Child-AI Co-Creation: A Review of the Current Research Landscape and a Proposal for Six Design Considerations

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Abstract

As generative AI becomes increasingly integrated into children's creative lives, designing responsible and meaningful tools for Child–AI co-creation is a growing concern in HCI and education. This paper presents a scoping review of 20 studies on Child–AI co-creation, analyzing the types of creative activities involved, the age groups studied, and the roles AI systems play. Based on this synthesis, we identify six key design considerations: protecting child data privacy, minimizing bias and hallucinations, fostering appropriate reliance on AI, balancing support and creative freedom, encouraging peer and family collaboration, and making AI's creative process understandable. This work contributes an initial framework to guide the design of child-centered and developmentally appropriate AI co-creation systems, and highlights directions for future research.

CCS Concepts

• **Human-centered computing** → *Interaction design theory, concepts and paradigms*; *HCI theory, concepts and models.*

Keywords

Human AI Co-creation, Creativity Support Tools, Child Creativity, Content Creation, Child-AI Co-creation

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1 Introduction

Children today are growing up in an era shaped by generative AI (GenAI). One of the core abilities of GenAI is recognizing patterns from trained data and generating content [1], allowing for human-AI co-creative tasks and activities like writing [21, 22, 31], drawing [19, 36], filmmaking [7, 27, 56, 57] and more. A recent *Common Sense Media* report found that nearly half of children (between 13-18) self-reported using GenAI tools for these activities, such as writing documents or creating other multimedia content [1]. While such self-directed engagement has potential benefits, as suggested by recent articles, such as expanding access to new forms of expression and augmenting creativity [16, 18], it also presents risks related to privacy, safety, and ethical considerations and may influence children's cognitive and social development in complex ways [8, 34, 38, 41].

This raises an important question: Is there a middle ground between fully allowing and completely disallowing children to use generative AI for creative activities? And if so, how might we design for that space? We are indeed seeing a growing effort in the Human-Computer Interaction (HCI) community to build tools that support children in co-creative engagements with AI, defined here as creativity shared between children and AI systems [45]. But before we move forward with designing and introducing such tools, we argue it's crucial to take a step back and ask: **What challenges might arise when children engage in co-creation with AI, and what design considerations can help mitigate them?**

To explore these questions, we reviewed the current research landscape on child–AI co-creation and identified 20 relevant papers. We focused on the age groups involved, the types of co-creative activities, and the roles AI plays in these interactions. From this review, we identified a set of challenges highlighted across studies and proposed six design considerations for building safe, responsible, and meaningful child–AI co-creation systems. This work-in-progress offers a scoping review that synthesizes existing efforts, serving as an initial step toward a more systematic investigation into how we might design more ethical and responsible for children's co-creative experiences with AI.

[1]https://www.commonsensemedia.org/sites/default/files/research/report/2024-the-dawn-of-the-ai-era_final-release-for-web.pdf

2 Background: From Creativity Support Tools to Child–AI Co-Creation

Creativity, in the HCI context, is commonly defined as the ability to produce ideas or artifacts that are fluent, novel, and valuable [3, 37]. In the context of children, creativity takes on unique forms that emphasize exploration, play, self-expression, and meaning-making [25]. The HCI community has a long tradition of designing creativity-support tools — systems that assist users at different stages of artifact and idea creation [12, 46]. These tools are typically designed to support phases such as brainstorming, composing, and refining creative outputs [46].

The rise of generative AI has blurred the boundaries between tool and collaborator. Increasingly, AI systems are not only supporting human creativity but also actively contributing to it, suggesting ideas, generating text or visuals, and adapting in response to user input. This shift gives rise to the concept of human–AI co-creation, a subset of creativity tools in which humans and AI engage in *"the act of collective creativity"* [45]. In our context, co-creative activities involve a child and an AI system mutually contributing to the development of an abstract idea or a concrete artifact, influencing both the process and the final product.

