level. This phased implementation emphasizes computational thinking development through plugged (with computers or digital devices) and unplugged (without devices, using physical activities and games) approaches, considering IT device limitations at most schools in this region—such as limited laptop access and unstable internet networks (Kong & Lai, 2021; Rich et al., 2024).

Table 2. Implementation Strategy Variations Across Schools School Primary

Implementation Form	Brief Description
SD-A	Integration into project-based learning + plugged coding club Coding introduced through thematic projects with Scratch for simple animations; extracurricular club uses available devices for plugged coding, training basic algorithms and loops
SD-B	Hybrid unplugged-plugged project-based co-curricular activities AI introduced through manual information search tasks (unplugged: sorting data with cards) and experiments with simple generative AI applications (plugged: alternating on limited school devices); teachers provide close guidance for AI ethics
SD-C	Unplugged coding concept integration into Science/Mathematics Using unplugged activities like "Human Robot" game (students move following algorithm instructions) and pattern puzzles with recycled materials; weekly regular meetings despite device limitations, training pattern recognition and debugging without computers
SD-D	Basic unplugged introduction through socialization and demos Not yet fully routine due to infrastructure limitations; focus on unplugged demos like "Think Like a Programmer" (arranging story sequences with cards) and AI ethics discussions; planned collaboration with local communities for future device access

At SD-A, which was relatively more infrastructure-ready with district support, the principal assigned one ICT-background teacher to develop a plugged coding club. This teacher utilized the Scratch platform for project-based learning, where grade 5–6 students created environmental animation programs. KS1 explained: "We started with plugged coding in the club, but integrated it into project-based lesson plans. Children are excited making simple animations, although devices are limited—we rotate groups. This trains them to think logically from early age." (KS1, SD-A, interview September 2025) This approach reflects implementation in schools where plugged coding supports digital creativity, aided by available computing devices from government programs. At SD-B, implementation was more flexible with hybrid unplugged-plugged approaches emphasizing project-based learning for AI introduction. Students compared manual information searches (unplugged: sorting data with whiteboards) and AI assistance (plugged: alternating on

limited school devices). Teachers ensured guidance to avoid dependency, consistent with recommendations emphasizing technology ethics and collaborative learning (Hsu et al., 2018). Conversely, at SD-C and SD-D, implementation relied more heavily on unplugged coding due to device limitations—only 1–2 computers per school with frequently disrupted networks, similar to challenges in rural areas. At SD-C, coding concepts were integrated into Science/Mathematics with regular activities like "Daily Algorithm" (unplugged: students arrange science experiment steps with sequence cards), fulfilling curriculum requirements without computer dependency. G6 revealed: "We use unplugged entirely, like loop games

with relay balls to teach repetition. Weekly routine, though the challenge is outdoor weather—but children are more active and understand computational thinking without gadgets." (G6, SD-C, observation October 2025) Meanwhile, at SD-D, initial socialization focused on unplugged demos for grade 6, such as ethical AI simulation through role-playing (students discuss "robot decisions" in simple scenarios), with planned evaluations for transition to plugged approaches if district support increases. Classroom Coding and AI Learning Practices (TPACK and Learning) From six observed learning sessions, variations in teacher TPACK readiness were evident. At SD-A and SD-B, coordinating teachers tended to possess better technological knowledge and took initiative in designing activities involving students actively. For instance, in one SD-A session, the teacher invited students to arrange flow steps to move characters on block coding applications, then asked students to discuss why their programs worked or failed. This demonstrates emerging integration of technological knowledge (TK), pedagogical knowledge (PK), and content knowledge (CK) as described in the TPACK framework (Koehler & Mishra, 2009). However, the development of Intelligent-TPACK competencies, which include AI-specific knowledge and ethical considerations, remained at early stages (Celik et al., 2023; Radloff et al., 2025). At SD-C and SD-D, teachers relied more on unplugged approaches, showing strong pedagogical knowledge but limited technological integration. Teachers demonstrated creativity in adapting computational thinking concepts through physical activities and games, aligning with research on unplugged computational thinking approaches (Trakosas et al., 2023). This illustrates that the technology dimension (TK) is emerging but not yet fully supported by specific pedagogical strength for coding and AI learning. Teachers require sustained professional development to develop comprehensive TPACK competencies for effective AI and coding integration (Yadav et al., 2014; Martinez-Maldonado et al., 2020). Computational Thinking Development and Student Experience From the student perspective, coding and AI learning was generally perceived as "new" and "interesting" activities, though not without difficulty. Some students expressed enjoyment because they could "move characters themselves" or "create animations," though requiring time to understand the steps. S1 stated: "When I first did coding, I was confused. Gradually it became exciting because if the blocks are wrong, the results are also weird. So you have to try several times." (S1, SD-A) Researcher observations across several sessions showed that: (1) students frequently engaged in trial-and-error activities; (2) they discussed with peers to find errors in block sequences; and (3) some students began simply explaining why certain commands needed placement at the beginning or end. This situation indicates emergent computational thinking elements, particularly in problem decomposition, error pattern recognition, and systematic step arrangement, though not yet explicitly narrated by teachers using CT terminology. These findings align with research on computational thinking development in elementary students through hands-on programming activities (Brennan & Resnick, 2012; Shute et al., 2017). In the AI introduction context, some SD-B students mentioned being "helped" when using AI applications for information or idea searches, though teachers explained they must still examine and evaluate answer appropriateness. S5 conveyed:

