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Teacher Development Models for Integrating Computational Thinking in Early Childhood Education: A Systematic Literature Review

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ABSTRACT

Computational Thinking (CT) is widely acknowledged as a core competency in 21st-century education; however, its integration in Early Childhood Education (ECE) is limited by the absence of systematic teacher development frameworks. This study conducts a systematic literature review of 12 peer-reviewed articles published between 2016 and 2025, sourced from ERIC and Scopus. The analysis focuses on identifying and categorizing existing teacher development models for CT in ECE and examining their implementation and outcomes. Three categories of teacher development models were identified: (1) unplugged play-based models using concrete manipulatives; (2) plugged models emphasizing robotics and block-based coding; and (3) hybrid models integrating concrete and symbolic learning through scaffolding and debugging. Implementation is primarily embedded in daily classroom routines (75%) and supported by peer collaboration (17%), while parental involvement remains limited (8%). Outcomes are predominantly cognitive, with significant improvements in CT skills, problem-solving, and geometric reasoning. Affective outcomes, such as motivation and engagement, show moderate gains. Notable gaps include the lack of validated assessment tools and limited longitudinal evidence on professional development design. This review advances the field by proposing an ECE-specific taxonomy of teacher development models that connects pedagogical approaches with cognitive and affective outcomes. It highlights the importance of a concrete-to-symbolic learning trajectory, sustained professional coaching, and structured home–school partnerships to support developmentally appropriate, scalable, and sustainable CT integration in early education.

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1. INTRODUCTION

Computational Thinking (CT) has emerged as a fundamental 21st-century competency that provides a cognitive framework for solving problems systematically through decomposition, pattern recognition, abstraction, and algorithm design (Mendrofa, 2024; Selamat et al., 2024). CT is defined as a set of interrelated skills and practices used to address complex problems across various disciplines. It is distinct from broader terms like computing and computer science as it focuses on a way of thinking that can be embedded into diverse learning activities rather than just technical programming (Aytekin & Topçu, 2024; Passey, 2017). To support its integration in education, a three-layer framework is utilized, consisting of foundational skills, applied practices, and inclusive pedagogy (Mills et al., 2021). Foundational skills such as abstraction, decomposition, and pattern recognition are introduced in early grades, while applied practices like data management and computational modeling are developed in higher levels (Sengupta et al., 2013; Sparapani et al., 2019). This entire process is grounded in inclusive pedagogy, which ensures that instruction is accessible, connects to student interests, and addresses biases in technology to make the practice relevant and fair for all learners (Bocconi et al., 2019; Muhaimin et al., 2025).

The evolution of research themes shows that between 2015 and 2018 the focus was primarily on using technology as a medium for pedagogical experimentation within STEM domains (Dolgopolovas & Dagiene, 2024). From 2019 to 2021 the field expanded to explicitly mention computational thinking and introduced data based frameworks through learning analytics and assessment. By the period of 2022 to 2024 these diverse themes consolidated with computational thinking emerging as a core cross disciplinary competency. Modern research now favors design based methodologies where programming and simulations serve as supporting infrastructures to cultivate computational ways of thinking (Hamidi, 2025; Yeni et al., 2024). At the Early Childhood Education (ECE) level, CT becomes particularly urgent as early childhood is a sensitive period for developing executive functions such as working memory, inhibitory control, and cognitive flexibility that directly intersect with CT processes (Liu, 2024; Perez Valdes et al., 2025). Unlike higher educational levels, CT integration in ECE must align with children's developmental stages through guided play, storytelling, concrete manipulatives, and unplugged activities rather than screen-dependent programming (Bers, 2021; Busuttil et al., 2025; Saxena et al., 2020a).

