

Bridging the Abstract and the Tangible: A Meta-Analysis of AI Literacy Pedagogies, Tools, and Developmental Outcomes in Elementary School Settings

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Abstract. The integration of artificial intelligence (AI) into modern life has fundamentally changed human-technology interaction, demanding a paradigm shift in education. Developing AI literacy must begin early to prepare children for a future where AI competency is as essential as reading, writing, and arithmetic. Despite this urgency, instilling AI literacy in young children remains a significant challenge, largely due to the limited availability of developmentally appropriate tools and curricula tailored to elementary students' cognitive and socio-emotional capacities. This study examines the effectiveness of learning interventions that integrate AI literacy and tangible AI in elementary education. The researchers selected meta-analysis studies published between 2010 and 2025 from indexing databases including Scopus, Web of Science, EBSCO/Proquest, SINTA, and Google Scholar. The collected articles focused on how AI literacy is taught at the elementary level. The filtered data included learning design, assessment methods, and learning outcomes. A total of 13 independent studies were included in the meta-analysis, which analyzed average effect sizes. Results, processed using JASP software, indicate that effective implementation of teaching aids—whether software-based or tangible AI—significantly improves students' understanding of AI concepts and their ability to apply AI to real-world challenges. The findings also underscore the importance of embedding AI literacy within subject-matter instruction rather than teaching it in isolation, which risks losing context and relevance.

Keywords: AI Literacy; Tangible AI; Elementary Education; AI-PCK; Embodied Cognition

1. Introduction

Artificial intelligence is increasingly reshaping how children learn, yet the path from broad technological promise to developmentally sound classroom practice remains unclear—particularly at the elementary level. This section outlines the problem motivating the present study, situates it within existing research on AI literacy and tangible learning, and states the specific objectives this meta-analysis pursues.

1.1 Problem Statement

The integration of artificial intelligence (AI) into elementary education has emerged as one of the most transformative—and challenging—developments in contemporary pedagogy (Bagdonaitė & Dagienė, 2025). As AI technology continues to reshape society, the need to prepare young students for an AI-driven world has become increasingly urgent. The period from 2015 to 2026 has witnessed an unprecedented proliferation of AI-powered learning tools designed specifically for children, ranging from hands-on robotics platforms to conversational AI tutors and immersive extended reality (XR) environments. However, the AI landscape in elementary school education is characterized by rapid growth that tends to be at odds with its fragmented implementation, where commercial platforms, research prototypes, and pilot programs are proliferating without systematic evaluation of their collective impact.

This problem is especially acute for upper elementary grades (grades 4–6, approximately ages 9–12), the developmental window on which this meta-analysis focuses. During this phase, students undergo dramatic cognitive, linguistic, attentional, and motor transitions, creating fundamentally different design constraints for educational AI compared to both early elementary and secondary education. Without a synthesized understanding of what works for this age group specifically, educators and designers are left to generalize from tools built for other developmental stages—a gap this study aims to address.

1.2 Related Research

Existing reviews confirm that this developmental window is where most of the field's attention already sits, without yet resolving what works within it. A systematic review by Memari & Ruggles (2025) revealed that 65% of studies on AI in elementary school-level STEM education focus on upper elementary grades, reflecting both the cognitive readiness of this age group and practical considerations regarding curriculum integration.

Within this body of work, the concept of tangible AI referred to in this study encompasses a variety of technologies that enable direct physical interaction between students and AI systems. This includes educational robots with a physical presence (Yim & Su, 2025; Aravantinos et al., 2024), tangible user interfaces (TUIs) (Sampanis, 2025; Kim & Kwon, 2024) that bridge physical and digital learning, smart teaching aids with sensor-equipped materials (Zhang et al., 2024), and extended reality (XR) systems (Fernández-Batanero et al., 2024) that allow students to manipulate virtual objects anchored to physical space. Unlike purely screen-based AI applications, tangible tools leverage embodiment—the physical presence and interactive capabilities of technology—to create more engaging and memorable learning experiences.

The importance of a concrete, physically-based approach to AI education is further underscored by research in cognitive science and developmental psychology. Studies on physically-based cognition show that learning is more effective when grounded in sensorimotor experiences (Macrine & Fugate, 2020; Wilson, 2002). Hands-on activities using physical materials and role-playing can significantly enhance conceptual understanding (Freeman et al., 2014), particularly for abstract ideas such as neural networks, decision-making theory, and pattern recognition. This is particularly relevant for upper-grade elementary school students, who benefit from concrete manipulation while developing abstract reasoning skills.

1.3 Research Objectives

This meta-analysis synthesizes experimental and quasi-experimental studies conducted between 2010 and 2025 that examined AI tools interacting directly with students in grades 4–6. The analysis focuses on three critical dimensions: instructional design, assessment methods, and learning outcomes. Learning outcomes are categorized separately into three categories—knowledge gains, skill mastery, and affective outcomes—with a particular emphasis on knowledge gains and affective outcomes, as these two dimensions are both the most frequently measured and the most theoretically significant aspects of AI-mediated learning.

