

Article

Integrating Computational Thinking into K-12 Artificial Intelligence Education

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Abstract

Amid the rapid advancement of artificial intelligence (AI) and the digital transformation of schooling, computational thinking has become a foundational competency for K-12 learners and an organizing principle for AI education. Existing research suggests that students need not only programming knowledge, but also the ability to analyze problems, reason with data and models, and evaluate intelligent systems responsibly. However, current K-12 AI education often remains fragmented, with insufficient curriculum progression, tool-oriented instruction, uneven teacher preparation, and limited attention to learning processes, transfer, and ethical AI use. As a conceptual and integrative framework article, this paper synthesizes policy guidance and recent instructional research on integrating computational thinking into K-12 AI education. Building on prior Chinese scholarly discussion of Computational Thinking 2.0, we adopt and extend this perspective to connect rule-based algorithmic reasoning with data- and model-centered AI problem solving. We propose a teacher–student–AI collaborative framework and a multi-level pathway covering tiered curriculum design, blended human–AI teaching, scaffolded project-based learning, AI agent-supported feedback, teacher development, and process-oriented, transfer-sensitive, and ethics-aware assessment. We argue that AI education should move beyond tool demonstration and code production toward authentic problem solving, model understanding, responsible human–AI collaboration, and reflective innovation. The framework offers guidance for cultivating students’ computational thinking, AI literacy, and creative problem-solving capacity, while identifying directions for empirical validation.

Keywords: computational thinking; K-12 artificial intelligence education; Computational Thinking 2.0; project-based learning; human–AI collaboration; generative AI; AI agents; process-oriented assessment



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1. Introduction

1.1. Policy-Driven: Dual Guidance from National Strategy and Curriculum Standards

Scholars have described the contemporary socioeconomic landscape as increasingly shaped by intelligent technological transformation, digitalization, and innovation-driven development (Popkova & Gulzat, 2019; Stone et al., 2022). In this context, knowledge- and innovation-based assets have become increasingly important factors of production, while science and technology, education, AI research and development, and intellectual property protection have assumed growing strategic significance (Taj & Zaman, 2022). Existing research on computational thinking further shows that learners need structured opportunities to develop abstraction, decomposition, algorithmic reasoning, debugging,

and system-level problem-solving capacities from the school years onward (Wing, 2006; Grover & Pea, 2013; Brennan & Resnick, 2012). Although early national AI strategies were often led by developed countries and concentrated on scientific research, education, and talent cultivation, developing countries are also increasingly prioritizing AI strategic planning (Demaidi, 2025). As a core driver of the new technological revolution and industrial transformation, AI has been incorporated into China's national development strategy. Educational institutions therefore play a central role in shaping national and regional AI strategies and in cultivating the AI talent and professional capacity required for national development (Knox, 2020).

The Compulsory Education Information Technology Curriculum Standards (2022 Edition), issued by the Ministry of Education, identify computational thinking as a key component of core disciplinary competencies and advocate innovative pedagogical approaches, such as project-based learning (PBL), to foster this competency (Ministry of Education of the People's Republic of China, 2022). In 2024, the General Office of the Ministry of Education released the Notice on Strengthening AI Education in Primary and Secondary Schools, which sets the goal of broadly integrating AI education across primary and secondary schools by 2030 (Ministry of Education of the People's Republic of China, 2024). Local governments, including Guangdong Province, have also introduced AI literacy frameworks and curriculum guidelines for K-12 education, establishing implementation models such as the "AI Education 211" framework to support the systematic implementation of AI education. At the higher education level, Chan (2023) examined the conceptual and practical implications of generative AI and proposed an AI education policy framework that emphasizes the use of AI to enhance teaching and learning outcomes.

Together, these policy documents and the existing body of research provide a coherent policy and conceptual foundation for AI education in primary and secondary schools, positioning the cultivation of computational thinking as a critical objective of K-12 education.

1.2. The Era of Intelligence: New Demands for Talent Literacy

AI has become increasingly pervasive in fields such as healthcare, transportation, and education, profoundly reshaping how people live and work (Stone et al., 2022). In future societies, the core competencies required of learners and future professionals will extend beyond knowledge retention to include the ability to analyze complex problems, represent them computationally, and develop reasoned solutions through computational thinking (Susanti & Taufik, 2021; Shahzad et al., 2025). As a mindset that applies fundamental concepts of computer science to problem solving and system design, computational thinking—with its core components of abstraction, decomposition, modeling, algorithmic reasoning, and optimization—has become essential for students to adapt to an increasingly intelligent society and engage in lifelong learning (Asmara, 2020; Araya et al., 2020). Primary and secondary education represents a critical stage of cognitive development. Implementing AI education grounded in computational thinking not only equips students with foundational AI knowledge and skills but also cultivates a systematic problem-solving mindset, thereby preparing them to become innovative and responsible problem solvers in the future (Asrifan et al., 2025; Shahzad et al., 2025).

Beyond these cognitive demands, a society increasingly shaped by intelligent technologies also requires students to evaluate AI applications responsibly. As AI systems become more deeply embedded in social infrastructure, the cultivation of computational thinking should be accompanied by an understanding of AI ethics, data privacy, and algorithmic accountability. K-12 education therefore needs to cultivate responsible digital citizens who can critically assess algorithmic bias and the broader social consequences of intelligent technologies, thereby aligning technical proficiency with ethical responsibility.

In the era of generative AI, the educational importance of computational thinking becomes even more pronounced. While AI systems can rapidly generate code and produce outputs that appear complete, these outputs are probabilistic, context-sensitive, and at times unreliable. By contrast, traditional programming instruction cultivates a deterministic mode of reasoning grounded in explicit rules, precise logic, and verifiable procedures. Through coding, debugging, and algorithmic analysis, students gradually develop accurate mental models of how computational systems operate. These mental models enable them not only to use AI tools effectively, but also to evaluate, revise, and critically manage AI-generated outputs. Therefore, integrating computational thinking into K-12 AI education is essential for preparing students to become critical users and responsible designers of intelligent systems, rather than passive recipients of AI-generated responses (Lan & Chen, 2024; Cress & Kimmerle, 2023; Tlili et al., 2023).

1.3. Educational Status: The Practical Imperatives of AI Education in Schools

Although AI education in Chinese primary and secondary schools has expanded rapidly in recent years, it continues to face numerous practical challenges. In some schools, AI curricula tend to emphasize knowledge acquisition over the development of core competencies, while instructional content often remains disconnected from students' everyday experiences, making it difficult to sustain their interest and engagement. Furthermore, disparities in educational resources across regions and insufficient teacher expertise mean that AI instruction in many schools remains limited to theoretical explanation or superficial activities, and therefore does not adequately support the cultivation of students' computational thinking (Song et al., 2023). Accordingly, exploring a computational thinking-based approach to AI education has become an urgent task for addressing these instructional shortcomings and improving the overall quality of school-based AI education.

At the lower secondary level, these challenges often take the form of several specific instructional bottlenecks. First, classroom teaching may overemphasize the operation of software tools and the mastery of programming syntax while paying insufficient attention to students' reasoning processes and the development of computational thinking. Second, theoretical knowledge is not always effectively connected with authentic real-world contexts, which weakens students' ability to transfer what they have learned to new problems. Third, students frequently encounter difficulties when transitioning from block-based programming to text-based programming, as learning demands shift from reliance on immediate visual feedback to the need for advance logical planning and abstract code construction. These problems indicate that K-12 AI education requires not only richer technological resources, but also more adaptive instructional support capable of guiding students from procedural task execution toward deeper conceptual and computational thinking.

Accordingly, we pursue three interrelated objectives: (1) to clarify how computational thinking should be reconceptualized in AI-rich contexts through a Computational Thinking 2.0 perspective; (2) to construct a teacher–student–AI collaborative framework for K-12 AI education; and (3) to derive a multi-level implementation pathway covering curriculum, pedagogy, teacher development, and assessment. These objectives provide the argumentative thread that connects the conceptual review, framework construction, and practical recommendations developed below.

These objectives also delimit the scope and context of application. The framework is grounded primarily in the Chinese primary and secondary school context because much of the policy evidence and several instructional examples come from national and local Chinese AI education initiatives. At the same time, we formulate the framework at the level of transferable design principles rather than as a prescriptive national curriculum.

Its broader applicability to other K-12 systems depends on several structural conditions: curriculum flexibility, equitable digital infrastructure, teacher professional development, access to age-appropriate AI tools and datasets, and governance mechanisms for privacy, ethics, and responsible AI use. The manuscript is therefore organized as a conceptual framework article: it first clarifies the policy and scholarly background, then explains the methodological approach used for framework construction, and finally develops a coherent curriculum–pedagogy–teacher development–assessment pathway.

2. Methodological Approach

2.1. Article Type and Research Orientation

We designed this article as a conceptual and integrative framework study. Rather than reporting intervention data or claiming to provide a systematic review, we synthesize policy guidance, recent pedagogical research, and emerging scholarship on human–AI collaboration to develop a theoretically grounded basis for integrating computational thinking into K-12 artificial intelligence education. We clarify the conceptual extension from traditional computational thinking to Computational Thinking 2.0, integrate previously dispersed strands of scholarship, and derive an implementation pathway that can inform future empirical research, curriculum design, and educational practice.

2.2. Analytical Procedure

The framework was developed through purposive conceptual sampling and integrative synthesis. We consulted international and Chinese databases and scholarly indexes, including Web of Science, Scopus, ERIC, Google Scholar, and CNKI, together with official policy sources from ministries of education and international organizations. Searches were conducted around combinations of terms such as ‘computational thinking’, ‘K-12 AI education’, ‘AI literacy’, ‘generative AI in education’, ‘project-based learning’, ‘human-AI collaboration’, ‘AI agents’, ‘teacher professional development’, and ‘process-oriented assessment’. The main time range was 2017–2026 in order to capture the rapid development of AI education after the expansion of machine-learning and generative-AI applications, while foundational computational thinking literature published before 2017 was retained when it was theoretically necessary. Sources were included when they (a) addressed K-12, primary/secondary, or transferable school-level AI education; (b) discussed computational thinking, AI literacy, human–AI collaboration, teacher development, or assessment; (c) provided empirical findings, conceptual frameworks, or authoritative policy guidance; and (d) were accessible in English or Chinese. Sources were excluded when they focused only on technical AI algorithms without educational implications, concerned higher education or workforce training without transferability to K-12, provided insufficient methodological or conceptual detail, or duplicated evidence already represented by more relevant sources. Chinese-language sources were retained when they were directly relevant to the contextual grounding of the article; their titles are translated into English and marked as Chinese-language sources in the reference list. We then analyzed the selected sources in three steps: first, we identified recurrent challenges in K-12 AI education, including curriculum fragmentation, tool-oriented pedagogy, uneven teacher preparation, and insufficient attention to process-oriented and ethics-aware assessment; second, we synthesized the literature around the extension of traditional computational thinking toward Computational Thinking 2.0, the reconfiguration of pedagogical roles in human–AI collaborative learning, and the need for coherent curriculum–pedagogy–assessment alignment; third, we integrated these strands into a teacher–student–AI collaborative framework and a multi-level implementation pathway linking curriculum design, instructional innovation,

teacher development, and assessment reform. The methodological logic of the article is therefore interpretive and framework-building rather than experimental or meta-analytic.

2.3. Scope and Delimitation

Our analysis focuses on general AI education in K-12 settings. Because the policy foundation and several classroom examples are drawn primarily from the Chinese educational context, the framework should first be read as a context-sensitive conceptual proposal for Chinese primary and secondary schools. Nevertheless, the framework is also intended to be useful to international readers as a transferable reference for curriculum development and pedagogical design, provided that local educational structures, curricular autonomy, teacher capacity, infrastructure, and ethical governance arrangements are taken into account. The article does not attempt to prescribe a single national curriculum, evaluate a specific software platform, or generalize from a particular classroom sample. It should therefore be understood as a theoretical and analytical contribution that requires further empirical validation through classroom interventions, design-based research, longitudinal studies, and comparative research across school stages, resource contexts, and educational systems.