The central challenge of CT integration in ECE lies not in the availability of digital tools but in the readiness of teachers as the critical leverage point for sustainable learning. Student success in mastering CT requires a coherent learning model that translates CT constructs into developmentally appropriate pedagogy, assessment, and classroom routines (Gane et al., 2021; Tauno Palts, 2012). Such a model must orchestrate guided play, storytelling, and concrete manipulatives so that decomposition, pattern recognition, and algorithmic planning emerge as observable behaviors. Without a robust teacher development model, CT integration risks becoming a series of disconnected activities rather than a sustained and measurable thread of learning (Zeng et al., 2023). In ECE specifically, a good model must also anticipate contextual constraints such as limited devices, time allocation, curriculum load, and developmental appropriateness requirements (Yang et al., 2022).

Despite the rapid growth of CT literature, a significant research gap persists in existing systematic reviews. Most prior reviews address K–12 broadly without highlighting the unique developmental context of ECE (Bandara & Syed, 2023; Davies & Seitamaa-Hakkarainen, 2025). Existing reviews are predominantly tool-focused, emphasizing the efficacy of robotics and coding applications (R. Liu et al., 2023), rather than analyzing the teacher development models that underpin sustainable practice. Many reviews also prioritize teacher perceptions and attitudes (Bubikova-Moan et al., 2019; Emi et al., 2024) while rarely examining process fidelity, working mechanisms, or measurable child outcomes. Theory-driven coding approaches such as TPACK, Activity Theory, and Implementation Science remain underutilized, leaving the mechanisms of effective models poorly explained. Furthermore, professional development design features such as coaching duration, collaborative design, and continuity are rarely linked to classroom practice quality or child learning outcomes, leaving policymakers without mechanism-based evidence about what works, for whom, and under what conditions in ECE contexts.

This Systematic Literature Review explicitly differentiates itself from prior reviews by shifting the analytical focus from tools and perceptions to teacher development models and their mechanisms. Grounded in sociocultural theory and learning trajectories, this review conceptualizes teacher learning as a socially mediated process that must align with children's cognitive development (Vygotsky, 1978). The 2016 to 2025 timeframe is specifically justified by the post-2016 emergence of ECE-focused CT frameworks and the rapid proliferation of unplugged pedagogical innovations following the release of ISTE and CSTA practice guidelines (Fessakis et al., 2018). Responding to the identified gaps, this review aims to identify and categorize teacher development models for CT integration in ECE, analyze their components, including inputs, learning mechanisms, and enactment supports, and synthesize evidence linking model features to outcomes at the teacher, classroom, and child levels. The targeted contributions include a taxonomy of ECE-specific CT teacher development models with their core mechanisms, and design principles applicable for policymakers, curriculum designers, and teacher educators to develop models that are scalable, equitable, and context-responsive. This study is guided by the following research questions.

1. How are the trends of CT at the ECE level based on the year of publication?
2. What learning models and components are used by teachers in integrating CT at the ECE level?
3. In what implementation contexts are those learning models applied at the ECE level?
4. What outcomes are achieved by those learning models in integrating CT at the ECE level?

2. METHODS

2.1 Type of Research

This study is a Systematic Literature Review (SLR) reported using the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) approach (Page et al., 2021). SLR was chosen because it synthesizes evidence comprehensively, transparently, and replicably to map and explain the evolution of teacher development models for the integration of Computational Thinking (CT) in Early Childhood Education (ECE) from 2016 to 2025. By following PRISMA, the review process begins with formulating measurable research questions, followed by standardized search strategies across selected databases with clear keywords and time ranges, then layered selection through the stages of identification, screening, eligibility, and inclusion, while documenting the number of studies and reasons for exclusion at each stage (Moher et al., 2009). This approach ensures that all decisions can be audited and replicated while minimizing selection bias and increasing the credibility of the findings.

It is important to clarify the conceptual distinctions used throughout this review. A teacher development model refers to a structured professional learning framework that builds teacher capacity to integrate CT, encompassing inputs such as training design, coaching, and collaborative planning, as well as mechanisms that mediate how teachers translate CT knowledge into practice. A learning model refers to the pedagogical framework or instructional approach that teachers enact in the classroom, such as project-based learning, inquiry-based learning, or scaffolded play. A classroom implementation strategy refers to the specific techniques or activities deployed within a learning model, such as debugging routines, step-by-step programming, or unplugged manipulative tasks. These distinctions guide the coding and synthesis throughout this review.