In parallel, there has been an increased focus on designing child-centered AI that are developmentally appropriate and sensitive to children's needs, capabilities, and rights [5, 44, 54]. Wang et al. [55] synthesized ten design principles across six regulatory frameworks, emphasizing themes such as fairness, transparency, privacy, and developmental alignment. This conversation has been extended in recent CHI and IDC workshops, which examine how to translate these principles into practice [5, 54], and also in specific domains like education and creative learning [44].

Our work sits at the intersection of these two domains: the evolution of human–AI co-creation and the design of child-centered AI. We explore how to responsibly and meaningfully support child–AI co-creation, where children and AI systems engage in joint creative processes.

3 Method

We conducted a scoping review to examine how AI technologies, especially emerging generative AI and large language models (LLMs), re used in co-creative practices involving children and youth. To ensure comprehensive coverage of both HCI research and broader interdisciplinary work, we searched Web of Science and the ACM Digital Library. The search query was designed to capture three core aspects: the target population (children and adolescents), co-creative activities, and AI technologies. Our initial search was guided by using terms related to "co-creation," but during backward and forward citation searches of key relevant papers, we noticed that many relevant studies described activities such as writing, drawing, and storytelling without explicitly using the term "co-creation." Based on these observations, we refined our search query to include these activity-related terms in addition to the core concept of co-creation.

We applied the following query to the title and abstract fields in both databases. The search was conducted on March 7, 2025, with no date restrictions applied:

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("child*" OR "young" OR "teen*") AND ("cocreation"
OR "co-creative" OR "creation" OR "co-creation"
OR "writing" OR "drawing" OR "storytelling") AND
("AI" OR "artificial intelligence" OR "LLM" OR
"large language model*" OR "genAI")
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We followed the PRISMA guidelines for screening and selection [40]. Studies were included if they: (1) involved children or adolescents under the age of 18 as participants, (2) focused on children's involvement in co-creative practices, and (3) engaged with AI technologies. We excluded papers in which adults were the primary co-creators with AI (e.g., children reading parent-AI co-created stories), as well as papers that solely described the AI tools without reporting empirical findings or discussing their potential limitations.

The initial search resulted in 127 studies (113 from Web of Science and 14 from the ACM Digital Library). After removing 11 duplicates, 116 unique studies remained. The first author screened titles and abstracts for eligibility, which resulted in 24 papers selected for full-text review. Full-text screening was then conducted by two authors, with discrepancies resolved through discussion. Fourteen empirical studies met the inclusion criteria. To supplement the database search, we also conducted backward and forward snowballing of key papers, which yielded six additional studies. The search process was carried out from March 7 to March 31, 2025. In total, 20 studies were included in the final analysis. All included publications were published in 2019 or later.

4 Results

4.1 Overview of the Current Research Landscape

Most studies focused on children aged 7–12 (thirteen out of 20 studies), with some including younger children (3–7) (eight out of 20 studies) or teens (13-20) (two out of 20 studies). Common activities included storytelling (oral and written stories) (nine out of 20 studies) and visual creation (drawing and other artistic creation) (nine out of 20 studies). The most common models used were GPT-based language models (featured in nine papers), followed by image generation tools such as DALL·E, Stable Diffusion, and LCM. One unique study used a rule-based system [29] that only provided syntactic templates and was perceived by children as "dumb."

We also analyzed the roles AI played in the child–AI creative process and identified four distinct roles: 1) **Generator**: The AI produces content with minimal input from the child. 2) **Facilitator**: The AI does not directly contribute to the final artifact but supports the child through prompts, questions, hints, or brainstorming ideas. 3) **Collaborator**: Both the AI and the child actively contribute to the final product, building on each other's contributions. 4) **Enhancer**: The AI works from a child-generated base and augments or transforms it, such as converting a drawing into a 3D model. These roles were relatively evenly distributed across the 20 studies, with several studies [4, 11, 59, 62, 63] involving multiple roles, such as the AI both facilitates the storytelling when children got stuck and also continues the children's storytelling after they tell their parts of a story (See detailed paper mapping in the Appendix).