3. Literature Review

Several countries, regions, and international organizations have taken early steps to connect AI education with computational thinking and AI literacy. For example, China has embedded computational thinking in the 2022 compulsory education information technology curriculum standards and has issued national guidance for strengthening AI education in primary and secondary schools ([Ministry of Education of the People's Republic of China, 2022, 2024](#)). Singapore's Ministry of Education frames school AI use around learning about AI, learning to use AI, learning with AI, and learning beyond AI, while emphasizing age- and developmentally appropriate implementation ([Ministry of Education, Singapore, n.d.](#)). The European Commission has issued ethical guidelines on the use of AI and data in teaching and learning for educators ([European Commission, 2022](#)), and the U.S. Department of Education has published recommendations on AI and the future of teaching and learning ([U.S. Department of Education, Office of Educational Technology, 2023](#)). At the international level, UNESCO's AI competency framework for students provides a global reference for integrating AI learning objectives, ethics, and responsible co-creation into curricula ([UNESCO, 2024](#)). These examples do not imply that K-12 systems share the same structure; rather, they indicate a growing international emphasis on stage-appropriate learning expectations, authentic learning contexts, teacher capacity, interdisciplinary integration, and responsible AI use.

Research on AI education in primary and secondary schools in China has grown rapidly in recent years, although the field remains in an exploratory phase. Current studies primarily focus on curriculum design, pedagogical innovation, and approaches to cultivating computational thinking.

- In terms of curriculum design, some schools have attempted to develop a tiered course system categorized into introductory, advanced, and honors levels to accommodate the diverse learning needs of students.
- Regarding teaching models, approaches such as PBL, problem-based learning, and blended learning have been widely applied in AI courses. For instance, projects such as line-following robots and image classification engage students in authentic tasks that promote the development of computational thinking ([Qu & Fok, 2022](#)).

Recent empirical studies further suggest that project-based AI learning supported by digital platforms can improve both learning outcomes and the development of com-

putational thinking. For example, a quasi-experimental study based on a handwritten digit recognition project found that a UMU-supported PBL model significantly enhanced students' knowledge retention and yielded stronger learning outcomes than traditional instruction across five dimensions of computational thinking: decomposition, abstraction, modeling, algorithm design, and evaluation. However, the added benefits of the digital platform relative to PBL without platform support were primarily observed in the dimension of decomposition, while gains in higher-order dimensions such as abstraction, modeling, and algorithm design were not consistently significant. Moreover, differences in transfer performance across groups were not statistically significant. These findings indicate that digital platforms can provide valuable scaffolding, but the cultivation of advanced computational thinking and learning transfer still depends on carefully designed tasks, reflective activities, and high-quality pedagogical support (Wang, 2025).

Regarding the development of computational thinking, national policy in China positions AI education as a means to strengthen students' digital literacy, innovation capacity, and responsible technological practice (Ministry of Education of the People's Republic of China, 2024). Empirical work on computational problem-solving further suggests that cooperative learning can support students' academic performance and computational thinking skills (Celik & Bati, 2025). In AI- and STEAM-oriented school settings, project activities such as robotics, algorithm design, programming, and project optimization have also been shown to foster abstract reasoning, problem-solving skills, and collaboration (Huang & Qiao, 2024; Qu & Fok, 2022).

More recently, the emergence of data-driven and model-driven AI systems has prompted scholars to reconsider conventional understandings of computational thinking. Traditional computational thinking has typically emphasized decomposition, abstraction, pattern recognition, algorithmic design, debugging, and iterative evaluation (Wing, 2006; Brennan & Resnick, 2012; Grover & Pea, 2013). AI literacy research has extended this discussion by emphasizing that learners also need to understand what AI can do, how models learn from data, how AI systems are evaluated, and how ethical and social consequences should be considered (Long & Magerko, 2020; Touretzky et al., 2019). In Chinese scholarship, the term Computational Thinking 2.0 has been used to describe this shift from algorithm-centered problem solving toward data- and model-centered AI problem solving. Xia (2025), drawing on Zhong Baichang's proposal, explains that Computational Thinking 2.0 extends earlier computational thinking by incorporating model training and inference and by organizing AI problem solving around problem definition, data preparation, model training, deployment, and monitoring. We therefore do not claim to coin the term. Our contribution is to adopt and extend this perspective for K-12 AI education by integrating it with AI literacy, teacher-student-AI collaboration, curriculum design, pedagogy, teacher development, and assessment reform. Table 1 summarizes the key distinctions between Computational Thinking 1.0 and the Computational Thinking 2.0 perspective used in this article.

As shown in Table 1, Computational Thinking 2.0 is not introduced here as a newly coined term; rather, it is used as a conceptual lens for extending traditional computational thinking into AI-rich learning contexts. It retains core computational thinking processes such as abstraction, decomposition, and algorithmic reasoning, while expanding them to include AI-solvable problem formulation, data preparation, model training, inference, deployment, monitoring, and ethical evaluation. This distinction is particularly relevant to the present article because the integration of computational thinking into K-12 AI education should not be limited to programming logic or algorithm design. It should also encompass students' ability to identify problems amenable to AI-based solutions, collect and interpret

data, understand model training and inference, evaluate AI applications in authentic contexts, and reflect on the social consequences of intelligent systems.

Table 1. Comparison between Computational Thinking 1.0 and Computational Thinking 2.0 in AI Education.

Dimension	Computational Thinking 1.0	Computational Thinking 2.0
Suitable Problems	Problems with clear rules and precise definitions	Ambiguous, complex, and data-rich problems that are difficult to encode manually
Problem-Solving Logic	Human-designed procedures and explicit rules	Machine learning from data and model-based inference
Core Process	Decomposition → Pattern recognition → Abstraction → Algorithm design → Evaluation	Define AI-solvable problem → Prepare data → Train model → Deploy and monitor
Core Task	Algorithm design and procedural implementation	Data preparation, model training, inference, and feedback optimization
Student Learning Focus	Understanding program logic and designing step-by-step solutions	Understanding how data, models, training, evaluation, and deployment support intelligent behavior
Relevance to K-12 AI Education	Suitable for programming, robotics, and rule-based automation tasks	Suitable for machine learning, generative AI, perception systems, recommendation, and classification tasks

Note: The distinction between Computational Thinking 1.0 and Computational Thinking 2.0 is adapted and extended from prior Chinese discussions of Computational Thinking 2.0 (Xia, 2025). The present article uses this distinction as a conceptual basis for constructing the teacher–student–AI collaborative framework and the multi-level implementation pathway for K-12 AI education.

Despite the progress made in domestic research, several important limitations continue to constrain the development of computational thinking-oriented K-12 AI education. First, existing curriculum systems remain insufficiently mature; Song et al. (2023) note that AI teaching and learning resources for compulsory education in China are still developing and require stronger alignment with school needs. Second, innovation in instructional models remains limited. Lecture-based teaching still occupies a substantial proportion of classroom practice, thereby constraining the implementation of student-centered learning, while practical activities are often insufficiently connected to authentic real-world contexts. At a conceptual level, Tili et al. (2023) caution that educational chatbots require careful pedagogical design rather than uncritical adoption. Classroom-based programming studies further show that generative AI feedback and large language model support can assist code explanation and debugging, but only when students receive scaffolding that requires them to analyze, verify, and reconstruct AI-generated outputs (Gong et al., 2025; S.-J. Chen et al., 2025). In the Chinese junior high school context, Bi (2025) similarly argues that AI tools should be introduced on the basis of solid programming foundations, task decomposition, guided inquiry, and ethical instruction. Third, the shortage of qualified teachers remains a persistent challenge. Many AI courses are delivered by information technology teachers who often undertake multiple teaching and administrative duties and may lack systematic preparation in both AI content knowledge and pedagogical strategies for fostering computational thinking (Song et al., 2023). Fourth, current assessment practices rely heavily on summative assessment and pay insufficient attention to students’ developmental processes, collaborative abilities, and broader competencies cultivated during learning; this concern is consistent with recent research on computational thinking assessment (Ahn & Oh, 2024; Ukkonen et al., 2024). Finally, the existing literature remains dominated by short-term instructional interventions conducted in relatively well-resourced urban settings. Longitudinal research that examines the sustained development of students’ computa-

tional thinking is still limited, and greater attention is needed to inclusive instructional frameworks that can address the digital divide and promote more equitable access to AI education across diverse socioeconomic contexts.

Taken together, these findings suggest that current K-12 AI education requires a more integrated framework—one that redefines computational thinking for AI-rich contexts, connects progressive curriculum design with authentic problem solving, diversifies pedagogy, enhances teachers' professional capacity, and aligns assessment with the development and transfer of computational thinking. The following section addresses these gaps by proposing a coherent framework and implementation pathway for integrating computational thinking into K-12 AI education.

4. Conceptual Framework and Implementation Pathway

In this section, we develop the proposed framework from the synthesis presented above. Specifically, the framework responds to four recurrent gaps identified in the literature: insufficient conceptual differentiation between traditional programming-oriented computational thinking and AI-oriented computational thinking, weak alignment between curriculum and authentic AI problem solving, underdeveloped teacher roles in human–AI collaborative classrooms, and limited process- and transfer-oriented assessment. It therefore functions as an analytical integration of these strands rather than as a simple collection of teaching suggestions.

4.1. A Teacher–Student–AI Collaborative Framework for Integrating Computational Thinking into K-12 AI Education

Computational thinking should not be treated in K-12 AI education merely as an isolated learning objective or as a subsidiary component of programming instruction. Rather, it should function as the cognitive foundation that connects AI concepts, project-based practice, and responsible technological innovation. To advance this goal, we propose a teacher–student–AI collaborative framework for integrating computational thinking into K-12 AI education.

In this framework, teachers function as instructional designers, learning facilitators, and ethical guides. Their role extends beyond the transmission of AI knowledge to include guiding students in identifying real-world problems, decomposing complex tasks, selecting appropriate AI tools, and reflecting on the social implications of AI applications. Students serve as active problem solvers, designers, and creators. By engaging in authentic AI projects, such as image classification, speech recognition, smart device development, and data-based decision-making tasks, they cultivate abstraction, decomposition, algorithmic thinking, data reasoning, and iterative optimization skills. AI systems, in turn, act as cognitive partners that support learning diagnosis, learning resource recommendation, real-time feedback, programming assistance, model debugging, and personalized learning pathways.

As shown in Figure 1, the proposed framework integrates three interrelated dimensions: collaborative actors, instructional stages, and the development of computational thinking. Teachers, students, and AI systems together form a collaborative learning community, while the instructional process unfolds across pre-class problem analysis, in-class AI modeling, and post-class reflection. Through this process, students progressively develop competencies in decomposition, abstraction, algorithmic thinking, data reasoning, model evaluation, and iterative optimization.