2.2 *Research Stages*

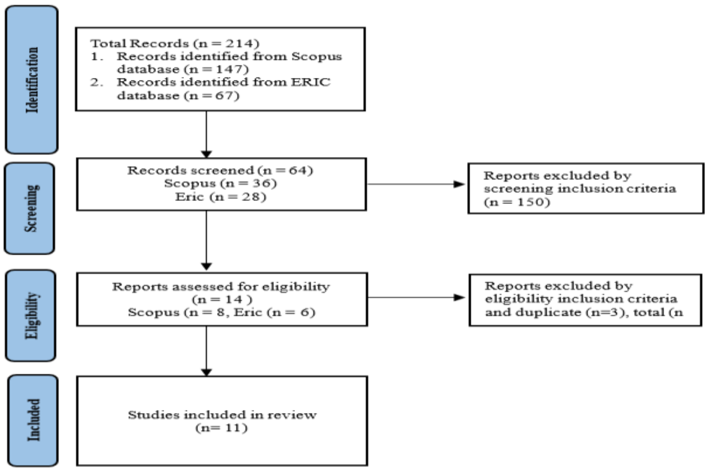

Figure 1. PRISMA flow diagram

2.2.1 Identification

At the Identification stage, the process begins by defining the search tools and locations for retrieving articles that form the research data. The primary search tool is a set of keywords constructed with Boolean operators to capture core terms and their derivatives while avoiding irrelevant results. The keywords used are ("computational thinking" OR "CT") AND ("early childhood" OR "preschool" OR "early years" OR "ECE" OR "PAUD") AND ("teacher model" OR "learning model" OR "teaching model" OR "pedagogical model" OR "instructional model" OR "PjBL" OR "project-based learning" OR "problem-based learning" OR "inquiry-based learning" OR "constructivist model" OR "TPACK" OR "professional development model" OR "training model" OR "framework" OR "approach" OR "strategy") AND ("teacher" OR "educator" OR "practitioner").

The search was conducted in two reputable databases, namely Scopus and ERIC, as both centralize peer-reviewed educational literature and apply globally recognized curation and indexing standards. It is acknowledged that other major databases including Web of Science, IEEE Xplore, ACM Digital Library, and Education Source were not included in this search, which may introduce a degree of publication bias and limit the visibility of studies from computer science and engineering education communities. This limitation is discussed further in the limitations section. All queries, search dates, applied filters, and initial hit counts were documented, while citation exports were automatically deduplicated using a reference manager and manually verified to ensure the integrity of the initial corpus. At this stage, a total of 214 articles were obtained, with 147 from Scopus and 67 from ERIC.

2.2.2. Screening

The Screening stage is the first selection focusing on bibliographic elements—title, abstract, metadata—based on preliminary inclusion and exclusion criteria. At this stage, the temporal boundary was set to the last ten years (2016–2025) to capture recent developments while maintaining relevance to current policy and technological contexts. The article type was limited to “research articles” because they provide designs, methods, and empirical findings that can be synthesized, while the publication type focused on peer-reviewed journal articles and excluded proceedings, editorials, or brief notes to maintain methodological quality consistency. The language was limited to English to ensure comparability of terminology and accessibility of conceptual measurement instruments; non-English articles were considered only if an official translation was available. In addition, preference was given to open-access articles to guarantee full access to methods and appendices; closed-access articles could be excluded if the full text was not accessible through institutional subscriptions or direct requests, as access limitations hinder quality appraisal and reliable data extraction. Articles that passed this stage totaled 64, consisting of 36 from Scopus and 28 from ERIC.