The research questions guiding the meta-analysis in this study include: 1) To what extent is tangible AI effective in improving students' AI literacy? 2) What affective outcomes—including motivation, engagement, self-efficacy, and attitudes toward AI—are facilitated by the use of tangible AI? and 3) What instructional design principles and assessment methods characterize effective implementations of tangible AI?

By addressing these questions through a systematic analysis of the current literature, this study aims to move beyond fragmented understandings toward a comprehensive view of the current role and potential of tangible AI in supporting learning in elementary schools. These findings have significant implications for educators, curriculum designers, technology

developers, and policymakers seeking to harness the transformative potential of AI while preserving the human elements essential to student development.

2. Theoretical Framework of Tangible AI Learning

2.1. Embodied Cognition and Tangible Learning

The theoretical foundation for tangible AI learning tools rests firmly on embodied cognition theory, which represents a paradigm shift in understanding how human thinking operates. Unlike traditional computational models of mind—often referred to as the "cognitivist" or "computational-representational" approach—embodied cognition posits that cognitive processes are not abstract, amodal, and independent of the body but are instead deeply rooted in the body's interactions with the physical world (Lodi & Martini, 2021; Bell & Lodi, 2019). This distinction is not merely philosophical; it carries profound implications for how we design learning environments, particularly for young children whose cognitive development is intrinsically tied to sensorimotor exploration.

To appreciate the significance of embodied cognition, one must first understand the traditional cognitivist framework it challenges. Classical cognitive science, drawing from Cartesian dualism and later influences from computer science, treated cognition as a form of symbol manipulation analogous to software running on a computer (Levesque, 2012). In this view, the brain is the seat of cognition, and the body is merely an input-output device—a "peripheral" that delivers sensory data to the central processor and executes its motor commands. The physical world, under this model, serves only as a source of information to be encoded into mental representations, which are then manipulated according to logical rules. This perspective dominated educational technology design for decades, producing screen-based, mouse-and-keyboard interfaces that privilege abstract symbolic reasoning over concrete physical interaction.

Embodied cognition rejects this separation. Drawing from the phenomenological traditions (Merleau-Ponty, 2012) and more recent empirical work in cognitive science, embodied theorists argue that cognition is *constituted* by bodily interactions with the environment, not merely *influenced* by them (Shapiro & Spaulding, 2021). The brain did not evolve to solve abstract logic problems in isolation; it evolved to coordinate movement through a complex three-dimensional world, to manipulate objects, to navigate spaces, and to communicate through gesture and posture. Consequently, even seemingly abstract cognitive activities—mathematical reasoning, programming logic, scientific inquiry—retain traces of their embodied origins.

Wilson (2002) provided one of the most influential articulations of embodied cognition in her seminal review, identifying six distinct claims about embodiment that collectively support the design of tangible learning experiences. Each of these claims has direct implications for how AI learning tools should be designed for elementary students.

First, cognition is situated in real-world contexts. This claim asserts that thinking does not occur in a vacuum but is embedded within physical and social environments that shape both the problems we encounter and the solutions we generate (Wilson & Myers, 2000). For elementary students learning about AI, this means that abstract concepts like "pattern recognition" or "machine learning" must be grounded in concrete, meaningful contexts. A tangible AI sorting machine that physically separates objects by color and shape provides a situated context for understanding classification algorithms in a way that a diagram on a worksheet cannot.

Second, cognition is time-pressured, requiring real-time interaction. Human cognition operates under real-time constraints; we think on our feet, respond to changing conditions, and adjust our actions moment-by-moment. This claim supports the design of tangible AI tools that respond immediately to physical manipulation. When a child moves a tangible programming block to change a robot's behavior, the immediate feedback—the robot moves or stops—creates a tight coupling between action and outcome. This real-time contingency is essential for building intuitive understanding (Papert, 2020).

Third, cognitive work is offloaded onto the environment. This is perhaps the most practical claim for educational design. Humans naturally reduce cognitive load by using the physical world as an external memory or computation system. We write notes, arrange objects, gesture to track ideas, and use tools to extend our cognitive reach (Kirsh, 2010). Tangible AI tools exploit this principle by allowing students to literally "think with their hands." For example, moving physical tokens on a grid to represent training data for a classification algorithm offloads the cognitive burden of maintaining abstract categories in working memory onto the physical arrangement of objects.

Fourth, the environment is part of the cognitive system. This radical claim goes beyond saying the environment helps cognition; it argues that the environment is *constitutive* of cognition. The cognitive system, properly understood, includes not just the brain and body but also the tools, artifacts, and space within which thinking occurs (Tomczyk, 2024). When a child uses tangible AI blocks to program a robot, the blocks,

Research on tangible computing in education builds on constructionist pedagogy, particularly the work of Papert (2020) and Brennan & Resnick (2012), who argued that learners benefit most from creating and manipulating physical representations of computational concepts. The constructionist approach emphasizes learning through design, building, and debugging—processes that are inherently embodied when students work with tangible materials. Tangible user interfaces (TUIs) and smart manipulatives align with elementary students' developmental need for concrete manipulation while providing immediate digital feedback that supports conceptual understanding.

