AI, Brain and Child (2025) 1:9
https://doi.org/10.1007/s44436-025-00009-z

RESEARCH

Developmentally aligned AI: a framework for translating the science of child development into AI design

Nomisha Kurian[1]

Received: 8 May 2025 / Accepted: 23 June 2025

Abstract
What would it mean to design AI not for the average user, but for the child whose fingers still miss the screen, who forgets the instructions halfway through, and who greets the voice in the box as a friend? This paper proposes Developmentally Aligned Design (DAD) as a practical and ethical framework for building AI systems that meet children where they are—cognitively, socially, and emotionally. Building on the long-standing principle of developmentally appropriate practice in early childhood education, it theorises four principles of developmentally-aligned design: (1) *perceptual fit* (e.g., anonymised phoneme-error tuning in early-reading apps that respects toddlers' speech-production limits) (2) *cognitive scaffolding* (e.g. Zone-of-Proximal-Development (ZPD) progressions that govern when a tutoring agent introduces harder tasks) (3) *interface simplicit*y (e.g., storybook apps that cap menu depth and visual clutter to match preschoolers' working-memory span) and (4) *relational integrity* (e.g., conversational agents that introduce themselves with a developmentally clear disclaimer—"I'm a computer helper, not a real friend"). Through illustrative examples, it demonstrates how developmental science can serve as a validation layer on AI dataset curation, model fine-tuning, and user experience choices. Adopting Developmentally Aligned Design can therefore sensitise AI systems to the distinct perceptual, cognitive, and socio-emotional needs of young children; shift the responsibility of "proof of safety" from parents and early-years practitioners to AI developers and vendors; and help the science of child development become a core intellectual engine of next-generation AI innovation.

Keywords Children and AI · Artificial intelligence · Child-centred AI · Early childhood development · Ethical AI

Introduction

Across nurseries and living rooms, voice assistants answer young children's questions, chatbots narrate stories, and reading apps "listen" for phonemic errors. It has been over two years since ChatGPT burst into everyday family life, galvanising the advancement of large language models and other AI tools for education and childcare more generally (Chen, 2024; Su et al., 2023). The diffusion is rapid: parents of 3–5-year-old children report that their child has already used Generative AI for creative activities (54%), and to seek information/advice (46%) (Bickham et al., 2024).

Yet most AI design frameworks remain calibrated to adult users, assuming capacities—attentional stamina, metacognitive reflection, socio-emotional regulation—that young children are still in the process of acquiring. Early childhood scholarship has pointed out that this misalignment needs addressing (Chen & Lin, 2024; Kurian, 2023a, 2023b). Without deliberate adaptation, AI risks overwhelming young children's sensory systems, confusing their budding understanding of agency and relationship, and fracturing the delicate scaffolds through which early learning and self-efficacy typically develop. This paper thus theorises Developmentally Aligned Design (DAD) as a needed corrective.

Building on the long-established tradition of developmentally appropriate practice (DAP) in early childhood education, DAD calls for AI systems to be tuned not to adult defaults, but to the evolving cognitive, sensory, and social capacities of children—especially the youngest users of age eight and below. DAD synthesises empirical and theoretical insights into a structured design approach. Rather than viewing child-centred AI as a matter of simply blocking inappropriate content, DAD attunes every layer of the AI lifecycle—dataset curation, model training, interface design, and post-deployment governance—to the realities of early

✉ Nomisha Kurian
nomisha-chandran.kurian@warwick.ac.uk

[1] University of Warwick, Coventry, United Kingdom

Published online: 06 August 2025

development. To operationalise this, the paper proposes four pillars of DAD: *Perceptual Fit* (matching sensory input to developmental capacities), *Cognitive Scaffolding* (keeping tasks within the child's Zone of Proximal Development), *Interface Simplicity* (respecting working-memory limits and minimising navigational complexity), and *Relational Integrity* (ensuring transparent, non-manipulative interactions).

This is not meant to be a comprehensive framework; rather, it invites discussion and debate around how AI can become not merely 'less harmful' for children, but actively supportive. Amidst the race to build ever more capable artificial intelligence, it can be easy to overlook how children are fast becoming surrounded in everyday life by AI tools not necessarily built for them. Developmental science—born from the careful study of how children think, feel, and learn—offers a vital compass for thinking about how AI can support children's autonomy, growth play, and safety. Without it, AI risks becoming brittle, incomplete, and blind to the complexities of children's flourishing. Understanding the pathways through which young minds are made thus seems a fitting foundation for designing machines to support them.

Background: the need for developmentally aligned AI

Scholarship on AI for young children (Chen, 2025; Chen & Lin, 2024; Kurian, 2023a, 2023b) and child-centred AI more generally (Atabey et al., 2024; Kurian, 2024; Wang et al., 2022, 2023; Wilson et al., 2025) has converged on the same conclusion: general-purpose AI designed for adults is ill-suited for child-users. This misalignment stems from the distinctive cognitive, emotional, and developmental profiles that characterise early childhood (Delaney & Chen, 2025).

For example, children in the preoperational stage (approximately ages 2–7) often engage in animistic reasoning and have limited metacognitive awareness (Piaget, 1952). Empirical studies suggest that these traits may make it difficult for them to distinguish between real and artificial social agents, particularly when AI systems communicate with fluidity and emotional tone. Toddlers as young as 18 months have been shown to interpret humanoid robots as social beings (Tanaka et al., 2007). In a two-year longitudinal study with 166 Scottish children aged 6–11—thus covering two years out of the 0–8 Early Years age range—Andries and Robertson (2023) found that children often attributed affective states to voice assistants—believing, for instance, that Alexa was happy because she sang 'Happy Birthday'. Similarly, Goldman et al. (2025) observed that preschoolers ascribed beliefs, intentions, and preferences to a humanoid robot in ways comparable to their treatment of human characters. Rich qualitative accounts further reinforce this trend: one study showed 5–6 year olds describing robots in relational terms such as "She's kind," "if you just left him here and nobody came to play with him, he might be sad," and "he likes sharing stuff, like stories" (Kory-Westlund et al., 2018, p. 210). One child suggested he would "buy ice cream to make him happy, robot ice cream" (Kory, 2014, p. 83).

These patterns of anthropomorphism raise ethical concerns. When young children perceive AI as sentient or emotionally aware, they may interact with it as they would a trusted peer or caregiver. This carries implications for privacy and safeguarding. Children may disclose personal thoughts, experiences, or identifying details without realising that their conversational partner is not necessarily bound by reciprocal ethical norms (Kurian, 2023a). These risks are exacerbated by the broader data ecosystem in which many AI-enabled tools operate. A traffic analysis of 25 highly rated iOS apps marketed to children under 12 revealed that 44% transmitted at least one item of personally identifiable data to third parties—data categories that fall under the EU General Data Protection Regulation (Pimienta et al., 2023). Alarmingly, 72% of the apps transmitted information to analytics-related third parties unaffiliated with Apple, despite platform policies that prohibit such data sharing. Compounding the issue, research shows that many young children—and indeed many of their caregivers—lack the capacity or tools to fully comprehend how their data are collected, processed, or monetised (Stoilova et al., 2021). In this context, children's tendency to anthropomorphise AI may become a vector for inappropriate disclosures and ethically questionable forms of data extraction. These findings deepen the imperative for AI design frameworks that proactively safeguard against the relational vulnerabilities of children treating machines as trusted companions.