"When using AI, answers come out quickly, but the teacher said we must read again and adjust so we don't just copy." (S5, SD-B) This demonstrates early efforts to cultivate critical

attitudes toward AI outputs, though not yet systematic. Such approaches are crucial for developing AI literacy and ethical understanding among young learners (Weintrop et al., 2016).

Discussion This study examined how elementary schools in Grobogan District enact coding and artificial intelligence learning policy, revealing critical insights into the complex dynamics between policy aspirations and classroom realities in resource-constrained contexts. The primary finding demonstrates that policy enactment proceeds neither as linear implementation nor uniform adoption, but rather as differentiated, contextually-mediated processes shaped by school leadership, teacher agency, and material conditions. Four distinct implementation models emerged across participating schools, ranging from integrated project-based plugged coding to introductory unplugged demonstrations, each representing unique adaptations to local constraints while maintaining alignment with national policy objectives. These findings substantively address the research questions by illuminating how teachers and principals interpret policy urgency, what contextual factors enable or constrain implementation, how schools develop adaptation strategies, and how students experience emergent computational thinking development. The differentiated implementation patterns observed align compellingly with Ball, Maguire, and Braun's (2012) policy enactment framework, which conceptualizes policy as enacted rather than merely implemented through processes of interpretation, translation, and creative adaptation by local actors. Schools in this study did not passively receive the coding and AI learning policy as a prescriptive mandate but actively negotiated its meaning within their specific situated contexts, professional cultures, and material conditions. This finding resonates with recent empirical work demonstrating that policy enactment in schools involves navigating tensions between structural constraints and professional agency (Braun et al., 2011; Cushing, 2021). Specifically, the presence of "champion" teachers and innovation-supporting leadership emerged as pivotal contextual factors, consistent with research on principal sensemaking in policy enactment (Spillane et al., 2002). Schools with principals who positioned coding and AI learning as strategic priorities allocated resources differently, designated coordinating teachers, and created enabling conditions for experimentation, while schools lacking such leadership remained at nascent implementation stages. This contextual dependency confirms Ball et al.'s (2012) assertion that material contexts, professional cultures, and external pressures interact dynamically to shape enactment trajectories. However, this study extends existing literature by demonstrating how such enactment processes operate specifically within elementary coding and AI education in developing country contexts, where infrastructure limitations and teacher capacity constraints are more pronounced than in the high-income country settings where Ball's framework was originally developed. The uneven development of teachers' TPACK competencies represents a second critical finding with significant theoretical implications. Analysis revealed that while pedagogical knowledge (PK) remained relatively strong among participating teachers, technological knowledge (TK) and its integration with content and pedagogy exhibited considerable variation. Teachers at SD-A and SD-B demonstrated emergent TPACK integration through activities combining coding content, active pedagogical strategies, and functional technology use, whereas teachers at SD-C and SD-D relied predominantly on strong pedagogical approaches with minimal technology

integration. This pattern corroborates international research documenting TK as teachers' primary constraint in technology integration (Jiménez Sierra et al., 2023; Valle et al., 2024). However, findings reveal an additional layer of complexity: even among teachers with adequate TK for general technology use, AI-specific competencies remained underdeveloped, supporting recent calls for extending TPACK to Intelligent-TPACK frameworks that incorporate AI literacy, ethical knowledge, and human-AI collaboration