4.2 Design Considerations for Child-AI Co-Creation

We analyzed both implicit (emerging from design methods, discussions, or empirical findings) and explicit (directly stated) challenges related to child–AI co-creation across the selected papers, and derived six design considerations to inform future research. Some of these considerations (e.g., #1, #2) are broadly applicable to generative AI tools for children, such as tutoring platforms and educational assistants.

4.2.1 Protect Child Data Privacy. Among the papers, only two directly addressed data privacy [2, 61], raising concerns about the use of children's data to train large language models and the potential issues of unauthorized data retention. This highlights a broader issue of how children's creative input might be collected, stored, or repurposed without explicit consent from children or guardians. Commonly used models like GPT and DALL·E in the reviewed papers are developed by OpenAI, whose policy states that developers should not build tools with ChatGPT[2] targeted at users under 13 [3].

Furthermore, OpenAI's updated data usage policy (as of March 1, 2023) states: *"Data sent to the OpenAI API is not used to train or improve OpenAI models unless you explicitly opt in."* However, even with these protections, API data may still be retained for up to 30 days to monitor for abuse unless *"zero data retention"* settings are enabled [4]. This temporary storage, even if not used for training, may raise concerns when tools are developed for children, especially if sensitive or personally identifiable information is involved [48]. For researchers, this means that how and what models are used can affect the privacy risks for child participants. For example, local deployments of AI models would offer greater control over how data is stored and retained. When using APIs, researchers should carefully check the platform's policy on data storage and usage, and ensure compliance with both platform and government regulations.

> **Design Consideration 1:** Be mindful of API and model choices, legal and platform regulations, and ensure guardian-accessible controls for using and retaining children's interaction and data during the creative process.

4.2.2 Minimize Bias, Harm, and AI Hallucinations. Several papers raised concerns about bias, harmful content, and hallucinations in AI-generated outputs, which can significantly affect children's learning, self-perception, and trust in technology. For example, [6] explicitly explored how image generation models reflect stereotypical representations of gender and race, encouraging children to reflect critically on the AI's limitations. Other papers [10, 24, 37, 61] discussed how misinformation or biased content can emerge unpredictably, especially when children rely heavily on generative models without understanding their underlying data sources.

One common risk is hallucination, where the AI generates content that is factually incorrect or unrelated to the child's intent. In [61], for example, the authors mentioned that AI created unusual connections between common story elements, such as *"using clouds to add speed to a journey."* While such an idea may appear imaginative in a fantasy narrative, it could be confusing in educational contexts, where unrealistic representations might lead to misconceptions. Similarly, Kim et al. [30] found that the AI introduced a random character that participants had not included, which caused confusion. This unpredictability may confuse children, disrupt their creative flow, or lead them to accept inaccurate outputs as correct—especially when the AI is perceived as a knowledgeable partner.

> **Design Consideration 2:** Use content moderation methods (such as auto-censor, parental/adult control, pre-defined dialogues etc.) to filter biased, harmful, or inaccurate content before showing it to children.

4.2.3 Foster Appropriate Reliance on AI and Cognitive Engagement with the Creative Tasks. In the reviewed papers, two studies [10, 24] explicitly suggest that when AI systems are allowed to freely generate content, students may rely on AI for the entire output, completing their work with minimal engagement in the creative process. This behavior may be partially explained by research on cognitive effort: children often avoid tasks they perceive as cognitively demanding, even when those tasks may lead to more meaningful or rewarding outcomes in the long term [13].

To mitigate such reliance, most of the reviewed papers attempt to constrain the role of AI in the creative process. Rather than enabling AI to generate full responses, some systems position AI as a facilitator [4, 10, 11, 29, 30, 35, 59, 61, 63], offering hints, prompts, or feedback to guide students' thinking. Others adopt an enhancer approach [11, 35, 59, 60, 62–64], where children are first encouraged to generate ideas or artifacts on their own, and only afterward receive alternative suggestions or elaborations from the AI. These approaches mirror the concept of cognitive forcing [9], used in HCI research to reduce overreliance on AI[5], by nudging children to engage more deeply before accepting AI suggestions.