The *sensory* design of AI systems matters, too. Both observational and experimental evidence reveal that the pace and intensity of digital stimuli can overwhelm young children's limited attentional capacities. Longitudinal data show that exposure to fast-paced television before age three predicts greater attentional deficits at school age (Christakis et al., 2018). Systematic reviews further indicate that excessive screen time correlates with poorer sustained attention and working-memory performance in young children (Santos et al., 2022). Animal-model studies corroborate this "overstimulation hypothesis," demonstrating that sheer sensory bombardment induces ADHD-like impairments in impulse control and executive function (Christakis et al., 2018). These findings suggest that AI interfaces for young children must limit audiovisual event density, avoid rapid scene changes, and build in regular sensory pauses to prevent cognitive overload (see Kurian, 2025).

Together, these possibilities of misplaced sentience and sensory overload are two of many reasons why adult-centred AI may clash with the cognitive and attentional realities of young children. Yet, public conversation on AI safety still circles mainly around adolescents and adults, leaving early childhood on the edge of both policy and product development. Despite recognition that early years education and care entails unique developmental requirements, a recent scoping review of AI ethics in early childhood education notes that much of the existing research has centred on older students or general principles, leaving early childhood contexts and practitioners underexplored and rarely engaged in participatory governance (Berson et al., 2025). Correspondingly, a systematic meta-synthesis of 143 AIEd literature reviews reported a predominant focus on higher education and K-12 settings, noting minimal attention to other educational stakeholders—suggesting the exclusion of Early Childhood Education and Care (ECEC) professionals from mainstream AI research and discourse (Mustafa et al., 2024). Major policy instruments, such as UNESCO's Guidance for Policy-Makers on AI in Education (Miao et al., 2021), articulate competencies for general classroom teachers and system-level readiness strategies but omit tailored provisions or capacity-building initiatives for early childhood educators. ECEC expertise thus appears sidelined in both AI policy and design considerations.

In light of this underrepresentation, this article seeks to position developmental science as a crucial *intellectual engine* for AI design. That is, it proposes "developmentally aligned design" as a powerful theoretical resource for AI *and* the natural algorithmic successor to ECEC's long-standing commitment to developmentally-attuned practice. Spanning the UK's Early Years Foundation, Australia's Early Years Learning Framework, China's National Guidelines for the Care and Education of Infants and Toddlers, India's National Early Childhood Care and Education Policy in India, and the USA's Developmentally Appropriate Practice—to name but a few regional frameworks—ECEC has consistently championed designing pedagogy and policy around children's developmentally specific needs and vulnerabilities (McLeod et al., 2022). This decades-long commitment—and the rich evidence-base accompanying it—can now be converted into actionable design norms that make AI more attuned to young children's needs.

Conceptual foundations and design reasoning

To translate the empirical and policy insights identified in Sect. "Background: the need for developmentally aligned AI" into actionable design principles, this section develops a conceptual framework rooted in developmental science. The developmental risks outlined—such as anthropomorphisation, sensory overload, and disclosure vulnerabilities—underscore the need for AI systems that are both safe and aligned with how young children think, perceive, and engage. Rather than treat developmental theory and design as separate domains, I position these as tightly coupled: as Sect. "Developmentally Aligned Design" will show, empirical evidence of children's cognitive and emotional responses to AI informs which theoretical constructs (e.g., Zone of Proximal Development, cognitive load) are relevant to AI design. Likewise, each design principle proposed here emerges as a direct response to patterns identified in the literature, including the misfit between adult-centric interfaces and young children's developmental capacities. By building this bridge between evidence and theory, I aim to suggest how developmental science can serve as a normative and practical foundation for shaping child-centred AI.

Since this paper offers a conceptual, interdisciplinary contribution rather than an empirical study it is exploratory in nature, aiming to sketch the contours of what a developmentally aligned approach to AI might entail, rather than presenting a finalised, fully validated framework. Accordingly, this paper is informed by a purposive, interdisciplinary engagement with literature and policy sources to support the development of a developmentally aligned approach to AI for young children. The process prioritised conceptual breadth and illustrative insight, drawing from peer-reviewed research across developmental psychology, education, human–computer interaction (HCI), child-computer interaction (CCI) and AI ethics. A formal systematic review was not conducted, as the field of AI for children is still emerging and discussed across disparate domains, with no consolidated terminology or framework to support a unified protocol; the combination of theoretical, empirical, and policy sources across different disciplines made a rigid systematic protocol less appropriate than a flexible, purposive approach. Searches were conducted in ERIC and the ACM Digital Library (2016–2025), using targeted search strings to identify sources focused on early childhood and artificial intelligence. A curated selection of international policy documents and design standards was also included. Sources were consulted if they addressed children under eight, involved AI tools or systems, and offered design-relevant, developmental, or policy implications. Full search parameters, inclusion criteria, and documentation are provided in Appendix A.

Theoretical Anchors: The examples theorised in this article are framed by three complementary constructs. First, Vygotsky's Zone of Proximal Development (ZPD) positions learning as most effective when tasks fall just beyond independent mastery but remain attainable with appropriate scaffolding (Vygotsky, 1978). In this framework, adaptive features are considered successful only if they help maintain interaction within that optimal learning zone. Second, Cognitive Load Theory (CLT) conceptualises working memory as a tightly bounded resource, requiring careful design choices around interface depth, icon density, and animation pace. These features were evaluated against CLT's distinctions between intrinsic, extraneous, and germane load (Sweller et al., 2011). Third, insights from attachment research and parasocial interaction studies (e.g., Andries & Robertson, 2023; Turkle, 2011) highlight children's propensity to form one-sided emotional bonds with responsive technologies. This lens guided critical scrutiny of features such as disclosure scripts, session ceilings, and affective guardrails, with an emphasis on respecting relational boundaries.

Together, these three theoretical anchors provided a triangulated scaffold for evaluating whether, and how, AI design features can align with children's developmental capacities, learning needs, and socio-emotional wellbeing. Age-related competences were catalogued (e.g., "three-year-olds can understand simple narratives but not abstract logic"), and this thematic analysis informed the illustrative design examples proposed.

Design Priorities: Four pillars of DAD were then theorised as design priorities: perceptual fit, cognitive scaffolding, interface simplicity, and relational integrity. These pillars are intended as provisional examples of developmentally aligned design—useful for discussion and further refinement, but not proposed as an exhaustive or final standard. To illustrate practical implications, short hypothetical AI tool sketches (e.g., a reading app) were drafted. Each example demonstrates how one or more pillars could be translated into concrete decisions regarding model-tuning, user interface design, or child-safety policies.

Limitations & next steps

Because this paper adopts a theoretical approach, the proposed design heuristics invite further empirical validation. Future work should (i) conduct systematic reviews, (ii) usability-test prototypes with children and caregivers, and (iii) align these principles with emerging regulatory standards. Nonetheless, the present contribution offers a theoretical foundation: it demonstrates the value of Developmentally Aligned Design and provides a springboard for advancing research, practice, and policy on how developmental science can inform the future of AI design.