2.2.3. Eligibility

The Eligibility stage is the second selection that assesses the substance of the full text against more detailed inclusion–exclusion criteria. Alignment with the research questions was examined in layers: first, the conceptual relevance among the title, abstract, and keywords with the focus on "learning models in CT integration in education"; second, contextual fit (educational levels such as elementary, middle, high school, or higher education; subject domains such as science, mathematics, ICT, or cross-disciplinary); third, clarity of interventions or pedagogical approaches explicitly related to CT (for example project-based learning, problem-based learning, design-based learning, unplugged CT, integration of programming or simulation as a strategy rather than a separate topic); fourth, methodological adequacy, including clarity of research design, sampling procedures, instruments for measuring CT or related learning outcomes, data analysis procedures, and transparency of reporting. Studies were excluded if CT was only mentioned implicitly without clear operationalization, if the focus was limited to pure programming without linkage to CT, if the context was non-educational, or if reporting quality was insufficient to enable extraction of key variables. At this stage, reasons for exclusion were recorded specifically—for example "not CT-focused," "publication type not eligible," "full text unavailable," or "design/method not sufficiently clear"—to be reported in the PRISMA flow diagram.

2.2.4. Included

The Included stage marks the final corpus of 12 studies that met all criteria and were ready for analysis. The list of included studies was compiled along with key characteristics covering year, country, educational level, domain, research design, form of intervention or learning model, CT indicators, learning outcomes, and key findings. The number of articles at each stage was reported in the PRISMA flow diagram (Figure 1), including detailed reasons for exclusion at the full-text stage.

The selection process was carried out sequentially by two independent reviewers. At the Identification stage, all search results were exported and deduplicated both automatically and through manual verification. At the Screening stage, titles and abstracts were filtered against the initial criteria independently by both reviewers, with disagreements resolved through discussion or consultation with a third reviewer. Inter-rater reliability was calculated using Cohen's kappa ($\kappa = 0.81$), indicating strong agreement between reviewers (Landis & Koch, 1977). At the Eligibility stage, full-text review was conducted to ensure focus on CT in ECE contexts, methodological adequacy, and reporting quality, with reasons for exclusion recorded in detail. A quality appraisal of each included study was conducted using an adapted version of the Mixed Methods Appraisal Tool (MMAT) (Hong & Choi, 2018), assessing clarity of research design, validity of CT measurement instruments, and transparency of reporting. Studies rated as high risk of bias were flagged and a sensitivity analysis was conducted by temporarily excluding them to assess whether their inclusion materially altered the synthesis conclusions. The findings confirmed that the overall patterns remained consistent, and all 12 studies were retained in the final synthesis. The findings of the articles resulting from the PRISMA selection process are presented in Table 1.

Table 1. Articles identified through the PRISMA process

Authors and Year	Strategy / Model	Components	Context	Outcomes
(Vassallo, 2025)	Hybrid	Block coding, scaffolding	Parental involvement, students' daily involvement	Computational Thinking (CT) skills, problem-solving skills, engagement
(Sala-Sebastià et al., 2025)	Plugged	Robotics and block coding	Peer group involvement	Computational Thinking (CT) skills, geometric thinking

Authors and Year	Strategy / Model	Components	Context	Outcomes
(Xing et al., 2025)	Unplugged	Play-based activity	Students' daily involvement	Computational Thinking (CT) skills, problem-solving skills, engagement
(Leung et al., 2025)	Unplugged	Play-based activity	Students' daily involvement	Computational Thinking (CT) skills, problem-solving skills, engagement, design skills
(Falloon, 2024)	Plugged	Problem-Based Learning (PBL), inquiry, robotics	Students' daily involvement	Computational Thinking (CT) skills
(Misirli & Komis, 2023)	Plugged	Step-by-step programming strategy, debugging framework	Students' daily involvement	Computational Thinking (CT) skills
(Akiba, 2022)	Hybrid	Robotics	Students' daily involvement	Computational Thinking (CT) skills, improvement in digital literacy
(Quinn et al., 2025)	Unplugged	Play-based activity	Students' daily involvement	Computational Thinking (CT) skills, problem-solving skills, learning motivation
(Critten et al., 2024)	Unplugged	Play-based activity	Students' daily involvement	Computational Thinking (CT) skills, problem-solving skills, engagement
(Lavigne et al., 2020)	Hybrid	Block coding, scaffolding	Peer group involvement	Computational Thinking (CT) skills, engagement
(Saxena et al., 2020a)	Hybrid	Play-based activity, robotics	Students' daily involvement	Computational Thinking (CT) skills