competencies (Celik et al., 2023; Kohnke et al., 2025; Ning et al., 2024; Radloff et al., 2025). The Intelligent-TPACK framework's emphasis on AI-TK (understanding AI tool autonomy), AI-CK (validating AI-generated content), Ethic-K (addressing algorithmic risks), and HAIC-K (structuring human-AI collaboration) provides conceptual grounding for understanding why teachers in this study struggled not merely with coding pedagogy but with fundamental questions about AI integration appropriateness, ethical considerations, and validation of AI outputs. This finding challenges traditional teacher professional development models emphasizing technical training on application usage, suggesting instead that comprehensive TPACK development requires sustained, job-embedded professional learning targeting synergistic domain integration (Kohnke et al., 2025). Interestingly, the study documented successful unplugged coding implementation at SD-C and SD-D despite severe infrastructure constraints, demonstrating that computational thinking development does not require extensive technological resources when supported by pedagogically sound approaches. Teachers designed activities such as "Human Robot" games, algorithm card sequencing, and pattern recognition puzzles that fostered foundational CT concepts including decomposition, pattern recognition, and algorithmic thinking. These findings align with research on unplugged computational thinking approaches demonstrating their effectiveness in developing CT concepts without digital devices (Trakosas et al., 2023) and extend recent evidence that unplugged methods can be particularly suitable for resource-constrained contexts while maintaining pedagogical integrity (Kong & Lai, 2021). However, this study also revealed tensions between unplugged and plugged approaches, with some teachers expressing concern that prolonged reliance on unplugged methods might create gaps in students' practical coding skills and technological fluency. This tension suggests that while unplugged approaches offer valuable entry points, sustainable implementation requires transitional pathways enabling progression toward technology-integrated learning as resources become available. From the student perspective, findings indicate emergent computational thinking development despite nascent implementation stages, evidenced through trial-and-error problem-solving, collaborative debugging, and systematic command sequencing. Students demonstrated what Brennan and Resnick (2012) characterize as foundational CT practices: experimenting and iterating, testing and debugging, and abstracting and modularizing. Observational data revealed students engaging in decomposition when breaking complex animation tasks into sequential steps, pattern recognition when identifying repeating command sequences, and algorithm design when planning character movements. These findings corroborate research documenting that CT development can begin at elementary levels through contextual, hands-on activities (Shute et al., 2017; Zhang & Nouri, 2019) and extend recent work demonstrating CT skill development through block-based programming environments (Chen et al., 2023; Chen & Chung, 2024). However, an important nuance emerged: while students exhibited CT

behaviors, they rarely articulated CT concepts explicitly using appropriate terminology, suggesting that implicit skill development requires complementary explicit instruction to develop metacognitive awareness of CT processes. This finding has implications for assessment approaches, as recent literature emphasizes the importance of multi-method CT assessment combining behavioral observation, artifact analysis, and verbal articulation to capture the full spectrum of CT competencies (Del Olmo-Muñoz et al., 2025; Rao & Bhagat, 2024). The study also revealed both anticipated and unexpected barriers to implementation. Anticipated barriers included limited IT infrastructure, inadequate teacher training, and time constraints within already dense curricula, consistent with international literature on technology integration challenges in developing country contexts (UNESCO, 2023; Santos et al., 2018). However, unexpected barriers emerged around parental understanding and support, with some teachers noting that parents questioned the appropriateness of coding and AI learning for young children or expressed concerns about screen time exposure. This finding extends existing research by highlighting how policy enactment in elementary contexts must account not only for school-level factors but also for broader community perceptions and family engagement. Additionally, ethical concerns emerged more