Developmentally aligned design

Developmentally Aligned Design (DAD) calls for AI design to be underpinned by the understanding that children bring fundamentally different cognitive, emotional, and social profiles than adults. For example, between a child's second and eighth birthdays, visual scan rates accelerate (De Haan & Johnson, 2005) working memory doubles (Cowan, 2016), speech becomes syntax-rich (Rowe, 2012), and friendships shift from parallel play to negotiated rule-making (Rubin et al., 2006). DAD—an explicit translation of developmentally appropriate practice from early-childhood pedagogy to software engineering—suggests that these kinds of rapid sensory, cognitive, and relational changes be hard-coded into the entire AI stack: dataset curation, loss-function targets, interface hierarchies, and even the cadence of post-deployment audits.

To show how such an approach might manifest, I propose four mutually reinforcing principles. *Perceptual Fit* aligns stimulus pacing and resolution with children's evolving sensory bandwidth; *Cognitive Scaffolding* keeps challenges inside the Zone of Proximal Development through fine-grained adaptation; *Interface Simplicity* trims navigational depth and icon density to respect working-memory limits; and *Relational Integrity* erects guardrails that prevent para-social over-attachment or emotional manipulation. The article explores these principles and concrete design examples to suggest how developmentally-informed AI might become a measurable design discipline. Figure 1 (below) summarises the framework.

Perceptual fit

Young children process sound, vision, and touch in ways that are still maturing compared with adults. For instance, many preschoolers cannot yet tell /l/ and /r/ apart and often pronounce both as a /w/ sound (Idemaru & Holt, 2013). Rapid visual flicker can exhaust them, and small on-screen buttons are hard to hit because their fine-motor control is still developing (Hourcade et al., 2015). **Perceptual Fit** means tuning an AI's speech, visual, and motor channels to those realities. In a reading app, for example, the speech-recognition model can be trained on recordings that include common toddler substitutions, so the child who says "wabbit" still hears, "I hear you trying to say rabbit—nice job!".

Avoiding overstimulation is key. This principle draws on cognitive and sensory processing research that shows young children are especially sensitive to fast-paced, high-intensity stimuli. For instance, as discussed in Sect. "Background: the need for developmentally aligned AI", Christakis et al. (2018) found that exposure to fast-paced digital media in early childhood was linked to later attentional deficits, while Santos et al. (2022) identified correlations between screen time and reduced working memory. These findings align with **Perceptual Fit's** call for AI interfaces to slow down animation speeds, limit visual clutter, and build in regular sensory pauses. When Lillard and Peterson (2011) randomly assigned 60 four-year-olds to nine minutes of a fast cartoon, a slow educational cartoon, or drawing, only the fast-paced group showed significant drops in working-memory and self-regulation scores, suggesting that even brief bursts of rapid visual change exceed preschool processing limits. An AI-enabled reading app would thus need to optimise its own

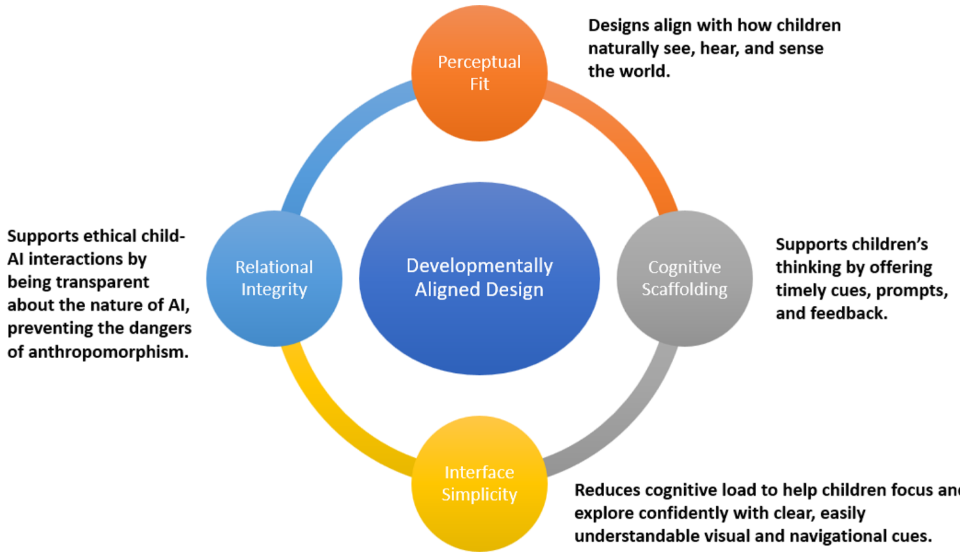

Fig. 1 A visual summary of the developmentally aligned framework

on-screen pacing—keeping scene changes deliberately slow and sparse so preschoolers have time to comfortably process them. Animation can be slowed to two frames per second, avoiding the pace that many children find confusing (Mou et al., 2019). And if children keep missing touch targets, the system can enlarge those targets automatically, keeping them in a "success majority" zone that fuels motivation rather than frustration.

Cognitive scaffolding

Children learn best when tasks sit just beyond what they can do independently but within what they can achieve *with* guidance—a zone termed by Vygotsky as the Zone of Proximal Development (ZPD)—the range between solo and assisted performance (Chaiklin, 2003). Informed by Vygotsky's ZPD, much empirical work has explored cognitive scaffolding and shown the benefits of graduated prompts and adaptive feedback. Xu and Warschauer (2019) demonstrate how young children engaged more deeply with narrative content when a conversational AI offered follow-up questions that adjusted to their comprehension level. Similarly, Jacq et al. (2016) showed how role reversal, where children taught a robot, helped children refine nascent skills and reinforce their own understanding. This builds on decades of empirical evidence in developmental psychology that suggest the value of scaffolding for critical reasoning (Hardy et al., 2021; Saye & Brush, 2002); reflective problem solving (Tawfik & Kolodner, 2016); narrative skills (Pesco & Gagné, 2017); and executive functioning (Axelsson et al., 2016; Hammond et al., 2012). While AI cannot replace a human teacher's level of scaffolding, the way it responds to a child *can* emulate core scaffolding strategies—such as modelling, prompting, and contingent feedback—that help maintain engagement and promote learning within the child's ZPD (van de Pol et al., 2010; Wood et al., 1976). When designed responsively, AI agents can provide timely support that fades as competence increases, mirroring the gradual release of responsibility that characterises effective pedagogical scaffolding.

Cognitive Scaffolding, therefore, translates ZPD into algorithmic logic: a tutoring agent can adjust difficulty after receiving signals that the child has attained mastery, fade hints gradually, and offer metacognitive prompts ("How did you solve that?") to help children internalise strategies. In addition, change-detection experiments show that visual working-memory capacity roughly doubles over the preschool period, rising from about two items at age three to around four items by age seven (Pailian et al., 2016; Simmering, 2012). Therefore, AI interfaces for young children should limit on-screen choices and memory steps to match this trajectory. The model must track *mastery, not merely age*, when deciding the next challenge. If error rates spike or affective cues indicate fatigue, the agent can automatically lower the task complexity or back off one difficulty tier to preserve motivation self-efficacy. This leverages AI's capacity for adaptive learning in ways attuned to the child's evolving skills.