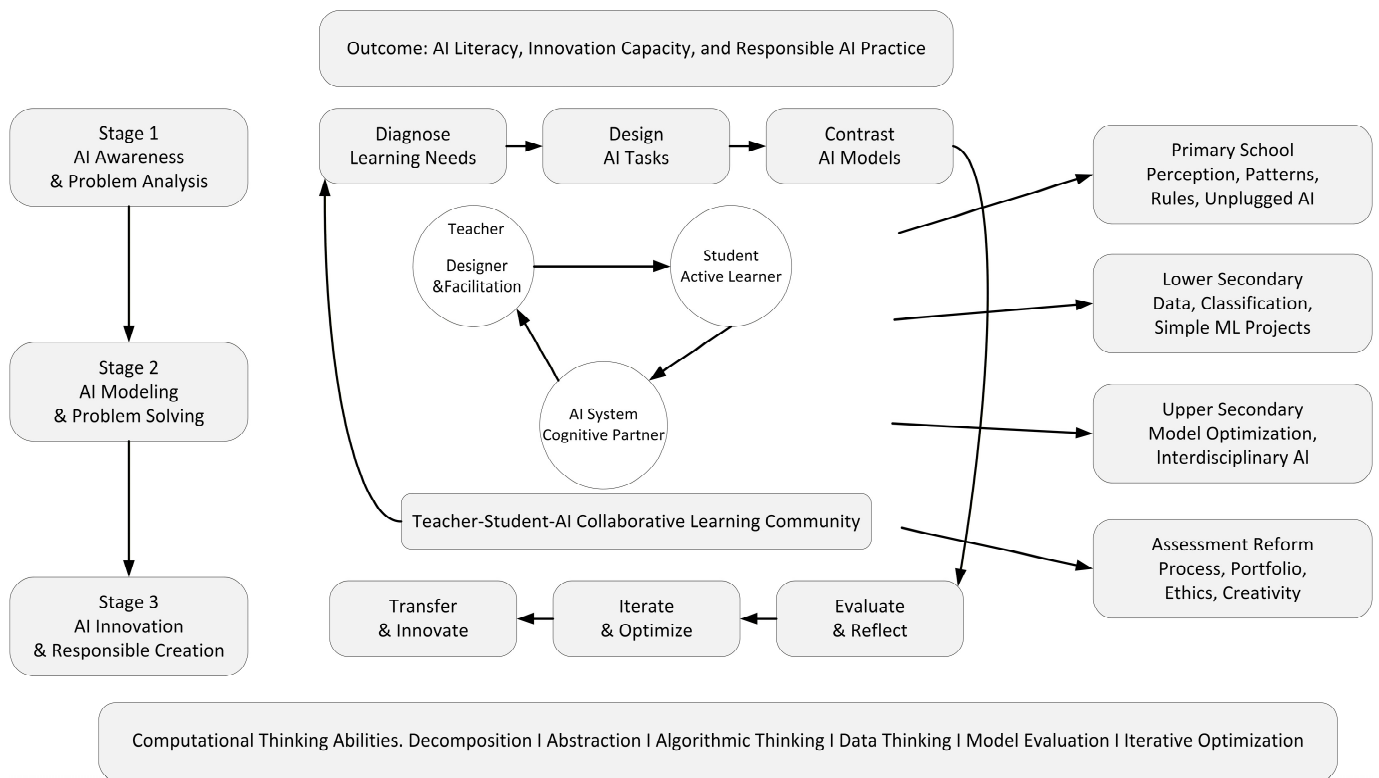


Figure 1. Framework for Integrating Computational Thinking into K-12 AI Education. Source: Authors' own work.

To further clarify the educational role of AI systems within this framework, AI systems can be framed as AI agents that operate through a closed-loop cycle of perception, decision-making, action, and optimization. Lan and Chen (2024) emphasize teachers' agency in designing pedagogical AI agents, while Yusuf et al. (2025) synthesize research on conversational AI agents as educational support systems. In the perception stage, AI agents capture multimodal learning signals, such as task logs, interaction data, coding traces, and project outputs. In the decision-making stage, they analyze students' learning difficulties, cognitive bottlenecks, and task-specific needs. In the action stage, they provide targeted support, including debugging hints, adaptive resource recommendations, project suggestions, and process-oriented feedback. In the optimization stage, they refine subsequent support strategies based on students' responses and learning outcomes. Classroom-oriented work on AI-agent-supported Python 3.9 instruction further illustrates how such systems can assist debugging and feedback while remaining subordinate to teacher guidance (H. Liu, 2025). This closed-loop agentic mechanism enables AI to function not merely as a passive tool, but as a dynamic pedagogical partner that supports the progressive development of computational thinking.

As shown in Figure 2, AI agents can provide systematic support for the development of computational thinking in K-12 AI education through a perception-decision-action-optimization loop. By collecting multimodal learning inputs, identifying students' learning needs, delivering targeted instructional support, and refining support strategies through feedback, AI agents can function as real-time debugging tutors, scenario and project generators, personalized learning coaches, interaction facilitators, and process-based assessment assistants. These functions jointly contribute to the cultivation of problem decomposition, algorithmic reasoning, data reasoning and model-based thinking, debugging and iteration, collaborative problem solving and creation, and ethical AI use. Importantly, AI agents should be positioned as pedagogical partners rather than substitutes for students' indepen-

dent reasoning, a principle consistent with scholarship on teacher agency and responsible educational AI (Lan & Chen, 2024; Ganguly et al., 2026).

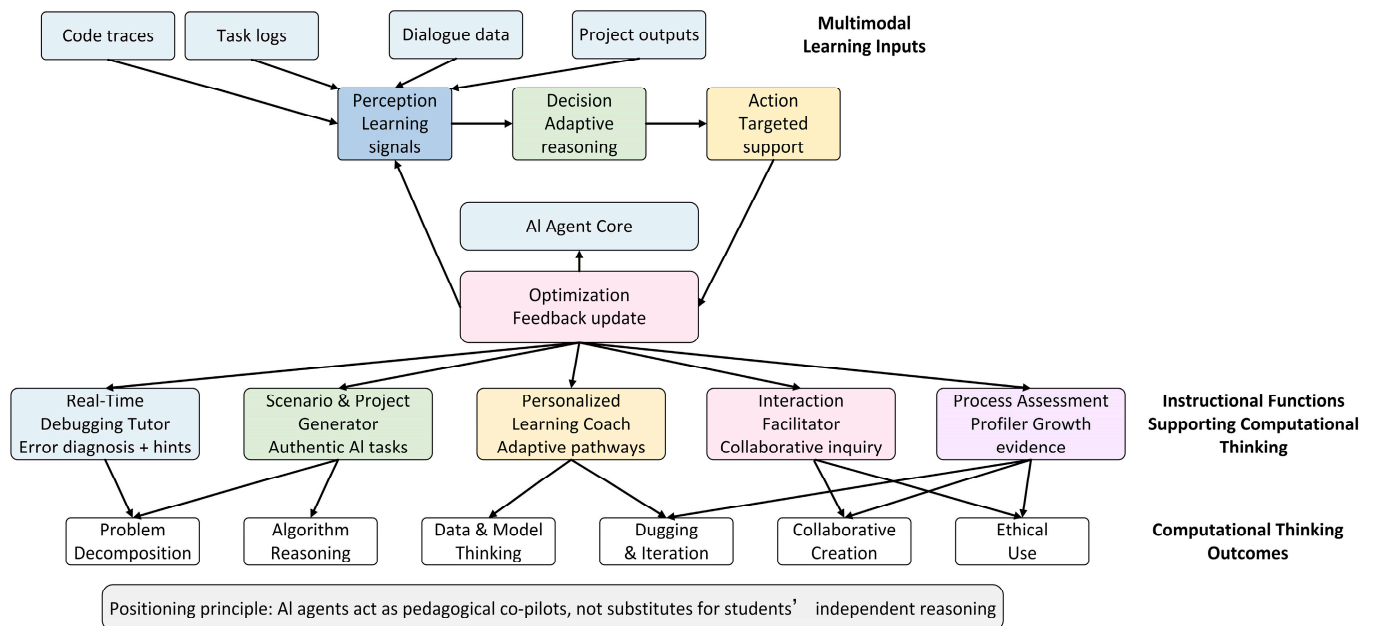


Figure 2. AI Agent-Enabled Support Framework for Computational Thinking in K-12 AI Education. Source: Authors' own work.

The proposed framework may be operationalized through a three-stage instructional pathway consisting of pre-class, in-class, and post-class learning. Before class, students engage in AI scenario exploration and problem analysis. With the support of digital learning platforms and AI tools, they define problems suitable for AI-based inquiry, clarify data requirements, and conduct preliminary task decomposition. During class, teachers organize project-based and problem-driven AI learning activities. Under teacher guidance and AI-assisted feedback, students collect data, construct models, test and refine model performance, and optimize solutions. After class, students engage in reflection, portfolio development, peer evaluation, and ethical discussion, thereby extending AI learning beyond technical implementation toward innovation and responsible application.

This collaborative framework helps shift K-12 AI education from tool-oriented instruction toward inquiry-based and data-informed learning. More importantly, it provides a coherent pathway for the development of computational thinking, progressing from foundational problem analysis, through authentic problem solving, to creative AI practice. Accordingly, the following sections elaborate on how this framework can be operationalized through curriculum design, pedagogical innovation, teacher development, and assessment reform.

4.2. Building the Curriculum System: Through Tiered Design and Interdisciplinary Integration

From a Computational Thinking 2.0 perspective, the design of K-12 AI curricula should move beyond traditional algorithm-centered programming instruction and reflect the full problem-solving logic of data- and model-driven AI. In this sense, curriculum design should align educational goals, content organization, teaching activities, and assessment mechanisms with four key AI learning processes: identifying problems amenable to AI-based solutions, preparing data, training models, and deploying, evaluating, or monitoring AI applications. This curriculum logic directly operationalizes the methodological claim of the article: the proposed framework is not an isolated pedagogical suggestion, but an integrated pathway derived from the conceptual synthesis developed above. Figure 3

presents the proposed Computational Thinking 2.0-oriented framework for general K-12 AI education.

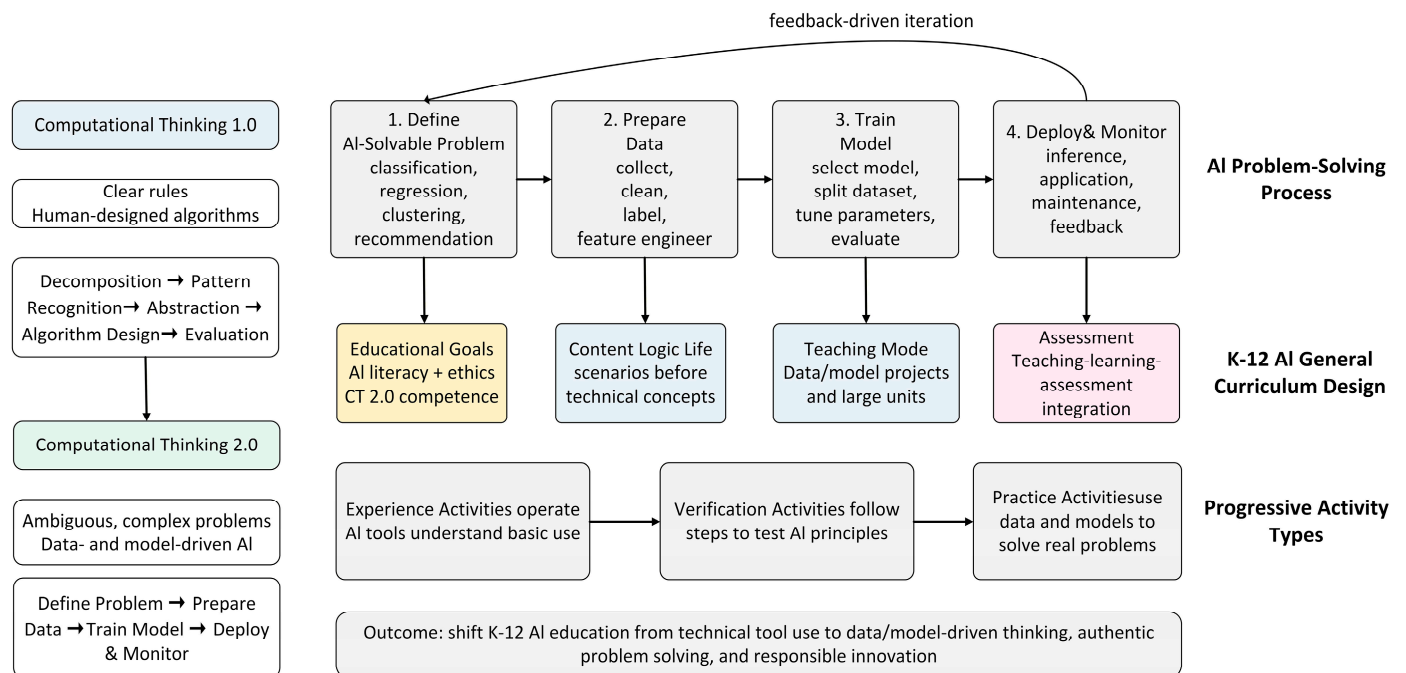


Figure 3. Computational Thinking 2.0-Oriented K-12 AI General Education Framework. Source: Authors' own work.

As shown in Figure 3, Computational Thinking 2.0 extends traditional computational thinking beyond rule-based algorithm design toward a broader AI problem-solving process centered on data, models, inference, and iterative feedback. Accordingly, K-12 AI curriculum development should not be limited to the teaching of isolated AI concepts or tools; rather, it should organize learning around authentic problem contexts, progressive activity types, and integrated teaching–learning–assessment mechanisms. This framework provides the conceptual foundation for the tiered curriculum design discussed below.