2.3 *Data Analysis*

The data analysis process combined narrative synthesis with descriptive statistics. Each of the 12 included studies was extracted using a standardized form covering metadata, research design, educational context, form of intervention, CT indicators, and key findings. The data were then cleaned and coded by themes including CT, programming, learning analytics, assessment, simulation, and design-based research, as well as by methods including experimental, qualitative, mixed methods, and design-based research. Descriptive statistics were used to map the distribution of studies per year, the spread of methodologies, and implementation contexts. These quantitative results were woven into a narrative synthesis that explains patterns and shifts, including how programming serves as a pathway toward CT and how design-based research strengthened as a methodological approach. Quality appraisal scores from the MMAT informed the weighting of evidence in the narrative synthesis, with higher-quality studies given greater interpretive weight. Visual mappings including tree maps and proportional diagrams were used to depict the distribution of learning models, implementation contexts, and outcome profiles across the included studies, complementing the narrative account with representations that are easy to interpret.

3. FINDINGS AND DISCUSSION

3.1 CT trends at the ECE level by year of publication

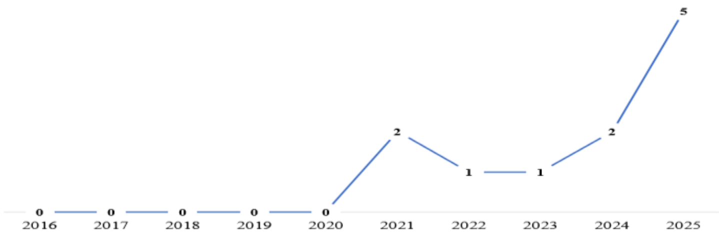

Figure 2. CT trend at the ECE level

This subsection addresses Research Question 1 regarding publication trends of CT at the ECE level between 2016 and 2025. The publication trend shows a gradual but clear acceleration of CT research in Early Childhood Education across this period. As shown in Figure 2, almost no studies appeared before 2020, reflecting the absence of CT as a formalized research agenda in early childhood contexts. The small increase in 2021 marks an early adoption phase influenced by pandemic-driven digital literacy growth, expansion of unplugged CT strategies, and the formalization of reference frameworks such as ISTE and CSTA guidelines (Fessakis et al., 2018; Strawhacker & Bers, 2019).

The relative stagnation in 2022 and 2023 appears to represent a consolidation period during which researchers refined instruments, adapted CT tasks for early childhood, and validated developmentally appropriate measures, processes that often do not produce immediate high-volume publications. This trend echoes long-standing challenges in CT assessment identified by Lye & Koh (2014), especially at preoperational developmental stages where standardized measurement tools remain scarce.

A marked rise in 2024 and 2025, culminating in five publications in 2025, signals that CT in ECE has entered mainstream research attention. This acceleration is supported by stronger theoretical anchoring in Piagetian concrete-to-symbolic progression and Vygotskian scaffolding, increasing availability of low-cost robotics and unplugged resources, and expanding policy support for early digital literacy initiatives (Jean Piaget, 2005; Muhaimin & Kholid, 2023; Vygotsky, 1978). Compared to earlier systematic reviews that focused mainly on K–12 or tool-based activities, the recent surge reflects growing interest in teacher-mediated CT integration at the early childhood level. The overall trend demonstrates a shift from exploratory to consolidation to growth, with research aligning increasingly with rigorous frameworks such as embodied cognition, sociocultural mediation, and early learning trajectories.