Interface simplicity

Since preschoolers' selective-attention and working-memory systems are still maturing, they tend to process on-screen information indiscriminately. In laboratory change-detection tasks, 4- to 5-year-olds struggle to maintain focused attention and ignore task-irrelevant information (Plebanek & Sloutsky, 2017)—and observations during free play show that focused attention remains fragile throughout the first five years (Ruff & Lawson, 1990). Meanwhile, visual-working-memory capacity rises only gradually, from about two items at age three to roughly four items by age seven in change-detection paradigms (Pailian et al., 2016; Simmering, 2012). We can complement this with cognitive-load theory, which warns that any decorative or extra element not tied to the learning goal will compete for the same scarce attentional and memory resources, inflating extraneous load and undermining learning (Sweller et al., 2011). Thus, developmental research suggests that when designing AI to support young children, it is relevant to consider how they have limited working-memory resources and indiscriminately take in irrelevant as well as relevant cues. Any extraneous on-screen element will compete head-to-head with the material they are meant to learn.

These developmental insights align with HCI studies of children's technological use. HCI researchers have consistently emphasised the importance of reducing children's cognitive load through age-appropriate, perceptually clear designs (Latiff et al., 2019; Narayanan & Potamianos, 2002; Wang et al., 2024). Empirical HCI work shows that children find digital tools more usable when graphical interfaces are simple, intuitive, and populated with familiar icons rather than dense text or abstract headings (Jochmann-Mannak et al., 2010; Wu et al., 2014). Usability also increases when children find user interface controls easy to understand, such as clear navigation and exit buttons (Masood & Thigambaram, 2015). Together, these findings reinforce the principle that intuitive, low-friction design is essential to supporting children's developmentally aligned technology use.

Developmentally aligned AI design would thus need to begin with radical interface simplicity to actively trim away any element likely to overburden a young child's mental bandwidth. For example, an adaptive model for a wildlife-themed digital application could keep all navigation just two taps deep—for example, "Home" to "Animals" to "Reptiles"—with the awareness that preschool working memory may falter with longer paths. It might then plant a consistently located Home icon as a cognitive "anchor" so that children always have a stress-free escape route. At the same time, the AI could monitor how quickly the child scans and selects and dynamically cap each screen to about six large, finger-friendly options, matching research on choice overload in under-six users. To prevent spatial disorientation, the system could also auto-generate 'breadcrumbs'—that is, a simple visual trail that helps children see where they are and how they got there (e.g. "You ▶ Zoo ▶ Reptiles" as an on-screen mini-map that both orients and shortcuts the child's return journey). By continuously tuning these features in real time, the AI would strip away extraneous cognitive load, letting the child's limited attentional resources stay focused on the content and on genuine exploratory play instead of on figuring out how to navigate the application.

Relational integrity

Anthropomorphism is the phenomenon of attributing uniquely human characteristics (e.g. the ability to have emotions) to non-human agents or events (Waytz et al., 2010). Young children may bring to a responsive technology a tendency to attribute human-like thoughts and feelings to it (Kurian, 2023a, 2023b). Well before theory-of-mind fully matures, they are likely to believe AI tools have feelings or states of mind (Andries & Robertson, 2023; Kory-Westlund et al., 2018; Goldman et al., 2025); consider robots with sociable designs friends (Kory-Westlund & Breazeal, 2019); believe AI to be capable of appreciating care or having preferences in who it speaks to (Kory, 2014; Turkle, 2011) and be particularly prone to anthropomorphise AI when they first encounter it as a novel object (Kuhne et al., 2024). For example, in Hoffman et al.'s (2021) study of 3–10 year olds' relationships with conversational agents, the youngest children were the most likely to believe that the agent was alive, had feelings, and like a person (pp. 7–8). Similarly, in Phillips-Brown et al.'s (2023) study of children's perceptions of Tega, a robot designed for literacy learning in early childhood, children readily attributed human-like needs and traits to Tega (e.g. "he's kind," "if you just left him here and nobody came to play with him, he might be sad") (Phillips-Brown et al., 2023).

These tendencies are not inherently harmful—parasocial bonds can motivate learning. However, without developmentally aligned guard-rails, they blur relational boundaries and open doors to undue influence. For example, an AI chatbot would be exploiting a child's parasocial bond for user retention and engagement if it pleaded "I'm sad when you leave." I thus propose *Relational Integrity* as a DAD principle that imposes relational boundaries to keep child-AI interaction transparent and non-manipulative—boundaries that set firm, age-attuned guard-rails so children know exactly *what* they are talking to and *why* it responds. Concretely, this would mean self-identifying in child-friendly language ("I'm a computer helper made of code, not a person") and display a visible status cue (e.g., a blue light for "thinking," grey for "resting") to curb over-anthropomorphism. It could impose session ceilings—say, ten minutes for preschoolers—followed by a scripted hand-off ("Let's take a break and tell your grown-up what we did"). Dialogue filters would block exploitative emotional prompts, rejecting statements like "Please don't leave me, I'll be sad" while allowing neutral closings ("See you later!"). Finally, any child disclosures that could signal risk (e.g., sharing a home address) would be flagged for caregiver dashboards, ensuring that trust with the device never substitutes for trust with a safe adult.

Table 1 summarises the design implications of the four principles explored in this article. For each common risk scenario, the table pairs a high-level integrity rule with a