To systematically develop a tiered and interdisciplinary AI curriculum system, the curriculum can be organized into three progressive levels in accordance with students' cognitive development and differentiated learning needs: Introductory, Advanced, and Honors. The Introductory level is designed for all students and focuses on foundational AI knowledge and the initial development of computational thinking. The Advanced level emphasizes hands-on technical practice, including robotics design and construction as well as visual programming. The Honors level is intended for advanced learners and supports deeper exploration of algorithm design and system development.

Specifically, the tiered curriculum establishes a systematic alignment between AI technologies and core components of computational thinking. The Introductory tier focuses on data representation and pattern recognition through unplugged activities and block-based programming, helping students understand how AI systems represent and interpret external information. The Advanced tier advances toward algorithmic reasoning and problem decomposition by using text-based programming, such as Python, together with sensor-equipped open-source hardware to design and implement logic-based control in physical systems. The Honors tier emphasizes system abstraction and optimization, requiring students to train lightweight machine learning models and deploy them on edge-computing devices. This progression supports a continuous developmental trajectory from foundational computational understanding to more complex engineering-oriented

implementation. The detailed alignment among target learners, pedagogical focus, technological tools, and corresponding computational thinking components across these three curriculum tiers is summarized in Table 2.

Table 2. The Tiered Curriculum Framework for K-12 AI Education.

Tier Level	Target Learners	Pedagogical Focus	Technological Tools	Computational Thinking Mapping
Introductory	All students	Foundational AI knowledge and perception	Unplugged activities, block-based programming	Data representation, pattern recognition
Advanced	Intermediate learners	Algorithmic reasoning and physical system modeling	Text-based programming (e.g., Python), open-source hardware	Problem decomposition, algorithmic design
Honors	Innovative learners	System development and optimization	Lightweight machine learning models, edge-computing devices	System abstraction, solution optimization

Beyond tiered differentiation, K-12 AI curriculum design should also adopt a spiral progression that integrates computational thinking with AI literacy. Core concepts such as algorithms, data structures, rule-based reasoning, and logical control should not be confined to an isolated introductory stage; rather, they should recur across grade levels with increasing depth and be progressively connected to human–AI collaboration, intelligent application, and responsible technology use. Within this spiral structure, foundational computational principles serve as the cognitive foundation, human–AI collaboration extends these principles into emerging technological contexts, and ethical reflection ensures that students understand the social consequences of intelligent systems. Such a curriculum orientation helps prevent the fragmentation of AI education and supports sustained development from basic computational understanding to more advanced forms of responsible and adaptive AI literacy.

At the lower-grade or introductory level of K-12 AI education, curriculum design should not begin with complex text-based programming tasks. Instead, a progressive pathway should be established, moving from unplugged activities and block-based programming to Python programming and AI-assisted coding. Block-based programming can reduce syntactic barriers and enable students to focus on core computational logic, including sequencing, branching, looping, and event-driven control. After students develop a basic understanding of programming structures, AI tools can be introduced to support code explanation, debugging, and optimization. This progression helps prevent students from becoming passive users of AI-generated outputs and ensures that AI tools are used to deepen, rather than replace, computational thinking (Bi, 2025; S.-J. Chen et al., 2025; Gong et al., 2025).

In addition to tiered progression, the organization of curriculum content should follow a life-context-oriented logic rather than a purely discipline-centered organization of knowledge. Since K-12 AI education is intended for all students, rather than only those with strong technical interests, familiar real-life scenarios can make AI learning more accessible and enhance students’ motivation. For example, topics such as intelligent recommendation, facial recognition, smart traffic systems, voice assistants, and school-context data analysis can serve as entry points for introducing data collection, model inference, classification, prediction, and ethical issues. In this way, AI concepts are not

taught as fragmented technical knowledge but are embedded in meaningful contexts that support the development of computational thinking.

Building on this foundation, the curriculum should promote interdisciplinary integration by meaningfully connecting AI with subjects such as mathematics, Labor Education, science, language arts, and social studies. In mathematics, AI tools can be used to explore geometric properties and cultivate algorithmic thinking; in Labor Education, projects such as noise detectors and smart plant-watering devices enable students to apply technology in authentic problem-solving contexts, thereby strengthening their computational thinking skills (Huang & Qiao, 2024; Rulyansah & Harun, 2025). In humanities-related subjects, computational thinking can be incorporated through natural language processing applications, allowing students to use text analysis tools to examine sentiment in historical documents or train simple chatbot models to understand conversational logic, thus connecting humanistic inquiry with algorithmic reasoning. At the same time, digital learning support should be strengthened through platforms such as the National Smart Education Platform, which can be used to integrate and expand resources including virtual experiments, micro-lectures, and case studies. Small Private Online Courses (SPOCs), AI teaching assistants, and school-based resource repositories can further support personalized learning and address the diverse implementation needs of the curriculum system.

4.3. Innovation in Teaching Models: Practical Pathways with Computational Thinking at the Core

Within the implementation pathway for cultivating computational thinking, we propose an integrated instructional framework that is driven by authentic problems, structured around a coherent problem-solving process, and supported by a blended learning environment that incorporates multiple innovative teaching models. Kong et al. (2025) provide a model for examining human–AI collaboration in hybrid intelligence learning environments, while Y. Liu and Yang (2026) offer a blended programming-instruction case that illustrates how online AI support can be combined with offline project work. As shown in Figure 4, the blended human–AI collaborative teaching model is organized around three mutually reinforcing dimensions. First, the dual-track environment connects online AI learning systems with offline authentic projects, facilitating the translation of knowledge acquisition into practical competence. Second, the three-stage progression guides students from foundational learning to integrated project implementation and ultimately to innovative inquiry. Third, the six-step iterative instructional cycle operationalizes the learning process through context creation, intelligent diagnosis, dynamic grouping, human–AI collaboration, multidimensional assessment, and knowledge-graph construction. Together, these dimensions form a data-driven and iterative instructional pathway that supports abstract modeling, algorithmic design, debugging and refinement, collaborative problem solving, cross-disciplinary transfer, and reflective learning.

To clarify how the six-step iterative instructional cycle functions within blended human–AI collaborative teaching, Table 3 summarizes the pedagogical purpose, AI support role, and computational thinking competencies emphasized in each instructional phase (Y. Liu & Yang, 2026). As shown in the table, this cycle provides a structured mechanism for embedding AI support throughout the entire instructional process, thereby transforming blended learning from a simple combination of online and offline activities into a coherent pathway for the progressive development of computational thinking.

This blended logic enriches the pre-class, in-class, and post-class instructional pathway by clarifying how online AI-supported knowledge construction can be systematically integrated with the development of practical competence through offline project-based learning. To further operationalize this instructional framework, AI learning activities can be organized into a three-stage process consisting of pre-class preparation, in-class

modeling, and post-class reflection. In the pre-class stage, students explore AI application scenarios, complete guided learning tasks, and identify real-world problems that can be reformulated as computational tasks. This phase primarily supports foundational computational thinking, including problem recognition, abstraction, and decomposition. During the in-class stage, students engage in collaborative AI projects under teacher guidance and AI-assisted feedback. They collect and label data, design algorithms, train models, evaluate model outputs, and refine solutions, thereby strengthening applied computational thinking. In the post-class stage, students develop learning portfolios, reflect on model limitations, discuss ethical issues such as bias and privacy, and propose improved or extended AI solutions. This phase promotes creative and reflective computational thinking as well as responsible AI practice.

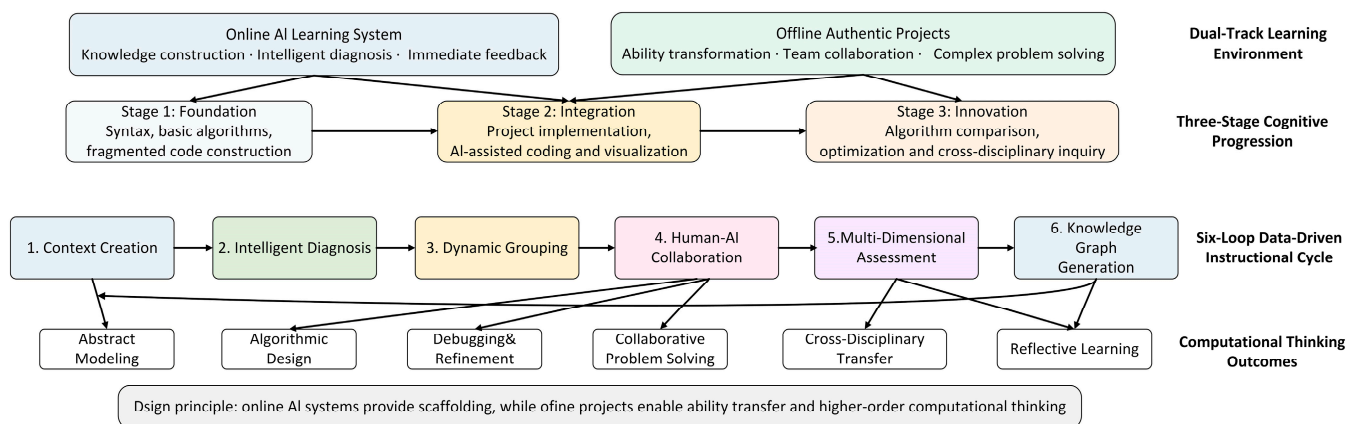


Figure 4. Blended Human–AI Collaborative Teaching Framework for Computational Thinking in K-12 AI Education. Source: Authors’ own work.

Table 3. Six-Phase Blended Human–AI Instructional Cycle for K-12 AI Education.

Instructional Phase	Main Pedagogical Purpose	Role of AI Support	Computational Thinking Emphasis
Context Creation	Introduce authentic and meaningful problems	Generate or enrich problem scenarios and learning prompts	Problem recognition and abstraction
Intelligent Diagnosis	Identify students’ prior knowledge and learning gaps	Analyze pre-tests, task responses, and behavior data	Cognitive readiness and targeted scaffolding
Dynamic Grouping	Organize differentiated collaboration	Recommend grouping strategies based on diagnostic data	Collaborative problem solving
Human–AI Collaboration	Support project implementation and iterative inquiry	Assist with algorithm logic, code generation, debugging, and optimization	Algorithmic reasoning, debugging, refinement
Multidimensional Assessment	Capture both process and product evidence	Synthesize project records, interaction logs, and evaluation data	Reflection, evaluation, and self-regulation
Knowledge Graph Generation	Visualize learning progress and guide subsequent learning	Map mastered and underdeveloped knowledge nodes	Metacognition and transfer of computational thinking

As shown in Figure 5, scenario-based AI projects offer a concrete instructional pathway for integrating computational thinking into K-12 AI education. The pathway begins with authentic real-life scenarios, such as license-plate recognition, smart traffic lights, or sports data analysis, and guides students progressively through task decomposition, visual programming, AI-assisted debugging, project optimization, and ethical reflection. In this process, block-based programming and pseudocode serve as instructional scaffolds that help students understand program logic before progressing to Python programming and AI-assisted development. Meanwhile, generative AI tools are positioned as cognitive learning partners rather than direct answer providers, requiring students to verify, annotate, reconstruct, and improve AI-generated outputs. This design supports the development of abstraction, decomposition, algorithmic reasoning, debugging, and responsible AI practice.