3.2 Learning models and CT integration components used by teachers in ECE

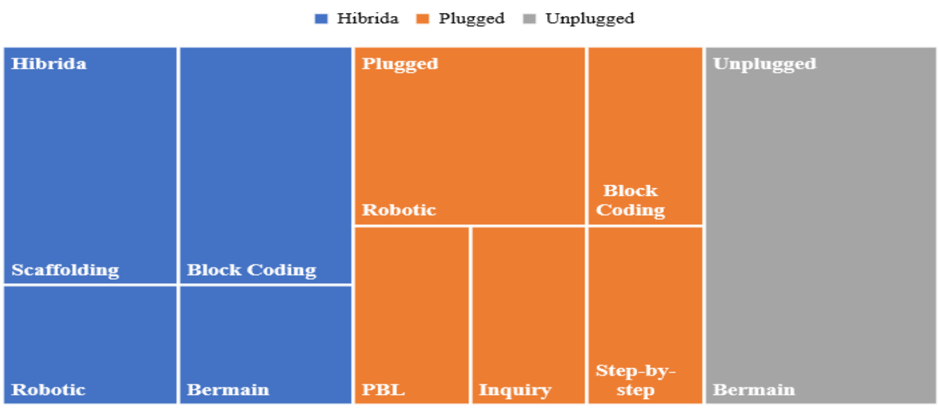

Figure 3. Trend of learning models and CT integration components used by teachers in ECE

This subsection addresses Research Question 2 regarding the teacher development models and components used in integrating CT at the ECE level. Figure 3 shows that CT integration in ECE is dominated by unplugged play-based learning models, followed by plugged models using robotics and block coding, and hybrid models that connect concrete play with symbolic representations. This distribution reflects a developmental logic in which children at the preoperational stage construct CT representations more effectively through tactile, visual, and social experiences before transitioning to on-screen symbolic coding (Piaget, 2005; Wadsworth, 1996).

Unplugged models documented by Xing et al. (2025), Leung et al. (2025), and Quinn et al. (2025) rely on manipulatives, stories, direction cards, and sequencing games grounded in embodied cognition, allowing children to physically enact algorithms before abstracting them. Plugged models documented by Falloon (2024) and Misirli & Komis (2023) emphasize guided inquiry with BeeBots, BlueBots, and block-based programming, providing instantaneous feedback loops that support early debugging skills. Hybrid models documented by Vassallo (2025), Lavigne et al. (2020), and Akiba (2022) structure learning by linking physical manipulation with block coding, typically supported by scaffolding, step-by-step deconstruction, and guided reflection.

Across these categories, the mechanisms that enable CT development are consistent. Scaffolding breaks complex tasks into manageable substeps aligned with Vygotsky's zone of proximal development (Vygotsky, 1978). Embodied cognition anchors computational ideas through action and physical manipulation (Xing et al., 2025). Iterative feedback through debugging cycles builds procedural understanding. Interest-driven problem creation under frameworks such as the Interest Driven Creator framework sustains engagement and identity as a creator (Vassallo, 2025). Compared to previous systematic reviews that focused mostly on robotics or digital tools, this synthesis reveals a clearer emergence of teacher-mediated developmental trajectories rather than tool-centric approaches. These models emphasize conceptual depth rather than mere exposure to devices. Learning models follow a concrete-to-symbolic developmental pathway, and hybrid models are the most pedagogically robust due to their alignment with both developmental needs and CT conceptual rigor.

3.3 Implementation contexts of CT integration learning models in ECE

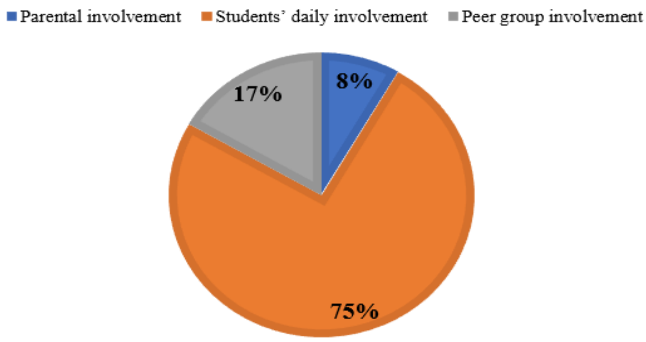

Figure 4. Trend of implementation contexts of CT integration learning models in ECE

This subsection addresses Research Question 3 regarding the implementation contexts in which teacher development models are applied at the ECE level. As shown in Figure 4, CT implementation in ECE occurs primarily in students' daily classroom activities at approximately 75 percent, followed by peer group interactions at approximately 17 percent, and parental involvement at approximately 8 percent.