However, the definition of "appropriate reliance" remains somewhat ambiguous. What counts as appropriate is rarely articulated clearly in the reviewed studies. Instead of relying solely on designers' assumptions about what is appropriate AI use, future work might explore more participatory approaches: for example, letting children themselves define what they consider appropriate. One study [32] found that teens viewed using AI to generate the entire output as inappropriate, but supported its use for brainstorming and inspiration. Another direction might be to reward cognitive engagement directly during the creative process by offering explanations and feedback, that reinforce thoughtful interaction with the AI, rather than passive acceptance [53].

> **Design Consideration 3:** Design AI tools that actively support thoughtful engagement and allow children to define and reflect on what they see as appropriate use within the creative process.

4.2.4 Design with Awareness of AI's Constraints on Creativity Across Stages of Creation. Several studies report that AI systems, due to inherent model limitations or the way interactions are structured,

[2]This policy does not apply when building with GPT API.
[3]https://openai.com/policies/usage-policies/. This policy is to comply with COPPA, which restricts the collection and use of personal information from children under 13 and requires verifiable parental consent.
[4]https://platform.openai.com/docs/guides/your-data

[5]here overreliance is typically defined as the uncritical acceptance of incorrect AI decisions or outputs

can narrow children's ideation or subtly shape the direction of their creative output [4, 11, 37, 62, 63]. These constraints can be either intended or unintended. **Intended constraints** are those deliberately designed by developers, such as AI-generated suggestions or facilitation strategies that, while helpful, may end up steering creativity in a specific direction [62]. **Unintended constraints** stem from the limitations of the AI itself, such as being unable to generate certain types of content or perform specific tasks. For example, Newman et al. [37] found that when an image-generation AI failed to produce results aligned with a child's expectations, the child gave up their original creative idea.

To better understand how AI might constrain creativity, it is helpful to revisit foundational theories of creativity. Creativity is a deeply complex phenomenon, and requires to integrate a variety of theoretical perspectives to understand [42]. Early philosophers such as Kant define creative genius, which is also accepted in HCI research [3, 37], as the ability to produce works that are not only *"original"* (novel) but also *"exemplary"* (valuable) ([28] as cited in [42]). A key cognitive process in creativity is divergent thinking, which, as what Torrance proposed, includes four components: flexibility (the ability to shift between categories of ideas), fluency (the number of ideas), originality (the uniqueness of ideas), and elaboration (the level of detail) [49]. In child development, researchers have observed the *"fourth-grade slump"*, a period during 3th–4th grade when children's divergent thinking abilities tend to decline [50]. This decline may be influenced by factors such as increased conformity to social norms, schooling structures, or fear of judgement. We found that some of the reviewed papers consider or attempt to mitigate this [37, 62]. Yet, questions arise, such as are children generating *"original"* ideas or are they simply accepting what the agent suggests for *"fluency"*? Would AI failure effects their confidence in their creative ideas as suggested in [37]?

In HCI, creativity is studied differently from system design and stages of creative tasks perspective. Shneiderman [20, 47] identified four stages of creative tasks and eight activities that tools can support, including consulting with peers and composing artifacts, and that tools can be designed differently depending on which activity or stage of co-creation they target. In the reviewed papers however, the boundaries of what stage of creation it intends for is blurry. Considering this, we suggest that several questions should be considered when designing child–AI co-creative tools from both psychology and HCI perspectives: Which stage of the creative activity is the tool intended to support? What psychological creativity theories inform its design? Does the design effectively support both short-term creative output and long-term creativity development? For example, consider the question of whether a facilitator AI that offers suggestions and hints might constrain children's idea flexibility and how might repeated interactions with such a bot affect their long-term ability of divergent thinking?

Design Consideration 4: Designers should reflect on which stage of the creative process the AI is intended for, how the design aligns with the goals of that stage, and whether the constraints introduced by the AI at that point support or limit children's creative expression.