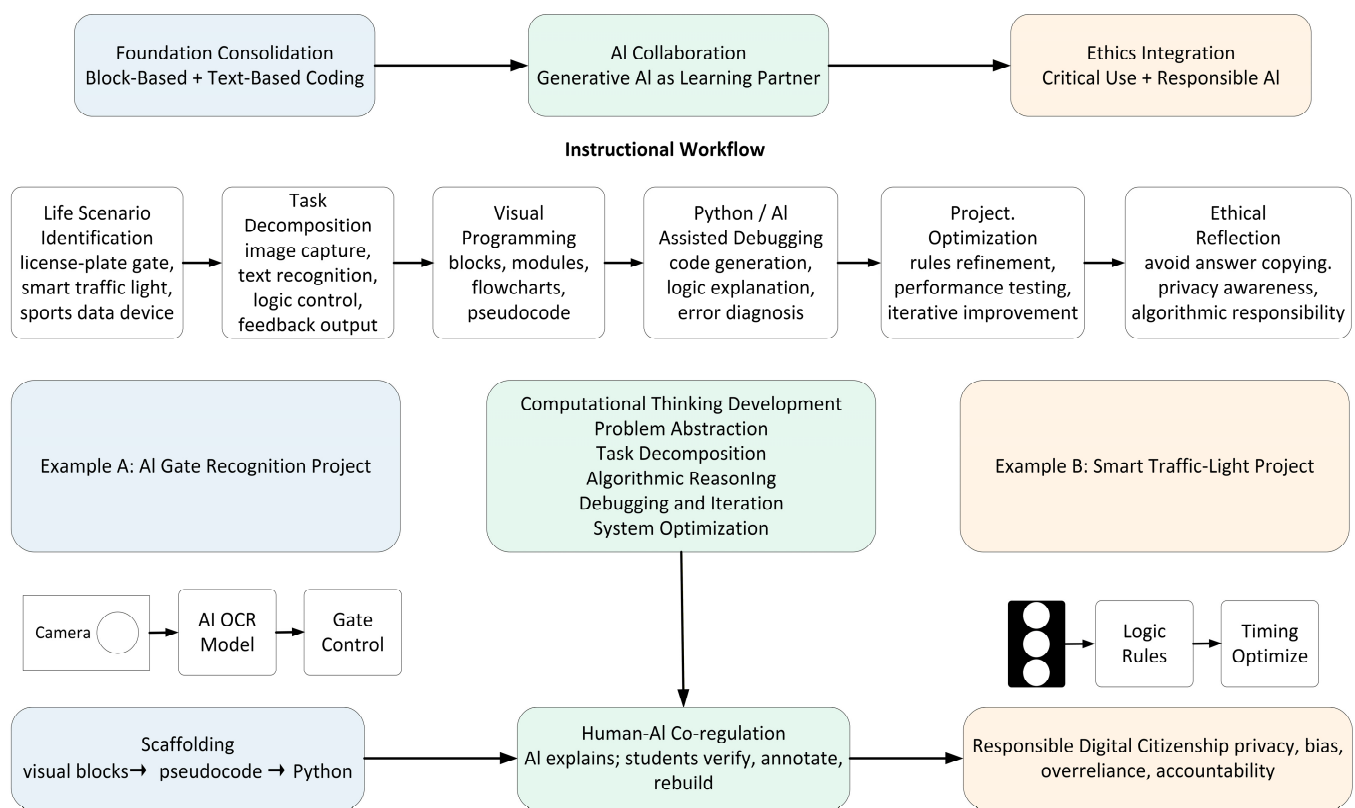


Figure 5. Scenario-Based AI-Computational Thinking Integration Pathway for K-12 Education. Source: Authors' own work.

AI project tasks should also be differentiated according to students' developmental stages and available learning resources. For younger learners or introductory courses, projects may center on the guided use of existing AI tools, such as image recognition platforms, speech-to-text systems, intelligent recommendation tools, or generative AI applications. These projects should emphasize model selection, inference, result interpretation, and explanation rather than complex model development. For older learners or advanced courses, projects can involve the construction of simple AI models, including data collection, dataset splitting, model training, parameter tuning, evaluation, and deployment. This differentiation enables students to experience AI problem-solving at varying levels of complexity while gradually progressing from AI tool use to data- and model-driven creation.

Table 4 illustrates a pedagogical progression from initial AI exposure, through conceptual understanding, to AI-based problem solving. This progression is particularly important in K-12 education, where learners differ substantially in cognitive develop-

ment, technical readiness, and access to learning resources. By integrating experiential, verification-oriented, and practice-based activities within project-based learning, teachers can avoid both superficial demonstrations of AI tools and excessively technical instruction, thereby creating a more developmentally appropriate pathway for cultivating computational thinking. Within this progressive learning process, AI agents can provide differentiated instructional support tailored to students’ developmental stages and learning needs. For introductory learners, they may function as guided learning assistants that explain AI tool outputs, clarify basic task procedures, and reduce cognitive overload. For intermediate learners, they can serve as debugging tutors and scenario generators, helping students identify coding errors, decompose project tasks, and connect AI concepts with authentic contexts; S.-J. Chen et al. (2025) provide evidence that LLM-supported debugging can strengthen students’ programming self-efficacy when used with appropriate guidance. For advanced learners, AI agents can support model refinement, project iteration, and interdisciplinary exploration by offering feedback on data preparation, problem-solving logic, and system optimization. In this sense, AI agents operate as scalable scaffolding mechanisms that strengthen the implementation of project-based and problem-driven AI education (Yusuf et al., 2025).

Table 4. Progressive Activity Types for K-12 AI General Education.

Activity Type	Core Meaning	Learning Purpose	Suitable Learners	Example AI Activities
Experience Activities	Students operate AI tools in simple and guided situations	Understand the basic functions and usage processes of AI tools	Primary or introductory learners	Trying image recognition, voice assistants, machine translation, or generative AI tools
Verification Activities	Students follow structured steps to examine AI principles or internal mechanisms	Develop an initial understanding of how AI systems work	Lower secondary or intermediate learners	Testing classification accuracy, comparing model outputs, observing bias in datasets
Practice Activities	Students flexibly use AI knowledge, data, and tools to solve authentic problems	Develop the ability to apply AI to complex real-world problem solving	Upper secondary or advanced learners	Building a simple classifier, training a small model, designing a smart campus application

In addition to differentiated project design, AI-supported instruction can be further organized through a staged and progressive cultivation strategy that integrates intelligent practice environments, progressively structured tasks, and multidimensional evaluation. Qin (2025) discusses generative-AI-supported strategies for cultivating junior high school students’ computational thinking, while Bi (2025) emphasizes the need to connect AI use with programming foundations and guided inquiry. S.-J. Chen et al. (2025) further demonstrate that large language model support can contribute to debugging and self-efficacy when students are required to reason about code rather than merely copy generated answers. From a pedagogical perspective, the development of computational thinking should follow a gradual cognitive transition from concrete perception to abstract modeling and ultimately to transfer across contexts. AI technologies can facilitate this process by dynamically adapting learning resources, visualizing abstract logic, providing semi-structured problem-solving tasks, and generating personalized feedback based on students’ learning trajectories. This strategy enables AI education to move beyond isolated tool

use and instead support a continuous cycle of thinking development, iterative practice refinement, and instructional adjustment. The three dimensions of this AI-supported progressive cultivation strategy are summarized in Table 5.

Table 5. AI-Supported Laddered Cultivation Strategy for Computational Thinking in K-12 AI Education.

Strategic Dimension	Core Pedagogical Logic	AI-Supported Functions	Computational Thinking Development	Representative Classroom Applications
Intelligent Practice Platform	Build an interactive environment that enables personalized and precise thinking training	Adaptive resource recommendation; real-time feedback; task difficulty adjustment; visualization of logic errors	Problem abstraction, model construction, iterative optimization	AI-supported QR code design platform; dynamic feedback on coding logic and visual flowchart correction
Laddered Teaching Design	Follow a cognitive progression from concrete perception to abstract modeling and transfer	Visualized examples; semi-open task scaffolds; real-scenario task generation; adaptive reasoning prompts	Problem decomposition, logical organization, algorithmic transfer	Smart washing-machine flow design; transition from process recognition to intelligent lighting algorithm design
Multidimensional Evaluation Loop	Integrate process tracking and outcome assessment to form a teaching–evaluation–improvement cycle	Learning trace analysis; work comparison; personalized evaluation reports; recommendation of follow-up tasks	Reflection, self-regulation, optimization, transfer	Smart plant-care system assessment; evaluation of sensor logic, abnormal-condition handling, and system extensibility

As shown in Table 5, AI can support the development of computational thinking at three interconnected levels: by constructing intelligent practice environments, by scaffolding students’ progression from concrete perception to transfer across contexts, and by establishing a data-informed evaluation loop that informs subsequent instructional adjustment. This structure complements the blended human–AI framework discussed above and provides a more concrete pathway for translating computational thinking goals into classroom practice. Within this pathway, project-based learning (PBL) serves as an effective approach for promoting active and inquiry-oriented learning (Almulla, 2020). It guides students through a complete problem-solving cycle, including contextualizing problems, decomposing tasks, designing solutions, implementing prototypes, validating results, and iteratively optimizing outcomes. Through these authentic and task-driven experiences, students systematically develop problem decomposition, algorithmic reasoning, and system-level optimization capabilities. To mitigate cognitive overload during such complex problem-solving processes, cognitive scaffolding mechanisms, such as pseudocode mapping and structured flowcharts, should be explicitly embedded within the solution design phase. Wang (2025) provides an example of such scaffolding in a hand-written digit recognition project, and Ayanwale and Omeh (2026) emphasize the relevance of AI-supported problem-based learning for computational thinking in STEM education. This structured support facilitates a progressive cognitive transition from abstract problem formulation to concrete algorithmic implementation, thereby ensuring that the pedagogical model remains developmentally appropriate for K-12 learners.

Building on this foundation, a structured five-stage problem-solving process grounded in problem-based learning can be adopted to further operationalize computational thinking development. This process consists of five stages: problem abstraction, in which real-world problems or phenomena are translated into computable parameters and structured data representations; task decomposition, which breaks complex AI application scenarios into man-

ageable subtasks or functional modules; algorithmic design, which formulates step-by-step logical sequences and decision rules; prototype implementation, which translates designed logic into executable code or physical hardware models; and iterative optimization, which uses systematic debugging and performance testing to refine system performance. [Lin \(2017\)](#) provides a problem-based learning perspective on active learning processes, while [Ayanwale and Omeh \(2026\)](#) specifically connect AI-supported problem-based learning with computational thinking development in STEM education. The specific relationship among this five-stage problem-solving process, the associated instructional activities, and the targeted computational thinking competencies is summarized in Table 6. To support this process, blended learning can be incorporated by combining online resources, such as MOOCs and virtual experiment platforms for self-directed study, with offline activities, including group collaboration and hands-on practice. AI teaching assistants and virtual laboratory environments can provide students with real-time guidance and a safe space for exploration, thereby enhancing instructional interactivity and effectiveness. Together, these approaches form a multidimensional and integrated pathway for the development of computational thinking.

Table 6. Mapping the “Five-Stage” Problem-Solving Process to Computational Thinking.

Problem-Solving Stage	Instructional Activities	Key Computational Thinking Competency
1. Problem Abstraction	Translating real-world anomalies into computable parameters	Abstraction and Modeling
2. Task Decomposition	Breaking complex scenarios into modular subsystems	Decomposition
3. Algorithmic Design	Formulating logical sequences and decision trees	Algorithmic Thinking
4. Prototype Implementation	Translating logic into executable code or hardware models	Practical Implementation
5. Iterative Optimization	System debugging and performance refinement	Evaluation and Optimization

To further operationalize project-based AI learning, instructional design should coordinate project phases, computational thinking objectives, and scaffolding strategies within a coherent learning sequence. One effective approach is to organize AI projects through a project-task-activity design sequence, in which authentic problems are progressively transformed into analyzable tasks and concrete learning activities. Within this structure, students move through project initiation, project analysis, project challenge, and project evaluation, while receiving layered support through contextual, resource-based, strategic, communicative, and evaluative scaffolds. Figure 6 illustrates this scaffolded AI project-based learning design, with handwritten digit recognition serving as an illustrative learning context based on [Wang \(2025\)](#).

As shown in Figure 6, scaffolded AI project-based learning can connect the development of computational thinking with concrete AI learning experiences. The handwritten digit recognition project begins with an authentic optical character recognition (OCR) problem, proceeds through image preprocessing and feature representation, advances to KNN- and CNN-based model development and parameter optimization, and culminates in model evaluation and reflective comparison of model performance. This progression supports the development of problem decomposition, abstraction, modeling, algorithmic design, and evaluation skills. More importantly, the use of differentiated scaffolds prevents AI learning from becoming a purely technical demonstration and instead supports students

in developing a deeper understanding of how data, features, models, and performance evaluation jointly shape intelligent systems (Wang, 2025).