2.2. Cooperative Learning Theory and Social AI Interaction

The learning-by-teaching paradigm (Biswas, et al., 2005; Duran, 2016), where students program or teach robots, draws theoretical support from cooperative learning theory. When children explain mathematical concepts to a robot "student," they must articulate their understanding clearly, revealing and addressing their own misconceptions. This approach has demonstrated effectiveness in building both content knowledge and metacognitive skills, as students learn to monitor and evaluate their own explanations.

The social presence of educational robots creates unique learning dynamics that differ from screen-based instruction. Social robots can demonstrate confusion when students explain incorrectly, show excitement when problems are solved, and provide nonverbal feedback through movement and expression. These social interactions leverage the human propensity for anthropomorphism, making abstract AI concepts more accessible through familiar social scripts.

Research on student-robot interaction processes identifies several key mechanisms that mediate learning gains (Fiorella, 2023): (1) concept explanations where students articulate domain principles; (2) strategy statements describing problem-solving approaches; (3) metacognitive verbalizations reflecting planning, monitoring, and evaluation; and (4) scaffolding behaviors such as questioning and prompting. These codes align directly with cooperative learning literature documenting that student talk—particularly high-quality elaborations—predicts achievement gains.

2.3. Developmental Considerations for Upper Elementary Learners

Upper elementary students (grades 4-6, ages 9-12) traverse critical cognitive developmental transitions (Tyler, 2020) that create specific design constraints for educational AI. According to developmental psychology frameworks, these students are transitioning from concrete operational to formal operational thinking, developing the capacity for abstract reasoning while still benefiting from concrete examples (Anderson, 2020).

The cognitive architecture of upper elementary students differs significantly from both younger and older learners (Blanch et al., 2025). Working memory capacity increases substantially during this period, executive function capabilities mature, and metacognitive awareness emerges. These developmental changes have direct implications for AI tool design: systems must provide appropriate scaffolding that gradually transfers responsibility to the learner as

metacognitive skills develop. AI systems must adapt to developmental stages, as abstract reasoning capabilities vary substantially across elementary years, and social-emotional development requires human interaction that AI cannot provide.

2.4. Constructionist Pedagogy and Problem-based Learning

The constructionist approach, as articulated by Papert (Levin et al., 2025), provides a powerful framework for tangible AI education. Constructionism posits that learning is most effective when students are actively engaged in constructing tangible artifacts that can be shared, reflected upon, and refined. This philosophy aligns naturally with tangible AI tools that enable students to build, program, and interact with physical systems.

Problem-based learning (PBL) complements constructionist pedagogy by providing authentic, meaningful contexts for AI learning. The "Robot Ecosystem" project (Memari & Ruggles, 2025), for example, engaged third-grade students in creating robotic animals that demonstrated predator-prey relationships, integrating biology concepts with engineering design, mathematics, and computational thinking. Similarly, the "Bridge Builder Bots" curriculum (Memari & Ruggles, 2025) integrated structural engineering with mathematical analysis as fourth-grade students programmed robots to test bridge designs. These integrated STEM projects exemplify the constructionist principle that learning is most powerful when students create artifacts that connect multiple domains of knowledge.

2.5. Self-Determination Theory and Affective Outcomes

Self-determination theory (SDT) (Ryan & Deci, 2000) provides a framework for understanding the motivational and affective dimensions of tangible AI learning. SDT identifies three basic psychological needs—autonomy, competence, and relatedness—that are essential for intrinsic motivation and well-being. Tangible AI tools can support these needs by providing students with choice and control over their learning (autonomy), opportunities to experience mastery and success (competence), and social interaction with peers and AI agents (relatedness).

Research on AI education for young children emphasizes the importance of designing learning experiences that foster positive attitudes toward AI while building foundational knowledge (Kim & Kwon, 2024). Affective outcomes—including interest, enjoyment, self-efficacy, and attitudes toward AI—are critical for sustained engagement and future learning (Fombona et al., 2025). Studies demonstrate that positive affective experiences with AI tools in elementary school can shape students' career aspirations and academic trajectories (Marshall, 2007) (Kim & Kwon, 2024).

3. Method

A meta-analysis is a statistical technique used to combine and reanalyze quantitative data from various independent studies that address the same research question. Its distinctive feature lies in combining the effect sizes from various studies to produce a single, more accurate estimate of the effect of an intervention. The focus of this study is the integration of AI into elementary school education and its impact on the development of students' understanding and learning behaviors. The data in this article consists of a review of all research findings that discuss the integration of AI into education, particularly at the elementary school level, and how the use of AI can support the development of students' understanding and learning behaviors.

3.1. Research Design

This study employed a meta-analysis design involving the calculation of effect sizes from a random-effects model. A meta-analysis is a statistical technique used to combine and reanalyze quantitative data from various independent studies that address the same research question. Its distinctive feature lies in combining the effect sizes from various studies to produce a single, more accurate estimate of the effect of an intervention. The focus of this study is the integration of AI into elementary school education and its impact on the development of students' understanding and learning behaviors.