The dominance of daily classroom activities aligns with early childhood learning principles, where CT skills such as decomposition, sequencing, and debugging arise naturally from familiar routine activities like navigation games, building tasks, and storytelling (Critten et al., 2024; Quinn et al., 2025). Peer interactions contribute socio-cognitive support for problem solving and debugging, consistent with Vygotskian perspectives on collaborative meaning-making (Vygotsky, 1978). Parental involvement appears limited, partly due to varying home resources and the absence of structured home-school CT programs. The evidence suggests that teacher development models work best when they embed CT into routine classroom structures, integrate peer scaffolding roles, and provide child-friendly transitions into plugged tasks.

In low-resource contexts, unplugged materials are especially scalable due to minimal cost and adaptability, supporting equity by reducing dependence on robotics or tablets. Home-school integration remains a major gap and represents a significant opportunity for more equitable implementation. CT thrives when embedded in everyday meaningful routines, peer interaction contributes socio-cognitive mediation but remains secondary to teacher guidance, and parental involvement represents an underutilized lever for extending CT learning beyond the classroom.

3.4 Outcomes of implementing CT integration learning models in ECE

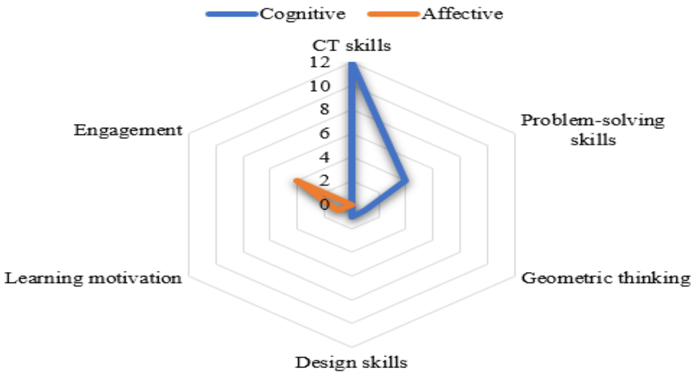

Figure 5. Trend of outcomes of CT integration learning models in ECE

This subsection addresses Research Question 4 regarding the outcomes achieved by teacher development models in integrating CT at the ECE level. Findings presented in Figure 5 show that cognitive outcomes dominate across studies. The strongest improvements occur in CT skills, followed by problem-solving ability. Enhancements in geometric thinking and design ability appear consistently but with smaller effect sizes. Affective outcomes such as engagement and motivation also increase but less sharply than cognitive gains.

This pattern aligns with the nature of CT tasks, which heavily target sequencing, patterning, decomposition, and debugging, skills associated with early executive function development (Bers, 2021; Falloon, 2024). Embodied tasks such as robot navigation and manipulatives foster spatial reasoning, which explains gains in geometric thinking (Foglia & Wilson, 2013). Affective outcomes appear modest because many interventions are short-cycle or skill-focused, lacking extended project autonomy that typically drives deeper motivation and sustained engagement. Compared with earlier reviews, these findings show stronger evidence that CT learning in ECE is not merely exposure-based but leads to measurable conceptual gains when supported by structured teacher models.

Vassallo (2025) found simultaneous improvements in CT ability, problem solving, and engagement, especially when iterative feedback and the Interest Driven Creator framework made activities feel close to children's interests. Xing et al. (2025) and Leung et al. (2025) both report strengthening of CT skills and problem solving as well as increased engagement, with Leung et al. also noting improvements in design ability when children design programmable artifacts or stories. Falloon (2024) emphasizes a surge in pattern recognition and application, which forms the foundation for increases in CT skills. Misirli and Misirli & Komis (2023) show how debugging knowledge grows through step-by-step practice, appearing as an increase in problem solving. Akiba (2022) adds that the integration of beginner digital devices also raises digital literacy alongside CT ability. Quinn et al. (2025) show boosts in CT ability, problem solving, and learning motivation when instruction is aligned with computer science Powerful Ideas. Critten et al. (2024) and Lavigne et al. (2020) document strengthening of CT ability and engagement when CT themes are embedded in structured play activities and classroom routines. Saxena et al. (2020b) reinforce findings on pattern recognition and sequencing that underpin cognitive scores.