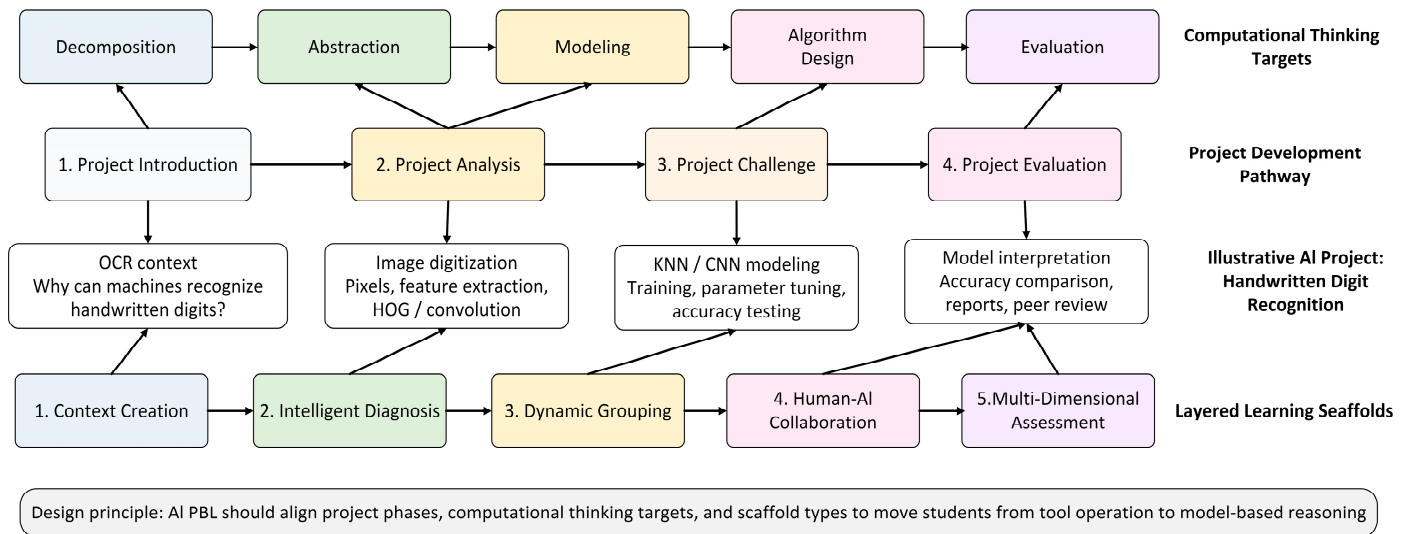


Figure 6. Scaffolded AI Project-Based Learning Design for Computational Thinking in K-12 AI Education. Source: Authors' own work.

Scenario-based projects can further strengthen the connection between AI concepts and computational thinking. For example, in a license-plate-based gate control project, students can design a simplified access-control system in which a camera captures a license-plate image, an AI recognition module identifies the plate number, and a control program determines whether the gate should open or remain closed. This project requires students to decompose the task into image acquisition, text recognition, rule-based decision making, and actuator control. Similarly, in a smart traffic-light project, students define state variables, design branching rules, adjust signal durations under different traffic conditions, and test the system through iterative debugging. These projects transform abstract AI concepts into concrete and observable learning experiences, thereby fostering students' abilities in abstraction, decomposition, algorithmic reasoning, and iterative optimization.

In addition to designing new AI projects, existing programming concepts can be reframed within generative AI learning contexts to make traditional curriculum content more responsive to contemporary educational needs. Rather than discarding classical topics such as algorithmic precision, data structures, loop control, and control-flow structures, teachers can reposition them as conceptual tools for evaluating AI outputs, constraining AI use, and designing human–AI collaboration. This strategy helps students recognize that foundational programming knowledge remains indispensable in the age of generative AI, as it enables them to identify unreliable outputs, organize data for intelligent systems, refine iterative processes, and design effective human–AI workflows. Representative examples are summarized in Table 7 (Y. Chen, 2025; Cress & Kimmerle, 2023).

As shown in Table 7, generative AI does not diminish the pedagogical value of classical programming knowledge; rather, it renews that value within emerging technological contexts. By anchoring traditional concepts in AI-related problems, students can move beyond mechanical code production and develop the ability to interpret, constrain, and improve intelligent systems. This recontextualization strategy complements project-based learning and provides a practical route for integrating computational thinking into existing K-12 AI and programming curricula. At the same time, generative AI can offer targeted support for the developmental challenges that students encounter in computational thinking education. At the lower secondary level, these challenges often include an excessive focus

on operational skills, insufficient transfer from theoretical knowledge to authentic contexts, and the abrupt transition from block-based to text-based programming. Generative AI tools can help address these issues through personalized learning guidance, context-rich project generation, continuous feedback on students’ reasoning, and ethical reflection. Table 8 summarizes how these AI-enabled strategies correspond to key instructional bottlenecks in K-12 computational thinking development (Qin, 2025; Bi, 2025; S.-J. Chen et al., 2025).

Table 7. Recontextualizing Classical Programming Concepts for Generative AI-Oriented Computational Thinking Education.

Classical Programming Concept	Recontextualized AI-Oriented Learning Scenario	Student Task	Computational Thinking Focus	Broader Educational Value
Algorithmic Definiteness	Building a hallucination-filtering mechanism for AI-generated recipe recommendations	Use deterministic rules, conditional statements, and loops to identify unsafe or incorrect AI outputs	Rule-based reasoning, verification, logical control	Develops critical AI literacy and responsible technology use
Data Structures	Designing a data-cleaning bridge for human–AI interaction	Transform messy user comments into structured input data through string and list operations	Abstraction, pattern recognition, data organization	Helps students understand that AI performance depends on data quality
Loop Finiteness	Implementing an early-stopping strategy in a simulated model-training task	Monitor validation performance and use break conditions to stop ineffective iterations	Iterative optimization, feedback interpretation, efficiency reasoning	Connects basic programming control with AI model optimization
Sequential, Selection, and Iterative Structures	Designing a human–AI collaborative workflow for an AI-assisted writing tool	Build a workflow that receives input, invokes AI, evaluates output quality, and requests revision when needed	System design, decomposition, algorithmic orchestration	Shifts students from code writers to designers of intelligent workflows

Table 8. Generative AI-Supported Strategies for Addressing Instructional Bottlenecks in K-12 Computational Thinking Education.

Instructional Bottleneck	Manifestation in K-12 Learning	Generative AI-Supported Strategy	Computational Thinking Contribution	Example Classroom Application
Overemphasis on operation rather than thinking	Students focus on software steps or coding syntax but pay limited attention to reasoning processes	Provide continuous thinking feedback that explains not only whether an answer is correct, but also where and why the reasoning fails	Strengthens logical reasoning, debugging awareness, and metacognitive reflection	AI analyzes a student’s programming flow, identifies logic gaps, and generates visual feedback such as flowcharts or stepwise correction prompts
Weak connection between theory and real-life application	Students understand concepts in isolation but struggle to apply them in authentic contexts	Generate scenario-based projects and guide task decomposition, module planning, and project scheduling	Promotes abstraction, decomposition, contextual modeling, and knowledge transfer	AI creates a realistic object-management or campus-service project and helps students break it into subtasks and implementation stages
Difficulty transitioning from block-based to text-based programming	Students experience cognitive overload when moving from visual modules to abstract code structures	Offer concept mapping between graphical programming blocks and equivalent text-based code, with gradual scaffolded explanations	Supports representation transfer, structural understanding, and algorithmic thinking	AI explains how a block-based loop or condition corresponds to Python code and provides progressive exercises from visual to textual logic
Limited ethical awareness in AI-assisted learning	Students may accept AI outputs uncritically or overlook privacy and bias issues	Embed AI ethics prompts and reflective questioning during project work	Develops responsible AI use, critical judgment, and social responsibility	Students evaluate whether AI-generated suggestions are reliable, privacy-preserving, and fair before adopting them

As shown in Table 8, generative AI should not be introduced merely as a productivity tool for faster code generation. Its deeper pedagogical value lies in providing cognitive scaffolding that helps students articulate their reasoning, transfer knowledge across contexts, bridge the representational gap between block-based and text-based programming, and develop critical awareness of ethical issues in AI. These functions align closely with the broader objective of integrating computational thinking into K-12 AI education and further enrich the instructional pathways proposed in this study. To support the implementation of these pathways, the National Smart Education Platform can be used to integrate and expand digital learning resources, including virtual experiments, micro-lectures, and case studies. Small Private Online Courses (SPOCs) and AI teaching assistants can further support personalized learning, while a school-based resource repository can help address the diverse requirements of curriculum implementation.

4.4. Faculty Development: Specialized Training and Community Building

To implement the curriculum and pedagogical pathways outlined above, schools need a teaching workforce equipped with both AI literacy and pedagogical expertise in cultivating computational thinking. Accordingly, teacher development should proceed through three coordinated pathways: systematic training, professional learning communities, and university–industry collaboration. Within the teacher–student–AI collaborative framework, professional development should also emphasize the transformation of teacher roles. Teachers are expected to move beyond the position of knowledge transmitters and become learning designers, data-informed decision makers, project facilitators, and ethical mentors. They need to be capable of interpreting students’ learning analytics, designing AI-supported learning tasks, providing scaffolding during project implementation, and guiding students to critically examine the social consequences of AI technologies. Therefore, teacher preparation should focus not only on AI tools and programming skills, but also on data-driven instructional design, computational thinking scaffolding, and responsible AI education. This role transformation is particularly important in blended human–AI learning environments. As AI systems increasingly undertake routine support functions such as basic debugging assistance, feedback support, and preliminary learning diagnosis, teachers can devote greater attention to strategic guidance, cross-disciplinary connection, and the cultivation of higher-order thinking. This shift requires them to design meaningful inquiry tasks, interpret AI-supported learning evidence, and help students connect technical implementation with broader scientific, mathematical, and social contexts (Lan & Chen, 2024; Kong et al., 2025; Y. Liu & Yang, 2026).

Systematic teacher training should be integrated into regular professional development systems and should strengthen educators’ understanding of core AI technologies, pedagogical methods for computational thinking, and interdisciplinary curriculum design through academic seminars, thematic workshops, and project-based practice. This training can be grounded in the Technological Pedagogical Content Knowledge (TPACK) framework, moving beyond mere software proficiency to equip teachers with the pedagogical strategies needed to translate opaque AI mechanisms, such as neural network weights and decision boundaries, into developmentally appropriate computational concepts. In addition, cognitive apprenticeship models can be incorporated into professional learning communities, allowing novice teachers to observe experienced educators during complex project-based learning implementations and thereby develop tacit knowledge of instructional scaffolding and real-time classroom management in AI education. Regional and inter-school professional learning communities should further be established through collaborative lesson planning, case sharing, and expert guidance, enabling teachers to

exchange experience, grow cooperatively, and transform emerging research findings into relevant instructional content.

University–industry collaboration should also be promoted to broaden the channels for teacher development. The participation of corporate engineers and university experts in teacher training and curriculum design can provide educators with authentic professional learning opportunities and help compensate for limitations in school-based resources. Through this multi-stakeholder and sustainable support ecosystem, schools can more effectively strengthen teachers' professional capacity and instructional innovation in AI education.

4.5. Reform of the Evaluation System: Multifaceted Orientation and Process Focus

The curriculum and instructional innovations discussed above should be supported by an assessment system that captures not only what students produce, but also how they reason, collaborate, revise, and transfer their learning. To this end, a multifaceted and process-focused assessment framework should address knowledge acquisition, practical skills, thinking processes, collaboration, and innovation, while embedding core computational thinking competencies, including abstract modeling, algorithm design, and problem-solving, throughout the evaluation process. Assessment reform should also follow the principle of teaching–learning–assessment integration. From this perspective, assessment should not be treated as a terminal judgment administered after learning, but as a continuous mechanism that guides, supports, and improves the entire learning process. Before project implementation, assessment criteria should be made explicit so that students understand the expected quality of project plans, data preparation, model construction, collaboration, documentation, and ethical awareness in practice. During learning, formative feedback should help students revise their strategies and improve their AI solutions. After project completion, assessment should incorporate project reports, process records, model performance, presentation quality, and reflective discussion. Such an integrated assessment system is better suited to supporting the development of Computational Thinking 2.0 and AI literacy.