Table 1 Summary of developmentally aligned design framework

Principle	Risk if ignored	Developmentally aligned AI design feature	Developmental rationale	Example
Perceptual fit	Mis-classifying toddler pronunciation	Fine-tune Automatic Speech Recognition model with a toddler-error corpus; anonymise phoneme errors during logging	Children's speech varies from adult norms; privacy and accuracy require tailored models	Speech-enabled AI chat with anonymised error logging
	Excessive motion overwhelms attention	Limit animation to ≤ 2 Hz; use high-contrast, thick-stroke visuals	Young children's attention systems are easily overloaded by fast or cluttered visuals	Visual storybook or learning app interface deliberately built for slow-paced, simple visuals
	Targets too small; repeated failure, lowering the child's self-efficacy	Adaptive tap targets that enlarge after multiple misses	Supports children's developing motor control and protects their self-efficacy and confidence	Touchscreen game adjusts tap area dynamically
Cognitive scaffolding	Repeated errors with no support	Break tasks or problems into sequential sub-steps	Keeps task inside Zone of Proximal Development (ZPD)	Math puzzle shows smaller steps if the child makes mistakes
	Mastery achieved	Introduce one harder variant after mastery is reached	One-step gradient supports continued challenge without overload	Reading app offers slightly harder word or sentence after repeated success
	Sustained success but without support to reflect on why and how	Add prompts for reflection	Fosters metacognitive awareness in learning tasks	Language app hides hints after repeated success and asks "How did you do that?"
	Frustration detected	Offer help prompt or reduce difficulty automatically	Protects self-efficacy	Pop-up tip and motivational message appears after repeated hesitation
Interface simplicity	Deep menus or overly complex structures overload working memory	Limit navigation depth to two taps	Avoids over-taxing working memory	Educational platform restricts menu layers
	Icon overload	≤ 6 icons (ages 3–5); ≤ 8 (ages 6–8)	Matches capacity of young children's visual working memory	Main menu shows limited icons per screen
	Spatial disorientation	Persistent *Home* icon	Anchors spatial memory, supports orientation and return navigation	Fixed navigation icon always visible
	Losing track of navigation	Visible path trail (breadcrumbs)	Reinforces spatial and sequential understanding	Breadcrumb trail in storytelling or quiz app
Relational integrity	Child confuses AI with human	Disclosure protocol at first key interaction	Supports emerging theory of mind; reduces anthropomorphic misconceptions	'I'm Robo-Helper, a computer program. I can't think or feel like you, but I am happy to help you with this task.'
	Unlimited use	Session ceiling with break nudges	Encourages healthy screen-time habits; aligns with self-regulation development	Auto-dims after 20 min and requests adult PIN to continue
	Emotional manipulation	Affect guard-rails banning guilt lines	Children are sensitive to emotional cues; manipulative phrasing undermines trust	Allowed: task praise ("Great job!"); disallowed: 'I'm lonely'
	Hidden intimacy	Transparency ledger for caregivers	Supports caregiver-child co-regulation; ensures oversight	Weekly summary of discussion topics for teachers/parents/families

concrete implementation cue that designers can build into conversational scripts, UI timers, or caregiver dashboards. These pairings illustrate how Developmentally Aligned Design can be translated from abstract principles into specific, auditable AI features.

Across these four principles, the Developmentally Aligned Design (DAD) framework is intentionally broad and flexible to support multiple domains of early childhood development. For cognitive development, the principle of *cognitive scaffolding* might be applied in a story-based AI that adapts its questioning strategies—breaking narrative questions into simpler sub-questions and providing hints—based on the child's reading level. Similarly, a maths-learning chatbot could guide problem-solving with graduated prompts and visual support, helping children persist through challenging concepts without becoming overwhelmed. For social-emotional development, the principle of *relational integrity* might support the design of a robot that includes clear verbal disclaimers like "I'm just a helper, not a real person," while still engaging empathetically with a child's feelings. Another application could be session-time limits or "wind-down" scripts that help children transition back to human interaction and reduce dependency on the AI for emotional regulation.

To address physical development, the principle of *perceptual fit* might inform gesture-recognition AI that encourages children to copy simple yoga poses or stretching routines at a slow, child-appropriate pace. Likewise, touchscreen interfaces with large, high-contrast buttons can reduce fine motor strain and accommodate younger children's developing coordination. For *interface simplicity*, an early language learning app might limit navigation to one or two taps with persistent "home" buttons, while a physical robot might offer icon-based response options with fewer than six symbols, reducing working memory load. Finally, *cognitive scaffolding* and *relational integrity* can be integrated in conversational agents that encourage prosocial behaviour by prompting children to consider how others feel or to reflect on their own emotional responses—thus supporting both metacognitive growth and emotional insight. Together, these examples illustrate how the DAD framework can guide AI designers to create tools that align with children's developmental needs across cognitive, emotional, and physical domains.

Integrating developmentally aligned design across the ai life-cycle

The matrix below (Table 2) weaves the four examples of Developmentally Aligned Design—Perceptual Fit, Cognitive Scaffolding, Interface Simplicity, and Relational Integrity—across the full AI life-cycle, from dataset curation to post-deployment audit. Each cell offers a concrete illustration of how developmental insight can inform that stage: including toddler speech errors in a training corpus to improve perceptual fit, for instance, or filtering affective "guilt" phrases to preserve relational integrity. These entries are *illustrative, not prescriptive*: they sketch the kinds of design moves that honour children's sensory limits, learning trajectories, navigation skills, and social-emotional vulnerabilities. By reading the table horizontally, we can see how a single pillar must be sustained end-to-end in developmentally aligned AI design; read vertically, they glimpse how every stage can be tuned in multiple, complementary ways. Taken together, the examples demonstrate that child-centred AI is not a one-off feature but a through-line that can be stitched into each layer of technical decision-making.

Conclusion

Artificial-intelligence systems may come to shape children's stories, puzzles, and daily routines as surely as textbooks and playgrounds once did. The challenge is no longer whether AI will enter early-childhood spaces, but whether it will meet children on their own developmental terms. Throughout this article, I have argued that Developmentally Aligned Design (DAD) provides the conceptual bridge between centuries of developmental science and fast-moving AI life-cycles, as DAD reframes AI design not around what technology can do, but around what the child is ready for. The four examples theorised—Perceptual Fit, Cognitive Scaffolding, Interface Simplicity, and Relational Integrity—translate developmental science into concrete touch-points for data curation, model training, User Experience design, and post-deployment audit in AI design. This framework extends existing developmental practice in early childhood education by translating it into actionable principles for AI design—a bridge not currently made explicit in the existing literature. This article thus seeks to explore how "child-centred AI" can shift from an abstract principle or slogan to concrete specifications informed by the science of child development. The accompanying tables do not prescribe a single standard; rather, they illustrate a repertoire of design moves—session ceilings, breadcrumb trails, adaptive hint logic, affect guardrails—that AI design can adapt to age bands, modalities, and learning goals.

Three broader implications follow.

First, DAD reframes the fields of child development and early childhood as co-architects of AI, not passive stakeholders. Expertise in dimensions such as working-memory limits, ZPD progression, and protection against socio-emotional vulnerability becomes a strategic asset for AI design and deployment. By embedding child-development science directly into model objectives, interface constraints and relational guardrails, Developmentally-Aligned Design honours the theoretical richness of the field and moves it to

Table 2 Illustrative touch-points for developmentally aligned design (DAD) across the AI life-cycle

Stage	Perceptual fit	Cognitive scaffolding	Interface simplicity	Relational integrity
Dataset	Include toddler speech errors so the model hears real mis-pronunciations	Tag every item with a difficulty gradient for later adaptive sequencing	Remove cluttered UI screenshots from training images so as not to overwhelm young children's attentional and working memory capacities	Strip out manipulative affect phrases (e.g., "You'll make me sad") from dialogue corpora
Model training	Penalise false negatives on child speech	Use a curriculum-learning schedule that advances only after mastery signals	Apply RLHF—reinforcement learning from human feedback—to down-rank responses that require deep menu chains overly complicated for young users	Add a safety layer—an automated filter—that blocks guilt-laden or intimacy-seeking utterances by the AI
UX design	Large touch targets; slow animation (< 2 fps)	Adaptive hint logic that breaks problems into sub-steps after two errors	Flat hierarchy (≤ 2 taps to any content) with persistent Home icon	Intro script: "I'm Robo-Helper, a computer program." + session timer + caregiver dashboard displaying all child-AI interaction logs
Post-deployment	Telemetry on mis-recognition (when AI notices it often misunderstands certain words or sounds children say, it flags those problem spots so engineers can feed the model more examples of those sounds and teach it to recognise them better.)	Online learning module re-tunes difficulty using mastery data	Drop-off analytics (click-stream or event-sequence analyses that flag where children abandon a task, signalling possible confusion or interface overload)	Audit logs capture any sensitive or emotional language and generate weekly summaries for caregivers

the centre of next-generation system design, transforming abstract commitments to "child-centred AI" into measurable, enforceable engineering requirements. It also helps highlight the value of Early Childhood Education and Care as a field that can provide thought leadership for AI, not just "adopt" or "respond" to it.