Cognitive outcomes are consistently strong, especially in CT skills and problem-solving (Muhaimin et al., 2023), while affective outcomes improve moderately, suggesting the need for longer interest-based projects. Gains align with developmental theory and the design of unplugged and hybrid interventions.

3.5 *Cross-cutting Discussion*

The findings across all four research questions can be interpreted through a coherent theoretical lens. Piaget's theory of cognitive development supports the concrete-to-symbolic progression observed across learning models, where manipulatives and play precede symbolic coding (Piaget, 2005). Vygotsky's sociocultural theory explains the central role of scaffolding and peer mediation in enabling children to surpass their zone of proximal development (Vygotsky, 1978). Embodied cognition accounts for strong spatial and sequencing gains observed in movement-based and manipulative-rich interventions (Foglia & Wilson, 2013). Together, these theoretical perspectives clarify why hybrid and play-based instruction are effective not merely as pedagogical preferences but as developmentally grounded mechanisms.

When compared with prior systematic reviews, this study reveals important distinctions. Earlier reviews emphasize tools, robotics, or broad K–12 patterns without addressing the unique developmental constraints of ECE. This review demonstrates that ECE requires stronger teacher development models, more explicit concrete-to-symbolic learning trajectories, more deliberate scaffolding and iterative design, and deeper integration into classroom routines rather than device-centered tasks. The mechanisms through which teacher development models achieve their effects include consistent scaffolding, structured debugging routines, interest-driven problem creation, manageable learning progressions, and low-cost pathways that fit ECE developmental and resource constraints.

On the question of equity and scalability, unplugged approaches are highly scalable for low-resource settings because they require no devices and can be adapted to local cultural and linguistic contexts. Hybrid models balance access, depth, and feasibility by combining affordable concrete materials with beginner robotics or block coding only when resources allow. Parental involvement remains weak across all included studies, presenting both an equity challenge and an opportunity. Families in low-resource contexts could be engaged through simple unplugged activity packages, direction games at home, picture recipes with sequential steps, or sequential stories that transfer to block coding environments, thereby extending the reach of CT learning beyond the classroom and reducing opportunity gaps in early computing education.

4. CONCLUSION

This study identifies three principal models of teacher development for integrating Computational Thinking (CT) in Early Childhood Education—unplugged play-based approaches, plugged robotics and block-coding approaches, and hybrid models that connect concrete and symbolic learning—and demonstrates that effective development follows a progression from concrete, embodied experiences to more abstract, digital representations. CT is most successfully normalized when embedded in everyday classroom routines and mediated through physical manipulatives before transitioning to screen-based environments. Core design principles emerging from the synthesis include the importance of explicit scaffolding to manage cognitive load, the use of embodied cognition to ground abstract processes in physical activity, and the incorporation of iterative debugging practices to cultivate resilience and problem-solving skills. Although peer mediation enhances CT internalization, limited structured parental involvement remains a notable gap. These findings suggest that teacher education programs should move beyond isolated, tool-focused workshops toward sustained professional development that prioritizes pedagogical content knowledge, enabling educators to identify and leverage CT opportunities within existing literacy, numeracy, and play-based curricula. Teacher educators should further emphasize guided inquiry, formative assessment, and collaborative design processes to support nuanced observation of children’s emerging algorithmic thinking. From a policy perspective, the results support positioning CT as a cross-disciplinary competency within early childhood frameworks, alongside the development of developmentally appropriate assessment tools that capture both digital and unplugged practices. Ensuring equitable and scalable implementation requires prioritizing low-cost unplugged and hybrid approaches and strengthening home–school partnerships through structured family engagement initiatives, thereby establishing an inclusive and sustainable foundation for early digital literacy.

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