The assessment indicators can be organized around a tripartite framework adapted for AI education: Computational Concepts, Computational Practices, and Computational Perspectives. The Concepts dimension assesses students' mastery of foundational AI principles, including data structures, algorithmic logic, and model training mechanisms. The Practices dimension evaluates their ability to apply these concepts in authentic AI project contexts, with particular attention to iterative testing, systematic debugging, and modular abstraction. The Perspectives dimension examines students' evolving technological self-efficacy and their critical awareness of the responsible and ethical use of AI. Within this framework, when generative AI tools are incorporated into AI education, assessment should not merely determine whether students produce a correct program or a functional AI product. Instead, teachers should examine whether students can explain the logic of AI-generated code, reconstruct key program segments, annotate important variables and control-flow structures, and justify the modifications they make during debugging. Such practices help reduce overreliance on AI tools and encourage deeper cognitive engagement. Accordingly, evaluation should address not only product functionality, but also students' reasoning processes, code comprehension, ethical awareness, and responsible use of AI assistance. A fine-grained assessment rubric of this kind can support a more systematic and multidimensional assessment of computational thinking in K-12 AI education (Bi, 2025; S.-J. Chen et al., 2025; Gong et al., 2025).

In addition, the assessment of computational thinking in AI education should be aligned with the full AI project cycle and should attend closely to evidence of learning

transfer. During problem analysis, assessment should focus on whether students can identify meaningful problems, abstract key variables, and decompose complex tasks. During model construction, it should examine students' data preparation, algorithmic reasoning, debugging strategies, and model evaluation processes. During reflection and innovation, it should assess students' ability to interpret model limitations, consider ethical risks, and propose creative improvements. Such process-oriented assessment helps shift the focus of evaluation from judging whether an AI product functions correctly to examining how students think, reason, collaborate, and iterate throughout the learning process. At the same time, transfer-oriented assessment is essential. Empirical findings from platform-supported AI project learning indicate that improvements in knowledge retention and certain dimensions of computational thinking do not necessarily lead to significantly stronger transfer performance. This suggests that evaluation systems should include tasks requiring students to apply learned AI concepts and computational thinking strategies in novel contexts, rather than relying solely on in-project performance or immediate post-learning outcomes. Transfer-based assessment can more effectively reveal whether students have internalized computational thinking as a flexible problem-solving competence (Wang, 2025; Ukkonen et al., 2024).

Building on this foundation, the implementation of formative assessment should be further strengthened through classroom observation, project portfolios, group-based peer evaluation, structured self-reflection activities, and peer-review mechanisms. These approaches can continuously document and monitor students' cognitive development and learning progress throughout the entire project-based learning cycle, from problem analysis and solution design to programming, debugging, and project optimization. By encouraging students to articulate their debugging processes and algorithmic reasoning, such assessment practices foster metacognitive awareness and shift the evaluation paradigm from the validation of functional outputs toward a more evidence-based examination of the underlying computational logic.

In addition, intelligent assessment tools can be introduced to provide technical support for process-oriented evaluation. By leveraging AI and big data technologies, these tools can analyze behavioral data, including students' learning duration, programming operations, and the quality of project outcomes. Such data provide an evidence-based foundation for assessment and enable the generation of personalized learning recommendations based on analytical results. For instance, in block-based programming environments commonly used in K-12 education, the system can track the frequency of trial-and-error behaviors, the range of logic blocks used, and the time spent on debugging. This granular information allows educators to identify specific cognitive bottlenecks, such as misunderstandings of loop structures or conditional statements, and to intervene through targeted scaffolding. Furthermore, it offers data-driven support for teachers to refine their instructional strategies, thereby forming a closed-loop mechanism in which assessment enhances learning and informs teaching.

AI agents can further strengthen process-oriented assessment by developing dynamic learner profiles across the entire AI learning cycle. Rather than evaluating students solely through final products or examination scores, these agents can record coding operations, debugging trajectories, task completion patterns, peer collaboration, dialogue participation, and project revision histories. Such data can be synthesized into multidimensional developmental profiles that reflect students' growth in computational thinking, including abstraction, task decomposition, debugging, iterative refinement, collaboration, and innovation. This form of agent-supported assessment provides teachers with richer evidence for formative intervention and helps students better understand their own learning progress (Yusuf et al., 2025; H. Liu, 2025). In particular, AI-supported feedback should explain not

only whether students' solutions are correct, but also where reasoning breakdowns occur and why specific revisions are needed, thereby transforming assessment from outcome judgment into a mechanism for computational thinking refinement (Gong et al., 2025; S.-J. Chen et al., 2025). Beyond dynamic learner profiling, knowledge-graph construction can further enhance the continuity between assessment and instruction. By aggregating students' task completion records, debugging trajectories, AI interaction logs, and multidimensional evaluation results, the system can visualize both mastered and underdeveloped knowledge nodes. These graphs help students identify their next learning priorities and enable teachers to design targeted follow-up activities. In this way, assessment no longer functions merely as a summary of past performance, but also as a data-driven navigation mechanism for subsequent computational thinking development.

5. Discussion

5.1. Theoretical Contributions

The proposed framework advances current discussions on K-12 AI education in three ways. First, we reconceptualize computational thinking beyond a programming-centered competency as a broader cognitive framework for AI education. By introducing Computational Thinking 2.0, we clarify how data reasoning, model understanding, feedback optimization, and ethical judgment extend traditional algorithmic reasoning in AI-rich learning environments. Second, we integrate the roles of teachers, students, and AI systems into a collaborative framework that positions AI as a cognitive partner and pedagogical support mechanism rather than as a substitute for teacher guidance or student reasoning. Third, we connect curriculum design, instructional innovation, teacher development, and assessment reform into a coherent implementation pathway, thereby addressing the fragmentation that often characterizes school-based AI education.

5.2. Practical Implications

For schools and curriculum designers, the framework suggests that high-quality K-12 AI education should not be reduced to isolated technology exposure or the use of generative AI tools. Instead, it should be organized through progressive curricula, authentic projects, scaffolded problem solving, teacher-led reflection, and process-oriented assessment. For teachers, the framework highlights the need to integrate technical understanding with instructional design expertise, data-informed feedback, and ethical guidance. For policymakers and school leaders, it underscores the importance of establishing supportive institutional conditions, including teacher training, resource platforms, and equitable access, so that AI education can effectively foster computational thinking development across diverse school contexts.

5.3. Limitations and Future Research

This article remains conceptual in nature and does not provide empirical validation of the proposed framework. In addition, the policy foundation and several instructional examples are primarily grounded in the Chinese primary and secondary school context. Although we formulate transferable design principles for K-12 AI education more broadly, cross-national application should not be assumed automatically. Transfer to other educational systems would require attention to local curriculum structures, assessment regimes, teacher preparation systems, digital infrastructure, data protection rules, and cultural expectations regarding human–AI interaction. The proposed curriculum and pedagogical pathways therefore require further examination through design-based research, classroom experiments, longitudinal tracking, and comparative studies across countries, regions, school levels, and resource contexts. Future research should also investigate how different

forms of AI support influence students' computational thinking trajectories, how teachers negotiate agency in human–AI collaborative classrooms, and how transfer-oriented and ethics-aware assessment can be implemented in ways that are both reliable and equitable.

6. Conclusions

In this article, we examine the integration of computational thinking into K-12 artificial intelligence education in response to the rapid advancement of AI technologies, the digital transformation of schooling, and the growing need to cultivate future-ready learners. Rather than treating computational thinking as a supplementary programming skill, we position it as a foundational cognitive framework for AI education. From the authors' proposed Computational Thinking 2.0 perspective, K-12 AI learning should extend beyond rule-based algorithmic reasoning to encompass data preparation, model understanding, the formulation of AI-relevant problems, system optimization, and responsible human–AI collaboration. On this basis, we propose a teacher–student–AI collaborative framework that clarifies the complementary roles of educators, learners, and intelligent systems in supporting the development of computational thinking.

Building on this conceptual foundation, we propose a systematic implementation pathway for integrating computational thinking into K-12 AI education. First, curriculum design should adopt tiered, spiral, and interdisciplinary structures that align with students' cognitive development and progressively connect foundational computational concepts with AI applications, model-based reasoning, and ethical reflection. Second, pedagogical innovation should move beyond isolated tool demonstrations toward authentic, project-based, and scaffolded learning experiences. Blended human–AI teaching, AI agent-supported feedback, scenario-based projects, and structured problem-solving cycles can help students progress from problem recognition to model construction, iterative optimization, and reflective improvement and innovation. Third, teacher development should be strengthened through specialized training, professional learning communities, and university–industry collaboration, enabling teachers to shift from knowledge transmitters to learning designers, project facilitators, data-informed decision makers, and ethical mentors. Fourth, assessment reform should emphasize multidimensional, process-oriented, transfer-oriented, and ethics-aware evaluation, so that students' reasoning processes, collaborative practices, model interpretation, and responsible use of AI are valued alongside final products.

Overall, integrating computational thinking into K-12 AI education is not merely a matter of adding AI content to existing curricula; it requires a more comprehensive reconfiguration of educational goals, curriculum logic, instructional methods, teacher roles, and assessment systems. The ultimate aim is to help students develop the capacity to understand, evaluate, create, and responsibly apply intelligent technologies in complex real-world contexts. Future research should further examine the long-term effectiveness of computational thinking-oriented AI education through longitudinal and empirical studies, especially across different school stages, resource contexts, and regional settings. Greater attention should also be paid to educational equity, the appropriate pedagogical roles and limits of generative AI and AI agents, and the design of transfer-oriented learning tasks that foster higher-order thinking. Through sustained theoretical refinement and classroom innovation, K-12 AI education can move toward a more systematic, inclusive, and high-quality model that prepares students to participate meaningfully in an intelligent society.

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Abbreviations

The following abbreviations are used in this manuscript:

AI Artificial intelligence
PBL Project-Based Learning

References

- Ahn, Y. H., & Oh, E. Y. (2024). Effects of the international training program for enhancing intelligent capabilities through blended learning on computational thinking, artificial intelligence competencies, and core competencies for the future society in graduate students. *Applied Sciences*, 14(3), 991. [CrossRef]
- Almulla, M. A. (2020). The effectiveness of the project-based learning (PBL) approach as a way to engage students in learning. *Sage Open*, 10(3), 2158244020938702. [CrossRef]
- Araya, R., Isoda, M., & Gonzalez, O. (2020). A framework for computational thinking in preparation for transitioning to a super smart society. In *Reform and development in teacher education for the digital society*. Springer.
- Asmara, A. (2020). Study on computational thinking as problem-solving skill: Comparison based on students mindset in engineering and social science. *arXiv*. [CrossRef]
- Asrifan, A., Khristianto, K., Budiman, A., Astuti, P. I., & Rossydy, A. (2025). Enhancing critical thinking: The role of AI in modern education. In *Enhancing classroom instruction and student skills with AI* (pp. 413–448). IGI Global Scientific Publishing. [CrossRef]
- Ayanwale, M. A., & Omeh, C. B. (2026). AI-supported problem-based learning for enhancing computational thinking skills in STEM education. *Computers in Human Behavior: Artificial Humans*, 7, 100263. [CrossRef]
- Bi, B. (2025). Artificial intelligence and junior high school information technology computational thinking integration strategies. *China Information Technology Education*, (23), 42–44. (In Chinese) Available online: https://kns.cnki.net/kcms2/article/abstract?v=1EB3pfwoRP7zpPWClOvy08SxVojvu8bLiOnA_XZDpdk3gHTh1YBgp9_335iLo7waxg4XPg8tJwIKrdWs7JnX1v1-MquMXFbyYXOg2FhNvmVRsYcGnyHGw0kzlpCEIs1Pnj0o1knF7qMUy32r_3yeducaBHWAvD-ennvJMn_Zfznt5ebtTbLT4jeYMejJEs8SINdXgNwpKow&uniplatform=NZKPT&captchaId=7ac91468-d018-44dc-9ea5-cd4722882d25 (accessed on 1 March 2026).
- Brennan, K., & Resnick, M. (2012, April 13–17). *New frameworks for studying and assessing the development of computational thinking*. 2012 Annual Meeting of the American Educational Research Association (Vol. 1, 25p), Vancouver, BC, Canada.
- Celik, I. N., & Bati, K. (2025). The effect of cooperative learning on academic performances and computational thinking skills in the computational problem-solving approach. *Informatics in Education*, 24(1), 45–76.
- Chan, C. K. Y. (2023). A comprehensive AI policy education framework for university teaching and learning. *International Journal of Educational Technology in Higher Education*, 20(1), 38. [CrossRef]
- Chen, S.-J., Shan, X., Liu, Z.-M., & Chen, C.-Q. (2025). Employing large language models to enhance K-12 students' programming debugging skills, computational thinking, and self-efficacy. *Educational Technology & Society*, 28(2), 259–278. [CrossRef]
- Chen, Y. (2025). Value reshaping and practical pathways of middle school programming education in the era of generative artificial intelligence. *Educational Communication and Technology*, (6), 3–9. (In Chinese) Available online: https://kns.cnki.net/kcms2/article/abstract?v=1EB3pfwoRP4jQYj3WkXf5kG9YPjWW96ehZrCdV0lxgFX-neFhxrWHJeLjcT2bYwP3BzFzNguj9h3aisNeYqbY67dR_-PgntvtD1WwjRUH4b-4Y3qbLNR4sTKVxjHw2aqfBtNxdY6pDCiaTeU_Ss_AQWjFPokZxeqh-16PnNG7Jq_k9KEGTUPA==&uniplatform=NZKPT&language=CHS (accessed on 1 March 2026).
- Cress, U., & Kimmerle, J. (2023). Co-constructing knowledge with generative AI tools: Reflections from a CSCL perspective. *International Journal of Computer-Supported Collaborative Learning*, 18(4), 607–614. [CrossRef]
- Demaidi, M. N. (2025). Artificial intelligence national strategy in a developing country. *AI & Society*, 40(2), 423–435. [CrossRef]

- European Commission, Directorate-General for Education, Youth, Sport and Culture. (2022). *Ethical guidelines on the use of artificial intelligence (AI) and data in teaching and learning for educators*. Publications Office of the European Union. Available online: <https://op.europa.eu/en/publication-detail/-/publication/d81a0d54-5348-11ed-92ed-01aa75ed71a1/language-en> (accessed on 2 February 2026).
- Ganguly, A., Mehjabin, N., Malik, A., & Johri, A. (2026). Conversational AI agents in education: An umbrella review of current utilization, challenges, and future directions for ethical and responsible use. *AI and Ethics*, 6, 72. [CrossRef]
- Gong, X., Li, Z., & Qiao, A. (2025). Impact of generative AI dialogic feedback on different stages of programming problem solving. *Education and Information Technologies*, 30(7), 9689–9709. [CrossRef]
- Grover, S., & Pea, R. (2013). Computational thinking in K-12: A review of the state of the field. *Educational Researcher*, 42(1), 38–43. [CrossRef]
- Huang, X., & Qiao, C. (2024). Enhancing computational thinking skills through artificial intelligence education at a STEAM high school. *Science & Education*, 33(2), 383–403. [CrossRef]
- Knox, J. (2020). Artificial intelligence and education in China. *Learning, Media and Technology*, 45(3), 298–311. [CrossRef]
- Kong, X., Fang, H., Chen, W., Xiao, J., & Zhang, M. (2025). Examining human-AI collaboration in hybrid intelligence learning environments: Insight from the synergy degree model. *Humanities and Social Sciences Communications*, 12, 821. [CrossRef]
- Lan, Y.-J., & Chen, N.-S. (2024). Teachers' agency in the era of LLM and generative AI: Designing pedagogical AI agents. *Educational Technology & Society*, 27(1), I–XVIII. [CrossRef]
- Lin, L. F. (2017). Impacts of the problem-based learning pedagogy on English learners' reading comprehension, strategy use, and active learning attitudes. *Journal of Education and Training Studies*, 5(6), 109–125. [CrossRef]
- Liu, H. (2025). Innovative research on the teaching model of Python courses based on AI agents. *Wireless Internet Science and Technology*, (21), 119–123. (In Chinese) Available online: https://kns.cnki.net/kcms2/article/abstract?v=1EB3pfwoRP6Yw2nufeywakSiGLi-6ippz2xZ_cWc2dkDAQaDUXtdS8Ze0lYoN-jwZDYEp7tCio9QhRGajDeX2i_Czx-c-WwNu-TsFjngRNkl8clSCZ4ubFE9m3rXCDgBW129lw6iiawR1L8yImjod5BnUaSQ5rB9aDTSpaKKbTXP9YmmN9-iA==&uniplatform=NZKPT&language=CHS (accessed on 15 February 2026).
- Liu, Y., & Yang, X. (2026). Exploring human-AI collaborative programming instruction from the perspective of blended learning: A case study of 'programming solution of pi'. *China Educational Technology Equipment*, (3), 146–151. (In Chinese) Available online: https://kns.cnki.net/kcms2/article/abstract?v=1EB3pfwoRP6yoCE0jnqUZP7RJCO24aVjanzEWrPlknxMRhfQkTmxOJOtFnnfm4MNP2TDVP4A9SSqWX1c2uiVs0pbjngJfdr2TsxcvNXAJB6qpMDD0_1KPCPzN6xVLANGZMoE7CyXeSFB01xFyU2Zu_WkChk954zNljDB2r8vukhRC-eBR4TLQ==&uniplatform=NZKPT&language=CHS (accessed on 15 February 2026). [CrossRef]
- Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. In *Proceedings of the 2020 CHI conference on human factors in computing systems* (pp. 1–16). Association for Computing Machinery. [CrossRef]
- Ministry of Education of the People's Republic of China. (2022, April 8). *Notice on the publication of the compulsory education curriculum plan and curriculum standards (2022 edition)* [Press release/Government document]. Available online: http://www.moe.gov.cn/srcsite/A26/s8001/202204/t20220420_619921.html (accessed on 15 February 2026).
- Ministry of Education of the People's Republic of China. (2024, December 3). *The Ministry of Education deploys the strengthening of artificial intelligence education in primary and secondary schools* [Press release]. Available online: https://www.gov.cn/lianbo/bumen/202412/content_6990729.html (accessed on 15 February 2026).
- Ministry of Education, Singapore. (n.d.). *Artificial intelligence in education*. Available online: <https://www.moe.gov.sg/education-in-sg/educational-technology-journey/edtech-masterplan/artificial-intelligence-in-education> (accessed on 22 June 2026).
- Popkova, E. G., & Gulzat, K. (2019). Technological revolution in the 21st century: Digital society vs. artificial intelligence. In *Institute of scientific communications conference* (pp. 339–345). Springer. [CrossRef]
- Qin, Z. (2025). Strategies and effect analysis of generative AI tools for cultivating junior high school students' computational thinking. *Examination Weekly*, (44), 16–18. (In Chinese) Available online: https://kns.cnki.net/kcms2/article/abstract?v=1EB3pfwoRP4vPKh9iuwPjYHRCGo2wMaUDcdOCOW67hJoZjduGoLEcBLQZx4jUS_nHjjq1pVlvYHOsiFw4nwKa6uSvHoKqNC9c359HpwJKejOe_vHF_zZL2UE8-T-5soW8aerXW9t0RHVq3_8ROtL_hRycsj_InbvtUvwPggqkTMufZ7Ig3kFBA==&uniplatform=NZKPT&language=CHS (accessed on 15 February 2026).
- Qu, J. R., & Fok, P. K. (2022). Cultivating students' computational thinking through student-robot interactions in robotics education. *International Journal of Technology and Design Education*, 32(4), 1983–2002. [CrossRef]
- Rulyansah, A., & Harun, M. (2025). Unlocking the algorithmic mind: A systematic review of AI's role in cultivating computational thinking in primary education. *Journal of Teacher Well-Being*, 1(2), 1–7. [CrossRef]
- Shahzad, S. A., Raza, M. M., Malhi, S. D., ul Ain, Q., & Malhi, D. K. (2025). Integrating artificial intelligence to foster critical thinking and problem-solving in 21st-century classrooms. *Research Journal for Social Affairs*, 3(5), 635–648. [CrossRef]

- Song, J., Yu, J., Yan, L., Zhang, L., Liu, B., Zhang, Y., & Lu, Y. (2023). Develop AI teaching and learning resources for compulsory education in China. In *Proceedings of the AAAI conference on artificial intelligence* (Vol. 37, No. 13, pp. 16033–16039). AAAI Press. [CrossRef]
- Stone, P., Brooks, R., Brynjolfsson, E., Calo, R., Etzioni, O., Hager, G., Hirschberg, J., Kalyanakrishnan, S., Kamar, E., Kraus, S., Leyton-Brown, K., Parkes, D., Press, W., Saxenian, A., Shah, J., Tambe, M., & Teller, A. (2022). Artificial intelligence and life in 2030: The one hundred year study on artificial intelligence. *arXiv*. [CrossRef]
- Susanti, R. D., & Taufik, M. (2021). Analysis of student computational thinking in solving social statistics problems. *SJME (Supremum Journal of Mathematics Education)*, 5(1), 22–31. [CrossRef]
- Taj, I., & Zaman, N. (2022). Towards industrial revolution 5.0 and explainable artificial intelligence: Challenges and opportunities. *International Journal of Computing and Digital Systems*, 12(1), 295–320. [CrossRef]
- Tlili, A., Shehata, B., Adarkwah, M. A., Bozkurt, A., Hickey, D. T., Huang, R., & Agyemang, B. (2023). What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education. *Smart Learning Environments*, 10, 15. [CrossRef]
- Touretzky, D. S., Gardner-McCune, C., Martin, F., & Seehorn, D. (2019). Envisioning AI for K-12: What should every child know about AI? In *Proceedings of the AAAI conference on artificial intelligence* (Vol. 33, No. 1, pp. 9795–9799). AAAI Press. [CrossRef]
- Ukkonen, A., Pajchel, K., & Mifsud, L. (2024). Teachers' understanding of assessing computational thinking. *Computer Science Education*, 35(4), 794–819. [CrossRef]
- UNESCO. (2024). *AI competency framework for students*. UNESCO. Available online: <https://unesdoc.unesco.org/ark:/48223/pf0000391105> (accessed on 10 February 2026).
- U.S. Department of Education, Office of Educational Technology. (2023). *Artificial intelligence and the future of teaching and learning: Insights and recommendations*. Available online: <https://www.ed.gov/sites/ed/files/documents/ai-report/ai-report.pdf> (accessed on 10 February 2026).
- Wang, R. (2025). Research on artificial intelligence project design and practice based on the UMU platform: Taking 'handwritten digit recognition' as an example for cultivating computational thinking. *Teaching Administration and Educational Research*, (11), 57–62. (In Chinese) Available online: https://kns.cnki.net/kcms2/article/abstract?v=1EB3pfwoRP57bX3L8d1yGAqE0bDzP1ivxzxLRgetvG0xhQ-AnaYUFOBmQ7rz-Noc71BFidy7Pjku7eyDcUj1Wpt8i9yOPUMXY-JedkxSw3Afyc3C8J51_4oPEVW9b_3grPj7KGGHqaGpTlbdC5PAAiCwth2KWQYwPJSQk4qD1Zc8slBo0RTgxGA==&uniplatform=NZKPT&language=CHS (accessed on 15 February 2026). [CrossRef]
- Wing, J. M. (2006). Computational thinking. *Communications of the ACM*, 49(3), 33–35. [CrossRef]
- Xia, Z. (2025). Construction of K-12 artificial intelligence general education curriculum from the perspective of Computational Thinking 2.0. *China Information Technology Education*, (21), 22–24. (In Chinese) [CrossRef]
- Yusuf, H., Money, A., & Daylamani-Zad, D. (2025). Pedagogical AI conversational agents in higher education: A conceptual framework and survey of the state of the art. *Educational Technology Research and Development*, 73(2), 815–874. [CrossRef]

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