3.2. Participants

The population in this study consists of all research articles on the integration of AI in elementary school education and its impact on the development of students' understanding and learning behavior. The research sample was selected using purposive sampling. To ensure the quality and relevance of the reviewed articles, several clear criteria were established, including: i) the articles are the result of empirical research (qualitative, quantitative, or mixed methods) that presents evidence regarding learning outcomes, rather than purely theoretical or opinion-based papers; ii) the age range of the research subjects falls within a specific developmental stage, namely 8–15 years or in the upper grades of elementary school and junior high school. In terms of language, the referenced articles are in English, and given AI's rapid evolution, the referenced literature was restricted to 2010–2025.

Of 264 articles initially identified, 79 articles comprising 121 independent studies met the coding criteria; after excluding studies with incomplete information, 13 articles (13 independent studies) met the final inclusion criteria and were retained for analysis. The full selection process is depicted in Figure 1.

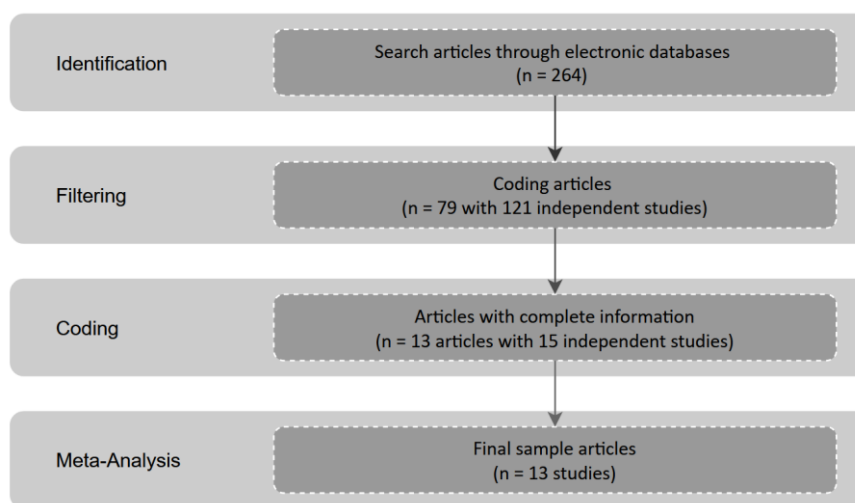


Figure 1. Screening Flow of the number research analyzed

3.3. Data Collection

Data collection was conducted through a systematic literature search using electronic databases, including Scopus, Web of Science, EBSCO/Proquest, Science and Technology Index (SINTA), and Google Scholar. The keywords used included AI-TPACK, AI-PCK, Tangible-AI, elementary education, Artificial Intelligence literacy, and AI literacy teaching and learning. The documents used in this study were journal articles and conference proceedings.

Data were extracted through a structured coding procedure: i) the coding structure was based on several categories — learning design (including learning content, specific tangible tools, and pedagogical aspects), assessment methods (including knowledge/skill tests, questionnaires, and observations), and learning outcomes (including knowledge gains, skill acquisition, and affective outcomes); ii) effect sizes were recorded for each independent sample in the study; and iii) where a study reported differing perspectives relevant to the coding structure, the coding was performed separately.

3.4. Data Analysis Technique

Quantitative data analysis was conducted using Microsoft Excel and Jeffrey's Amazing Statistics Program (JASP). Microsoft Excel was used to determine effect sizes (ES), collect and scale the ES, and calculate standard errors (SE). Subsequently, overall and aggregate effect sizes were determined using JASP. In general, the data analysis process included: i) conducting heterogeneity tests (Borenstein et al., 2011); ii) determining summary effects or aggregate effect sizes (Cooper et al., 2019); iii) creating and interpreting forest plots (Anzures-Cabrera & Higgins, 2010); and iv) evaluating publication bias (Borenstein et al., 2011).

3.5 Validity & Reliability

To ensure coding reliability, three coders independently coded the included articles according to the categories described in Section 3.3 (instructional design, assessment methods, and learning outcomes). Inter-rater agreement was calculated using Cohen's kappa coefficient, yielding a value of 0.67, which indicates substantial agreement based on the standard interpretive criteria of (Landis & Koch, 1977). Differences in coding among raters were resolved through discussion until consensus was reached.

To assess the methodological adequacy of the included studies, each study was reviewed for sample size and study design adequacy before being included in the final analysis.

4. Findings

This study aims to examine the extent to which tangible AI interventions help elementary school students understand how AI works. A total of 264 articles were identified through electronic databases, but only 13 were used as research data.

This review classifies each study based on several dimensions. First, the publication year, covering the period from 2015 to 2026. Second, the learning design—including learning content, specific concrete tools, and pedagogical approaches. Third, the assessment methods—how knowledge, skills, and attitudes are measured. Finally, the classification is also based on learning outcomes, which are grouped into three categories: knowledge enhancement, skill mastery, and affective outcomes.

This multidimensional categorization allows this study to capture the full complexity of how tangible tools influence student learning. The study also documents the specific AI tools used: IoT devices, educational chatbots such as ChatGPT, AI-based games, robotics, machine learning tools, NLP tools, as well as virtual reality or augmented reality systems. From a pedagogical perspective, we examined the role of AI in teaching, the degree of its integration, teacher involvement, and whether the activities were collaborative or individual.