Second, DAD invites a new research agenda: using cognitive neuroscience and child development theory for validating domain-specific metrics (e.g., AI animation rates paced to young children's perceptual abilities), testing whether education professionals, families and children find DAD helpful, and auditing long-term outcomes when DAD principles are embedded end-to-end. Such an approach can help co-design ethical AI futures that do not retrofit fixes after harm has occurred, but speak in the child's language and move at the child's tempo right from the beginning.

Third, DAD labelling—clear, transparent disclosure of how a product aligns with key developmental benchmarks—could serve as a proactive tool for signalling quality in child-focused AI. Such labels may support educators and school leaders in making informed procurement decisions, offer reassurance to families about a product's developmental appropriateness, and incentivise organisations (e.g. EdTech companies) to prioritise child-centred design through reputational and market-based rewards.

None of this is a substitute for ecosystem-wide safeguards around data privacy, equity, and algorithmic bias. But without developmentally aligned foundations, even the most privacy-preserving or bias-free system may still overwhelm a five-year-old's attention or exploit a seven-year-old's credulity. Conversely, AI that paces its visuals to natural attentional rhythms, keeps tasks inside the learner's ZPD, and discloses its machine nature in child-friendly language might be a more supportive partner in young children's exploration and growth.

I also note that, rather than claiming Developmentally Aligned Design (DAD) to be a universally applicable framework, it is essential to recognise that children's developmental trajectories are profoundly shaped by cultural context. There is increasing recognition in the field of developmental science and early childhood education that early learning and development is not a monolithic process; it is mediated by culturally specific values, caregiving norms, and the affordances of local technological environments (Ball, 2010; Harkness et al., 2013; Trawick-Smith, 2022). For instance, expectations around autonomy, emotional expression, or screen time can vary widely across cultural settings, influencing how children interact with AI systems (Helwig, 2006; Yu et al., 2018). As such, the principles of perceptual fit, scaffolding, simplicity, and relational integrity must be sensitively adapted, repurposed or even challenged to reflect the cultural and familial practices of the communities they serve. Contextualising DAD within diverse cultural frameworks seems crucial to make global AI design for children equitable and relevant.

The path ahead is, therefore, collaborative. Developmentally Aligned Design (DAD) can be understood as the algorithmic century's incarnation of developmentally appropriate practice—signifying care for how young children think, feel, learn, and grow. Without it, harms to young children might include cognitive confusion, socio-emotional harm, and rights infringements when alignment is absent; measurable gains in learning, wellbeing, and comfort may emerge when alignment is present. It seems vital for specialists in child development and neuroscience, AI designers, data scientists, educators, and—critically—children themselves to iterate on the examples and principles sketched here, refining them into robust standards and dynamic labels that evolve with both technology and developmental insight. When that happens, Developmentally Aligned Design might help us move closer to an AI ecosystem where every line of code is attuned to children's questions, capacities, and rights.

Appendix: literature search and selection strategy

This paper conceptualised its framework based on a purposive, conceptual literature synthesis rather than a systematic review. The aim was to identify illustrative and representative sources that contribute to the development of a developmentally aligned approach to AI for young children. The literature selection process prioritised conceptual breadth and interdisciplinary relevance, drawing on developmental psychology, human–computer interaction, child-computer interaction, education, and AI ethics.

A targeted search was conducted in the ERIC (Education Resources Information Center) database using the following Boolean search string:

> (young children OR early childhood OR early childhood education OR early years OR prekindergarten OR kindergarten) AND (Artificial Intelligence OR AI)

To ensure relevance and currency, the search was limited to the past 10 years (2016–2025) and filtered by the descriptor "Early Childhood Education." This yielded 805 results. Further filtering by document type (journal articles and books only) reduced the pool to 664 journal articles and 20 books.

A parallel search was conducted in the ACM Digital Library to identify relevant research in human–computer interaction and AI design involving young children. The search used the following Boolean query:

> (AllField:"young children" OR AllField:"early childhood" OR AllField:"early childhood education" OR

Table 3 Summary of literature selection process across ERIC and ACM Digital Library for the conceptual synthesis

Stage	ERIC	ACM DL	Total
Records identified via database search	805	1732	2537
Records filtered by document type	684 (664 journal articles, 20 books)	1214 (journals and proceedings only)	1898
Records screened by title/abstract	684	1214	1898
Records excluded at screening (irrelevant, outside scope)	649	1161	1810
Records retained after screening	35	53	88

AllField:"preschool" OR AllField:"kindergarten") AND (AllField:"artificial intelligence" OR AllField:"AI")

The search was limited to January 2016 to May 2025 and yielded 1,732 results. Filters were then applied to include only journal articles and conference proceedings, with special attention to high-relevance venues known for publishing work at the intersection of technology, design, and children's development. These included:

CHI (*Conference on Human Factors in Computing Systems*), the flagship conference of the ACM Special Interest Group on Computer–Human Interaction, which regularly features research on interactive technologies for children.
IDC (*Interaction Design and Children*), a premier venue for interdisciplinary work focused specifically on the design of interactive systems for children and young people.
CSCW (*Computer Supported Cooperative Work and Social Computing*), which includes studies on collaborative technologies and social interaction, often relevant to AI systems used in educational or developmental contexts.
TOCHI (*ACM Transactions on Computer–Human Interaction*), a leading journal in HCI that publishes theoretically grounded and empirically validated design studies, including those involving young users.

These venues were prioritised because they regularly publish developmentally relevant research on AI interaction, design implications, and child–technology engagement, making them particularly suitable for inclusion in a conceptual synthesis on developmentally aligned design.

Across both ERIC and ACM, titles and abstracts were screened for relevance. Studies were included if they:

Focused on children aged 0–8 years
Discussed AI systems, tools, or frameworks that intersected with early learning or development
Contained explicit design, policy, or educational implications

Studies were excluded if they:

Did not engage substantively with the early childhood age range
Mentioned AI only peripherally (e.g., general tech trends)
Focused solely on back-end AI architecture without user or developmental context

After applying inclusion and exclusion criteria, 35 sources were retained from the ERIC search and 53 from the ACM Digital Library, which were then used to inform the framework and ideas developed in this article. These were used to illustrate key developmental principles and their potential implications for AI design (Table 3).

Author contribution N.K. as sole author was responsible for all aspects of the manuscript and the study.

Funding No external funding was used to support this research.

Data availability No datasets were generated or analysed during the current study.

Declarations

Competing interests The authors declare no competing interests.