prominently than anticipated, with teachers at SD-B deliberately designing activities emphasizing critical evaluation of AI outputs and discussing scenarios involving algorithmic decision-making. These practices suggest growing awareness of AI ethics importance, though systematic frameworks for elementary-level AI ethics education remain underdeveloped in current policy guidance. The local adaptation strategies schools developed represent a particularly significant finding, demonstrating teacher agency and professional creativity despite constraints. Schools initiated small-scale pilot projects, integrated coding into existing thematic units to minimize curricular disruption, leveraged informal teacher collaboration networks for resource sharing, and combined unplugged and plugged approaches based on device availability. These adaptive practices exemplify what Braun and Maguire (2020) characterize as "doing without believing"—enacting policies pragmatically while maintaining professional skepticism about their feasibility. However, findings also suggest more optimistic interpretations: teachers' creative adaptations demonstrate professional commitment to providing students with learning opportunities even when ideal conditions are absent. This resonates with Mason and Rich's (2019) documentation of elementary teachers' resourcefulness in developing CT pedagogies despite limited preparation. Yet, reliance on individual teacher initiative creates sustainability risks, as implementation quality becomes dependent on particular "champion" teachers whose departure could cause program collapse. This underscores the necessity of systemic support structures rather than depending solely on teacher voluntarism. This study contributes theoretically by demonstrating the explanatory power of integrating policy enactment, TPACK, and computational thinking frameworks for analyzing educational technology policy implementation. The synthesis reveals that successful enactment requires alignment across multiple levels: policy must be interpretable and adaptable (policy enactment), teachers must possess integrated knowledge domains (TPACK/Intelligent-TPACK), and learning designs must authentically engage students in CT practices. This multi-level framework offers analytical leverage for examining implementation dynamics beyond single-theory approaches, suggesting productive directions

for future research on educational innovation adoption in complex systems. Findings generate several actionable recommendations for policy refinement and implementation support. First, teacher professional development must shift from isolated technical training toward sustained, collaborative TPACK development emphasizing pedagogical integration and ethical considerations. Second, district-level support systems should facilitate teacher learning communities enabling practice sharing and collaborative problem-solving. Third, policy guidance should explicitly legitimize diverse implementation pathways including unplugged approaches while providing transitional frameworks for infrastructure development. Fourth, implementation timelines should acknowledge the incremental nature of enactment, avoiding unrealistic expectations for rapid uniform adoption. This study's scope presents several limitations. The four-school sample, while enabling in-depth case analysis, limits generalizability to broader populations. The cross-sectional design captured implementation at single timepoints, potentially missing developmental trajectories. Reliance on self-reported data from interviews introduces potential social desirability bias, though triangulation with observations and documents provided corroboration. Additionally, the study's six-month duration precluded assessment of long-term CT development or implementation sustainability. This research demonstrates that coding and AI education policy enactment in elementary schools represents a complex sociotechnical process mediated by contextual factors, teacher capacities, and local adaptation strategies. The value of these findings lies in illuminating the gap between policy aspirations and implementation realities while documenting how schools navigate this gap through creative adaptation. By revealing both constraints and possibilities, this study provides empirical grounding for more realistic, context-sensitive policy design and support systems essential for equitable technology integration in diverse educational settings.

CONCLUSION

This study examined coding and artificial intelligence education policy enactment in elementary schools within Grobogan District, Indonesia, revealing that implementation proceeds as differentiated, contextually-mediated processes rather than uniform adoption. Four distinct implementation models emerged—integrated project-based plugged coding, hybrid unplugged-plugged activities, unplugged concept integration, and introductory demonstrations—each representing creative adaptations to local constraints while maintaining policy alignment. Findings demonstrate that successful enactment depends critically on school leadership, teacher agency, and the presence of "champion" teachers rather than solely on infrastructure availability or regulatory mandates. The study contributes theoretically by integrating policy enactment, TPACK, and computational thinking frameworks to analyze educational technology policy implementation, demonstrating that successful adoption requires alignment across policy interpretability, teacher knowledge integration, and authentic student engagement in CT practices. Empirically, the research addresses significant knowledge gaps regarding AI education policy enactment in developing country contexts, providing evidence that unplugged approaches can foster computational thinking development despite severe resource constraints while highlighting tensions between pragmatic adaptation and comprehensive implementation. Practically, findings suggest that policy refinement should legitimize diverse implementation pathways, teacher professional development must

shift toward sustained TPACK integration emphasizing ethical dimensions, and district-level support systems should facilitate collaborative practice-sharing networks. However, the study's four-school sample and cross-sectional design limit generalizability and preclude longitudinal analysis of CT development trajectories. Future research should employ longitudinal designs tracking implementation evolution over extended periods, conduct comparative analyses across districts with varying resource contexts, investigate student CT development using multi-method assessments, and examine how Intelligent-TPACK competencies can be systematically developed through pre-service and in-service teacher education. Such research will provide essential evidence for designing equitable, sustainable coding and AI education policies responsive to diverse educational contexts.

ACKNOWLEDGMENT The authors express gratitude to the Education Office of Grobogan District, school principals, teachers, and students who participated in this research. Appreciation is also extended to Universitas PGRI Semarang for supporting this study.

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