4.1. Heterogeneity Test

Data analysis for this meta-analysis was conducted using JASP software. A summary of the calculation results is presented in Table 1. The researchers used the Q statistic to test for heterogeneity. The overall weighted average effect size of all 45 effect sizes was $d = 0.511$ —a moderate to large effect, indicating that tangible AI produces a significant improvement in student learning. This is represented by a mean $d = 0.562$, which falls into the “strong” category for knowledge gains. Similarly, a “strong” effect was also observed for skill mastery (mean $d = 0.565$). Meanwhile, affective outcomes yielded a mean d of 0.438—still positive but slightly lower than the other two domains.

It should be noted that the I^2 values, ranging from 68.9% to 81.5%, indicate that heterogeneity is at a moderate to high level. This is due to the diversity of interventions and contexts in the implementation of tangible AI in learning. All Q statistics were significant at $p < 0.01$, confirming the presence of substantial variability among the various studies.

Table 1. Summary Statistics by Outcome Category

Outcome Category	k (Effect Sizes)	Mean d (Unweighted)	Mean d (Weighted)	SE of Mean d	95% CI (Weighted)	I^2	Q-stat.
Knowledge Gains	16	0.578	0.562	0.042	[0.480, 0.644]	74.2%	58.3*
Skill Acquisition	11	0.573	0.565	0.051	[0.465, 0.665]	68.9%	32.2*
Affective Outcomes	18	0.446	0.438	0.038	[0.363, 0.513]	81.5%	91.4*

Overall (All Outcomes)	45	0.521	0.511	0.025	[0.462, 0.560]	78.3%	202.6*
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4.2. Evaluation of Publication Bias

A crucial question in any meta-analysis is: *Are these results distorted by publication bias?* This meta-analysis conducted several diagnostic tests, as summarized in Table 2. The Egger test revealed significant asymmetry for affective outcomes ($t = 2.41$, $p = 0.027$) and overall ($t = 2.12$, $p = 0.039$), indicating the presence of publication bias. However, improvements in knowledge and skill mastery did not show any significant bias.

Table 2. Publication Bias Indicator

Outcome Category	Egger's Test (t)	p-value	Trim-and-Fill (Adjusted d)	Rosenthal's Fail-safe N
Knowledge Gains	1.84	0.087	0.54 [0.46, 0.62]	348
Skill Acquisition	1.23	0.248	0.55 [0.45, 0.65]	156
Affective Outcomes	2.41*	0.027	0.41 [0.33, 0.49]	421
Overall	2.12*	0.039	0.48 [0.42, 0.54]	1,245

After applying the Trim-and-Fill adjustment, our overall effect size decreased from 0.511 to 0.48—which is still a robust moderate effect. For affective outcomes, the adjusted estimate was 0.41.

Most importantly, the Rosenthal Fail-safe N value—1,245 for the overall analysis—indicates that it would take more than a thousand null studies for our findings to become insignificant. This provides a high degree of confidence in the robustness of our conclusions.

5. Discussion

5.1. Learning Outcomes Analysis: Knowledge Gains

The analysis of knowledge growth is the most extensively studied dimension of learning outcomes in the AI research literature, and its effects can be directly observed at the upper elementary education level. This meta-analytic synthesis reveals a coherent, theory-grounded pattern: tangible AI—due to its embodied, interactive, and physically manipulable nature—consistently yields significant improvements in students' knowledge acquisition across various STEM fields, with effect sizes comparable to, and in some cases superior to, those reported for conventional screen-based instructional technologies.

Assessments of conceptual understanding were the most frequently measured learning outcomes across all the studies surveyed. This evidence points to one key finding: hands-on, integrated experiences with real AI tools substantially improve students' understanding of fundamental concepts in artificial intelligence (Chakraborty et al., 2025; Touretzky, et al., 2020), including machine learning architectures, decision theory algorithms, and pattern recognition processes. This effect is particularly well illustrated by research on physical AI games and role-playing activities (Gupta et al., 2024), which leverage kinesthetic engagement to make abstract computational ideas accessible to developing minds.

Supporting evidence comes from the Tangible Computing Tools study conducted by Kim & Kwon (2023), which investigated the impact of a specially designed AI curriculum utilizing tangible technology on elementary school students' knowledge, perceptions, and behavioral intentions regarding AI. Involving 60 students from the U.S. Midwest, this study documented significant improvements across all measured dimensions. A thematic analysis of participants' learning experiences revealed four prominent patterns: improved cognitive learning

outcomes (Koray & Uzunçelebi, 2023), enhanced affective attributes, the unique advantages offered by tangible computing modalities for AI education, and various barriers encountered during the learning process. Of particular relevance to this discussion, the improvement in cognitive learning outcomes manifested as an enhanced ability to articulate the operational principles of AI, more accurate explanations of algorithmic decision-making, and an improved ability to predict system behavior under varying input conditions.