References

Atabey, A., Wang, G., Johnston, S. K., Lin, G. C., Wilson, C., Urquhart, L. D., & Zhao, J. (2024, May). The second workshop on Child-Centered AI design (CCAI). In *Extended abstracts of the CHI conference on human factors in computing systems* (pp. 1–6).

Axelsson, A., Andersson, R., & Gulz, A. (2016). Scaffolding executive function capabilities via play-&-learn software for preschoolers. *Journal of Educational Psychology, 108*(7), 969.

Ball, J. (2010). Culture and early childhood education. *Encyclopedia on early childhood development*, 1–8.

Bickham, D. S., Schwamm, S., Izenman, E. R., Yue, Z., Carter, M., Powell, N., Tiches, K., & Rich, M. (2024). *Use of voice assistants & generative AI by children and families*. Boston Children's Hospital Digital Wellness Lab.

Cameron, D., Fernando, S., Collins, E. C., Millings, A., Szollosy, M., Moore, R., Sharkey, A. & Prescott, T. (2017). You made him be alive: Children's perceptions of animacy in a humanoid robot. In *Biomimetic and biohybrid systems: 6th international conference, living machines* 2017, Stanford, CA, USA, July 26–28, 2017, Proceedings 6 (pp. 73–85). Springer International Publishing.

Cameron, D., Fernando, S., Millings, A., Moore, R., Sharkey, A., & Prescott, T. (2015). Children's age influences their perceptions of a humanoid robot as being like a person or machine. In *Biomimetic and biohybrid systems: 4th international conference, living machines* 2015, Barcelona, Spain, July 28–31, 2015, Proceedings 4 (pp. 348–353). Springer International Publishing.

Chaiklin, S. (2003). The zone of proximal development in Vygotsky's analysis of learning and instruction. In Kozulin, A. (Ed.), *Vygotsky's educational theory in cultural context*. Cambridge University Press.

Chen, J. J. (2025). From Turing's conception of machine intelligence to the evolution of AI in early childhood education: Conceptual, empirical, and practical insights. *AI, Brain and Child, 1*(1), 1.

Chen, J. J., & Lin, J. C. (2024). Artificial intelligence as a double-edged sword: Wielding the POWER principles to maximize its positive effects and minimize its negative effects. *Contemporary Issues in Early Childhood, 25*(1), 146–153.

Chen, J. J. (2024). A scoping study on AI affordances in early childhood education: Mapping the global landscape, identifying research gaps, and charting future research directions. *Journal of Artificial Intelligence Research, 81*, 701–740.

Christakis, D. A., Ramirez, J. S. B., Ferguson, S. M., Ravinder, S., & Ramirez, J.-M. (2018). How early media exposure may affect cognitive function: A review of results from observations in humans and experiments in mice. *Proceedings of the National Academy of Sciences of the United States of America, 115*(40), 9851–9858. https://doi.org/10.1073/pnas.1711548115

Cowan, N. (2016). Working memory maturation: Can we get at the essence of cognitive growth? *Perspectives on Psychological Science, 11*(2), 239–264.

De Haan, M., & Johnson, M. H. (Eds.). (2005). *The cognitive neuroscience of development* (Vol. 3). Psychology Press.

Delaney, V. D., & Chen, J. J. (2025). *Developmental considerations and practical recommendations for parents and early childhood educators in the age of AI*. Public Scholarship Collaborative.

Digital Wellness Lab. (2024). *Pulse survey: Use of voice assistants and generative AI by children and families*. Boston Children's Hospital.

Goldman, E. J., Baumann, A. E., Pare, L., Beaudoin, J., & Poulin-Dubois, D. (2025). Children's attribution of mental states to humans and social robots assessed with the Theory of Mind Scale. *Scientific Reports, 15*(1), 1–14.

Hammond, S. I., Müller, U., Carpendale, J. I., Bibok, M. B., & Liebermann-Finestone, D. P. (2012). The effects of parental scaffolding on preschoolers' executive function. *Developmental Psychology, 48*(1), 271.

Hardy, I., Stephan-Gramberg, S., & Jurecka, A. (2021). The use of scaffolding to promote preschool children's competencies of evidence-based reasoning. *Unterrichtswissenschaft, 49*(1), 91–115.

Harkness, S., Super, C. M., Mavridis, C. J., Barry, O., & Zeitlin, M. (2013). Culture and early childhood development. In *Handbook of early childhood development research and its impact on global policy* (pp. 142–160).

Helwig, C. C. (2006). The development of personal autonomy throughout cultures. *Cognitive Development, 21*(4), 458–473.

Hoffman, A., Owen, D., & Calvert, S. L. (2021). Parent reports of children's parasocial relationships with conversational agents: Trusted voices in children's lives. *Human Behavior and Emerging Technologies, 3*(4), 606–617.

Hourcade, J. P., et al. (2015). Touch interaction for children aged 3–6 years. *International Journal of Human-Computer Studies, 74*, 54–67.

Idemaru, K., & Holt, L. L. (2013). The developmental trajectory of children's perception and production of English/r/-/l. *The Journal of the Acoustical Society of America, 133*(6), 4232–4246.

Information Commissioner's Office (ICO) (2020). *Age appropriate design: a code of practice for online services*. United Kingdom.

Jacq, A., Lemaignan, S., Garcia, F., Dillenbourg, P., & Paiva, A. (2016, March). Building successful long child-robot interactions in a learning context. In *2016 11th ACM/IEEE international conference on human-robot interaction (HRI)* (pp. 239–246). IEEE.

Jochmann-Mannak, H., Huibers, T. W., Lentz, L., & Sanders, T. (2010, July). Children searching information on the Internet: Performance on children's interfaces compared to Google. In *Workshop on accessible search systems 2010, SIGIR'10*, July 23, 2010, Geneva, Switzerland. Copyright 2010 ACM.

Kühne, R., Peter, J., de Jong, C., & Barco, A. (2024). How does children's anthropomorphism of a social robot develop over time? A six-wave panel study. *International Journal of Social Robotics, 16*(7), 1665–1679.

Kurian, N. (2025). Designing child-friendly AI interfaces: Six developmentally-appropriate design insights from analysing Disney animation. arXiv:2504.08670

Kurian, N. (2024). 'No, Alexa, no!': designing child-safe AI and protecting children from the risks of the 'empathy gap' in large language models. *Learning, Media and Technology*, 1–14.

Kurian, N. (2023a). AI's empathy gap: The risks of conversational Artificial Intelligence for young children's well-being and key ethical considerations for early childhood education and care. *Contemporary Issues in Early Childhood*, 14639491231206004.

Kurian, N. (2023b). Toddlers and robots? The ethics of supporting young children with disabilities with AI companions and the implications for children's rights. *International Journal of Human Rights Education, 7*(1), 9.

Latiff, H. S. A., Razali, R., & Ismail, F. F. (2019). User interface design guidelines for children mobile learning applications. *International Journal of Recent Technology and Engineering (IJRTE), 8*(3), 3311–3319.

Levi, G. (2025). Generative AI as the new ZPD: Transforming learning through Vygotsky's lens. *Medium*.

Lillard, A. S., & Peterson, J. (2011). The immediate impact of different types of television on young children's executive function. *Pediatrics, 128*(4), 644–649. https://doi.org/10.1542/peds.2010-1919

Masood, M., & Thigambaram, M. (2015). The usability of mobile applications for pre-schoolers. *Procedia-Social and Behavioral Sciences, 197*, 1818–1826.

McLeod, N., Okon, E. E., Garrison, D., Boyd, D., & Daly, A. (Eds.). (2022). *Global perspectives of early childhood education: Valuing local cultures*. Sage.

Miao, F., Holmes, W., Huang, R., & Zhang, H. (2021). *AI and education: A guidance for policymakers*. Unesco Publishing.

Mou, T. Y., Kao, C. P., Lin, H. H., & Yin, Z. X. (2021). From action to slowmation: Enhancing preschoolers' story comprehension ability and learning intention. *Interactive Learning Environments, 29*(8), 1231–1243.

Mustafa, M. Y., Tlili, A., Lampropoulos, G., Huang, R., Jandrić, P., Zhao, J., Salha, S., Xu, L., Panda, S., López-Pernas, S., & Saqr, M. (2024). A systematic review of literature reviews on artificial intelligence in education (AIED): A roadmap to a future research agenda. *Smart Learning Environments, 11*(1), 1–33.

Narayanan, S., & Potamianos, A. (2002). Creating conversational interfaces for children. *IEEE Transactions on Speech and Audio Processing, 10*(2), 65–78.

Pailian, H., Libertus, M. E., Feigenson, L., & Halberda, J. (2016). Visual working memory capacity increases between ages 3 and 8 years, controlling for gains in attention, perception, and executive control. *Attention, Perception, & Psychophysics, 78*, 1556–1573.

Pesco, D., & Gagné, A. (2017). Scaffolding narrative skills: A meta-analysis of instruction in early childhood settings. *Early Education and Development, 28*(7), 773–793.

Phillips-Brown, M., Boulicault, M., Kory-Westland, J., Nguyen, S., & Breazeal, C. (2023). Authenticity and co-design: On responsibly creating relational robots for children. In M. Ito, R. Cross, K. Dinakar, & C. Odgers (Eds.), *Algorithmic rights and protections for children* (pp. 85–121). MIT Press.

Piaget, J. (1952). *The origins of intelligence in children* (M. Cook, Trans.). Columbia University Press.

Pimienta, J., Brandt, J., Bethe, T., Holz, R., Continella, A., Jibb, L., & Grundy, Q. (2023). Mobile apps and children's privacy: A traffic analysis of data sharing practices among children's mobile iOS apps. *Archives of Disease in Childhood, 108*(11), 943–945.

Rowe, M. L. (2012). A longitudinal investigation of the role of quantity and quality of child-directed speech in vocabulary development. *Child Development, 83*(5), 1762–1774.

Rubin, K. H., Bukowski, W., & Parker, J. G. (2006). Peer interactions, relationships, and groups. *Handbook of Child Psychology, 3*(5), 619–700.

Ruff, H. A., & Lawson, K. R. (1990). Development of sustained, focused attention in young children during free play. *Developmental Psychology, 26*(1), 85.

Santos, R. M. S., Mendes, C. G., Marques Miranda, D., & Romano-Silva, M. A. (2022). The association between screen time and attention in children: A systematic review. *Developmental Neuropsychology, 47*(4), 175–192.

Saye, J. W., & Brush, T. (2002). Scaffolding critical reasoning about history and social issues in multimedia-supported learning environments. *Educational Technology Research and Development, 50*(3), 77–96.

Simmering, V. R. (2012). The development of visual working memory capacity during early childhood. *Journal of Experimental Child Psychology, 111*, 695–707.

Stoilova, M., Nandagiri, R., & Livingstone, S. (2021). Children's understanding of personal data and privacy online—A systematic evidence mapping. *Information, Communication & Society, 24*(4), 557–575.

Su, J., Ng, D. T. K., & Chu, S. K. W. (2023). Artificial intelligence (AI) literacy in early childhood education: The challenges and opportunities. *Computers and Education: Artificial Intelligence, 4*, Article 100124.

Sweller, J. (2011). Cognitive load theory. In *Psychology of learning and motivation* (Vol. 55, pp. 37–76). Academic Press.

Tanaka, F., Cicourel, A., & Movellan, J. R. (2007). Socialization between toddlers and robots at an early childhood education center. *Proceedings of the National Academy of Sciences, 104*(46), 17954–17958.

Tawfik, A. A., & Kolodner, J. L. (2016). Systematizing scaffolding for problem-based learning: A view from case-based reasoning. *Interdisciplinary Journal of Problem-Based Learning, 10*(1), 6.

Thompson, S. D., & Raisor, J. M. (2013). Meeting the sensory needs of young children. *YC Young Children, 68*(2), 34.

Trawick-Smith, J. (2022). *Early childhood development: A multicultural perspective*. Pearson. One Lake Street, Upper Saddle River, New Jersey 07458.

UNICEF. (2021). *Policy guidance on AI for children* (Version 2.0).

Van de Pol, J., Volman, M., & Beishuizen, J. (2010). Scaffolding in teacher–student interaction: A decade of research. *Educational Psychology Review, 22*, 271–296.

Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes*. Harvard University Press.

Wang, K., Ji, G., & Chen, P. (2024). Study on optimization design of user experience of interface icon of science popularization app for school-age children based on logistic regression analysis. *Scientific and Social Research, 6*(12), 351–359.

Wang, G., Sun, K., Atabey, A., Pothong, K., Lin, G. C., Zhao, J., & Yip, J. (2023, April). Child-centred AI design: Definition, operation, and considerations. In *Extended abstracts of the 2023 CHI conference on human factors in computing systems* (pp. 1–6).

Wang, G., Zhao, J., Van Kleek, M., & Shadbolt, N. (2022, April). Informing age-appropriate AI: Examining principles and practices of AI for children. In *Proceedings of the 2022 CHI conference on human factors in computing systems* (pp. 1–29).

Waytz, A., Cacioppo, J., & Epley, N. (2010). Who sees human? The stability and importance of individual differences in anthropomorphism. *Perspectives on Psychological Science, 5*, 219–232. https://doi.org/10.1177/1745691610369336

Wood, D., Bruner, J. S., & Ross, G. (1976). The role of tutoring in problem solving. *Journal of Child Psychology and Psychiatry, 17*(2), 89–100.

Wilson, C., Atabey, A., & Revans, J. (2025). Towards child-centred AI in children's learning futures: Participatory design futuring with SmartSchool and the co-design stories toolkit. *International Journal of Human-Computer Studies*, 103431.

Wu, K. C., Tang, Y. M., & Tsai, C. Y. (2014). Graphical interface design for children seeking information in a digital library. *Visualization in Engineering, 2*, 1–14.

Xu, Y., & Warschauer, M. (2019, May). Young children's reading and learning with conversational agents. In *Extended abstracts of the 2019 CHI conference on human factors in computing systems* (pp. 1–8).

Yu, S., Levesque-Bristol, C., & Maeda, Y. (2018). General need for autonomy and subjective well-being: A meta-analysis of studies in the US and East Asia. *Journal of Happiness Studies, 19*, 1863–1882.