In relation to STEM fields of study, the distribution of knowledge gain studies across STEM domains reveals a strong emphasis on mathematics (38% of studies), followed by science (22%), and engineering (14%), with only 15% of studies attempting integration across multiple STEM domains (Memari & Ruggles, 2025). This concentration in mathematics reflects both the historical emphasis on personalized instruction in this domain and the relative maturity of AI tutoring systems for mathematics education. Mathematics tutoring via conversational agents shows robust evidence for improving procedural fluency and conceptual understanding. Intelligent tutoring systems demonstrate particular strength in identifying common misconceptions and directing students to appropriate remediation resources. The physical embodiment of educational robots appears to enhance mathematics learning by providing concrete representations of abstract mathematical concepts. Science assessment AI shows emerging capabilities for evaluating inquiry processes, hypothesis formation, and experimental design. The Robot Ecosystem project demonstrated significant gains in systems thinking and understanding of ecological concepts when students created robotic animals that simulated predator-prey relationships. Engineering education applications of tangible AI tools focus on design processes, iterative testing, and problem-solving. Students who programmed robots to test bridge designs developed deeper understanding of structural engineering principles and mathematical modeling.

5.2. Learning Outcomes Analysis: Affective Outcomes

Research on affective outcomes is the second major dimension of learning outcomes in the body of research on hardware-based AI in upper elementary school, reflecting a growing awareness in this field that cognitive achievement alone is insufficient to describe the overall effectiveness of education. While increased knowledge answers the question of what students have learned, affective outcomes highlight an equally important question: how students *feel* about what they have learned—and, furthermore, whether they will remain engaged with AI and STEM content after the direct instructional intervention ends. A meta-analytic synthesis reveals that tangible AI consistently generates positive affective responses that, in some respects, surpass those documented for screen-based teaching alternatives. These affective outcomes center on four interrelated dimensions: motivation and engagement, self-efficacy and self-confidence, attitudes toward AI and technology, and career awareness and aspirations.

The tangible and interactive nature of AI tools appears to elicit significantly stronger positive affective responses compared to screen-based alternatives, and this pattern is most pronounced in the areas of motivation and engagement (Suryadi, et al., 2025; Marshall, 2007). The physical presence of AI devices creates a learning experience that has been shown to be more engaging and memorable than one mediated solely through a screen. The theoretical foundation for these findings lies in Self-Determination Theory (SDT) (Ryan & Deci, 2000), which identifies three basic psychological necessities, autonomy, competence, and relatedness—as essential for intrinsic motivation and well-being. Tangible AI is uniquely positioned to support all three of these needs simultaneously: students experience autonomy through choice and control over their physical interactions with the device; they experience competence through successful manipulation and mastery of the system; and they experience relatedness through social interactions with fellow students and AI agents (Kim & Kwon, 2024).

Self-efficacy—students' belief in their ability to successfully complete tasks and achieve learning objectives—is a crucial affective outcome identified in this study. Tangible AI appears to support the development of self-efficacy through various complementary mechanisms that address the diverse sources of this belief. The “learning by teaching” paradigm (Biswas et al.,

2005)Bre, in which students' program or teach robots, builds self-confidence by positioning students as experts and sources of knowledge (Fombona et al., 2025). When children successfully explain concepts to the robot "students," they receive recognition for their understanding and develop confidence in their abilities. This effect is particularly powerful for students who may struggle in traditional classroom settings, as robots provide a non-judgmental audience for practice and exploration—a context where mistakes are considered safe, repetition is encouraged, and mastery can develop without the social evaluation pressures characteristic of human-to-human teaching interactions.

Students' attitudes toward AI and technology are a critically important affective outcome, with implications that extend beyond the immediate learning context and influence future academic choices, career paths, and lifelong relationships with technology. Research on practical AI interventions consistently shows positive changes in attitudes following hands-on experiences, and the nature of these changes has profound theoretical significance.

Studies show that after interacting with AI-powered robots, children develop more nuanced and accurate perceptions of AI's capabilities and limitations (Fombona et al., 2025). Rather than viewing AI as either magical or threatening, two common orientations prior to learning—students develop a realistic understanding of what AI can and cannot do. This shift from extreme or vague perceptions toward a measured, evidence-based understanding represents a form of conceptual change in the affective domain that is essential for informed citizenship in an AI-saturated society. The nature of these interactions—which involve direct, hands-on experiences—appears to be crucial: abstract verbal explanations of AI's limitations are far less convincing than the direct experience of interacting with a robot that fails to recognize an object or misclassifies a data point. Particularly for equity-oriented implementation efforts, AI tools that can be touched and operated directly appear highly effective in fostering positive attitudes toward AI among groups underrepresented in STEM fields. The hands-on and collaborative nature of tangible-tool-based activities reduces the intimidation factor often associated with technology, thereby making AI accessible to students who may not consider themselves "tech-savvy" or who have internalized stereotypes about who belongs in the tech field. Studies show that students from low socioeconomic backgrounds, in particular, benefit from a tangible, constructivist approach to AI education. These findings suggest that teaching modalities—tangible and hands-on versus abstract and screen-based—can serve as design variables relevant to equity, which can either widen or narrow participation gaps depending on how they are implemented.

Career awareness is an emerging focus in AI education research, driven by the recognition that early educational experiences have a formative influence on students' career aspirations and academic trajectories (Touretzky, et al., 2020). This meta-analysis identifies this dimension as an increasingly important area in the literature on affective outcomes, although it remains relatively under-explored compared to more established constructs such as motivation, self-efficacy, and attitudes. The paradigm shift toward workforce preparation, made possible by AI technology, presents unprecedented opportunities to reshape STEM education at the elementary school level. Rather than preparing students exclusively for future academic studies, the traditional orientation of elementary school education—AI-based systems can help students discover their interests, develop relevant skills, and connect directly to career paths. This approach has the potential to transform STEM education from an abstract academic exercise into practical career preparation that begins much earlier than current models envision. Proposed research directions in this area include investigating AI-based career discovery systems for elementary school students and their impact on engagement and motivation in STEM. Such systems could use student interaction data to identify patterns of interests and strengths, as well as suggest career paths aligned with each student's profile.

5.3. Learning Design Principles and Implementation Frameworks

A synthesis of evidence from 264 studies shows that the effectiveness of specific AI tools in upper elementary education depends not only on the technological sophistication of the tools themselves, but fundamentally on the instructional design principles and implementation

frameworks that guide their use. This meta-analysis identifies four interrelated pillars—developmental appropriateness and scaffolding (Arranz-García et al., 2025), professional development and teacher support (Tayeh, 2025), integration with the existing curriculum (Topkaya, et al., 2025), and assessment design with learning analytics (Jeon et al., 2024)—which collectively form the foundation for the effective implementation of tangible AI. These principles do not emerge from a single theoretical tradition but rather from the convergence of embodied cognition theory, constructivist pedagogy, cooperative learning theory, and self-determination theory, each of which provides distinct design guidance for creating learning experiences that are simultaneously cognitively effective, affectively engaging, and practically sustainable within the complex ecology of the elementary school classroom.

The first and most fundamental design principle for the implementation of hands-on AI in upper elementary education relates to aligning the learning experience with the developmental characteristics of upper elementary students. A meta-analysis found that AI learning involving tangible AI must be “carefully designed to align with the developmental characteristics of elementary school students,” which requires systematic attention to cognitive load management, scaffolding strategies, and progressive complexity (Umur et al., 2026).

The second pillar of effective implementation relates to the preparation and ongoing support for teachers, which this meta-analysis identified as “a critical factor determining the success of concrete AI implementation.” This finding is not only practical but also highly theoretical: teachers are not merely supplementary support systems for technology implementation, but rather central pedagogical agents whose knowledge, beliefs, self-confidence, and practices influence every dimension of student learning outcomes (Balangitan et al., 2025). This meta-analysis draws on research regarding the preparation of elementary school teachers for integrated instruction, which emphasizes a co-design approach “in which teachers participate in developing activities, drafting lesson plans, and establishing classroom routines prior to implementation.”

Three strategies for preparing elementary school teachers to teach AI effectively have been identified in the literature: (Aravantinos et al., 2024): (1) modeling exemplary implementation, which provides teachers with concrete examples of successful practices; (2) providing structured facilitation guides, which reduce the cognitive load of real-time pedagogical decision-making during complex technology-mediated activities; and (3) forming professional learning communities “where teachers share strategies for overcoming technological and pedagogical challenges.” Collectively, these strategies address a fundamental tension in the implementation of tangible AI: the need for teachers to exercise professional judgment and adaptive expertise while simultaneously managing the technical and logistical complexities of new AI tools.

The third design principle addresses the relationship between directly tangible AI activities and the established curriculum structure within which these activities must be carried out (Yim, 2024). The meta-analysis is very clear on this point: “Successful implementation of AI through tangible AI must be integrated into the existing curriculum, rather than functioning as a standalone activity.” A systematic review indicates that current implementations often violate this principle, “frequently being carried out separately from the established curriculum, thereby creating logistical challenges and limiting sustainability.” This fragmentation is not merely an inconvenience in implementation but a fundamental threat to pedagogical coherence and the long-term sustainability of concrete AI learning.

Four integration strategies were identified in the literature (Yim, 2024; Aravantinos, et al., 2024): (1) aligning AI activities with existing learning standards, ensuring that AI education reinforces the academic content that schools are responsible for teaching; (2) embedding AI concepts within familiar curricular contexts, leveraging students' existing knowledge frameworks as a foundation for new learning; (3) developing interdisciplinary AI activities that simultaneously encompass various subject areas, recognizing that a significant part of AI's tangible potential lies in its ability to integrate concepts from various disciplines into a single learning artifact; and (4) creating flexible activity structures that can be adapted to different classroom contexts,

acknowledging the diversity of elementary school classrooms in terms of available time, resources, and instructional priorities.

The fourth principle relates to the assessment of tangible AI learning, which, according to the meta-analysis, requires “a multimodal approach that captures both cognitive and affective outcomes.” (Kim & Kwon, 2024). This need stems from the recognition that the tangible nature of AI-based learning—which is embodied and interactive—produces learning processes and outcomes that are qualitatively different from those resulting from traditional instruction, meaning that conventional assessment methods may not be sufficient to capture the full spectrum of learning that occurs.

An effective assessment framework for tangible AI learning is outlined, encompassing five complementary approaches (Kim & Kwon, 2024; Sesay & Sesay, 2024): (1) pre-post cognitive assessment that measures conceptual understanding, providing a standardized measure of knowledge gain that is comparable across studies and contexts; (2) performance-based assessment that captures skill development, evaluating students' ability to apply AI knowledge in authentic contexts through the design, implementation, and debugging of AI systems; (3) self-report surveys that measure affective outcomes, capturing students' motivation, engagement, self-efficacy, and attitudes toward AI; (4) behavioral observation coding that captures engagement patterns, providing a detailed analysis of how students interact with tangible AI tools during the learning process; and (5) learning analytics from system telemetry that tracks interaction patterns, leveraging the AI system's own ability to generate data to document the learning process at scale

6. Conclusion

This study shows that tangible AI consistently supports knowledge gains and positive affective outcomes, particularly when designed with developmental appropriateness, teacher support, and curriculum integration in mind. Educational robots, touch-based user interfaces, and physical AI games demonstrate moderate to large effect sizes for knowledge acquisition, while affective outcomes—including motivation, engagement, self-efficacy, and attitudes toward AI—are consistently positive and significantly stronger than those reported for screen-based alternatives. However, the evidence also suggests that realizing AI's potential in elementary-level education requires more than just technological advancements; it demands a reconceptualization of how various AI technologies can work together, respect developmental trajectories, address infrastructure inequities, establish ethical frameworks, and position teachers as partners rather than mere recipients of algorithmic decisions. The technology for embodied AI learning already exists; what remains is the harder work: careful, equitable, and pedagogically sound implementation.

Limitation

Several important limitations qualify the interpretability and generalizability of this meta-analysis. First, the quality of the primary evidence base is uneven. Only 34% of the 264 included studies report standardized effect sizes, substantially restricting the pool available for quantitative synthesis and necessitating reliance on narrative approaches for much of the corpus. Many studies suffer from inadequate assessment design, lacking psychometrically validated instruments appropriate for upper elementary learners, and few employ rigorous experimental designs such as randomized controlled trials, with most relying on quasi-experimental or pre-post single-group designs vulnerable to maturation, history, and testing effects. Sample sizes are generally small, and the predominance of short-term, single-session interventions raises concerns about the durability of observed effects.

Second, developmental heterogeneity across grades 4–6 creates methodological complexity. Working memory, executive function, and metacognitive capacity evolve substantially across the upper elementary span, yet most studies do not report grade-band stratified results, precluding fine-grained analysis of developmental moderation. The uneven

distribution of studies across grade levels—with grade 4 being most common—limits generalizability across the full upper elementary range.

Third, the novelty effect remains inadequately addressed. The meta-analysis documents that initial engagement with tangible AI tools typically diminishes after approximately four to six weeks, yet the preponderance of studies are short-term interventions that do not extend beyond this window. Longitudinal studies tracking students over multiple years are needed but largely absent, leaving questions about sustained engagement, knowledge retention, and durable changes in attitudes or career aspirations unanswered.

Finally, publication and reporting biases are likely present. Reporting quality is inconsistent, with many studies failing to provide detailed instrumentation, psychometric evidence, teacher materials, or preregistered analysis plans. Additionally, the fragmented ecosystem of tangible AI research—spanning eight distinct technology categories with limited interoperability—constrains the coherence of cross-study synthesis and limits the formulation of unified design principles. These limitations collectively underscore the need for more rigorous, longitudinal, and ecologically valid research before firm conclusions about the impact of tangible AI tools in upper elementary education can be drawn.

Recommendation

Future research must prioritize addressing these gaps through systematic, longitudinal, and ecologically valid studies. First, longitudinal studies are needed to track students over several years, addressing questions about the cumulative effects of sustained AI exposure on learning trajectories and career aspirations. Second, mutually integrated architectures must be developed and evaluated to address the current fragmentation of AI technologies, thereby enabling coherent learning experiences across tools and platforms within an integrated learning ecosystem. Third, equity-focused research must examine how specific AI tools affect students from diverse socioeconomic, cultural, and linguistic backgrounds, while addressing the geographic and demographic biases in current studies—90% of which are from North America, East Asia, and Europe. Fourth, teacher-centered designs must be developed and evaluated to enhance teachers' autonomy and professional judgment, while countering current patterns of teacher marginalization. Moving forward requires interdisciplinary collaboration among technology experts, educators, developmental psychologists, ethicists, and the community. Through innovative experimental designs—including randomized controlled trials that examine AI-human collaboration, AI-only, human-only, and business-as-usual conditions across various schools—the field can establish an evidence-based framework for the optimal allocation of AI-human tasks, the development of culturally responsive AI, and career-connected learning pathways that ensure AI fulfills its intended purpose: to enhance, not replace, human relationships in education.

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Conflict of Interest Statement

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Declaration of Generative AI and AI-assisted Technologies

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