4.2.5 Support Family and Peer Collaborative Creativity, Not Just AI Interaction. While many co-creation tools emphasize child–AI interaction, research suggests that peer and family collaboration remains essential for meaningful and developmentally supportive creative experiences for children. In the study by Kantosalo and Riihiaho [29], children who co-wrote poems with AI reflected that something felt *"missing"* compared to working with peers—suggesting the lack of social cues, and shared meaning-making typical in peer collaboration. Similarly, Xu [58], in her article in Child Development Perspectives, suggests that children engage in more complex conversations with humans, particularly because humans can use nonverbal cues (e.g., nodding, eye contact), which AI currently lacks. She also recommends future research on how AI might influence broader family dynamics.

In co-creative contexts, this means considering how AI can facilitate joint creativity between people, not just between a child and a machine. Prior research shows that parents and peers bring rich scaffolding, emotional support, metacognitive prompting, good role models, and collaborative negotiation to the co-creation process [14, 26, 39, 43]. These forms of social interaction, which help with development of creativity and learning, might not be able to be replaced by AI, which underscores the importance of designing AI systems that preserve space for human connection, rather than encouraging isolated AI use. Some papers in this review have explored this direction. Some studies in the reviewed paper already [30, 33, 59] designed AI as facilitators for intergenerational or family-based collaboration. Future research could explore theory-driven designs for peer/family co-creation.

Design Consideration 5: Designing for AI to facilitate joint creativity between peers and family, not just between a child and a machine.

4.2.6 Make AI's Creative Process Transparent and Understandable to Children. In the context of the child–AI interaction, transparency refers to using child-friendly, accessible language to help children understand how AI systems work and may impact them [52, 55]. In co-creation, this also involves helping children evaluate the AI-generated outputs: whether those outputs represent "real" creativity, what the AI is good or bad at producing, and how much the AI contributes compared to human input. In our review, a few papers [2, 6, 23, 30] explicitly raised concerns about the opaque nature of AI tools, with children and adults questioning where the AI-generated information comes from, why certain outputs were created, or how the system made decisions. However, most papers did not offer concrete design strategies to deliver AI's inner workings for children's understanding. Specific design ideas or implications can refer to existing learning experience designs for children's AI literacy, such as MIT's inclusive AI Literacy initiative [17] [6].

Design Consideration 6: Designing AI that makes its creative process transparent and understandable to children.

[6] https://mitmedialab.github.io/GenAI-Lab/about. Also see this collection of learning resourses designed by Safinah Ali in collaboration with MIT educators and experienced facilitators

5 Limitations and Future Work

We aim to highlight recurring challenges and concerns raised in the literature surrounding child-ai co-creation. However, given the scope of this work-in-progress, we did not detail which specific challenges appeared in each paper or explicitly trace how those challenges informed each design recommendation. Second, while our review identifies key trends, it remains largely descriptive. Finally, although the proposed design considerations offer practical starting points, their real-world implementation remains speculative.

To address these limitations, future work should: (1) map specific findings from empirical studies to the proposed design considerations to increase transparency and traceability; (2) conduct a more critical synthesis of the literature by examining conflicting assumptions and aligning insights with child development theory, child-centered AI frameworks, and institutional and government AI policy guidelines; and (3) provide concrete case studies or guidelines to suggest how these considerations can be applied in practice. In sum, our goal is to develop a more synthesized and theoretically grounded framework that integrates perspectives from child development, AI policy, creativity support tools, and child-centered AI to understand and guide responsible child–AI co-creation.

6 Conclusion

This paper presents a preliminary synthesis of 20 studies on child–AI co-creation, examining how children engage in creative activities with AI systems. We identified four distinct roles that AI plays in these co-creative processes: Generator, Facilitator, Collaborator, and Enhancer. These roles reflect different interaction dynamics between children and AI, ranging from passive content generation to joint creation and content augmentation. Based on recurring challenges and concerns throughout the literature, we proposed six key design considerations to guide the development of responsible and developmentally appropriate AI tools for children: (1) protecting child data privacy, (2) minimizing bias and hallucinations, (3) fostering appropriate reliance on AI, (4) balancing support and creative freedom, (5) supporting collaborative creation with peers and families, and (6) making the creative process of AI transparent and understandable.

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Appendix

Age group	Papers
Early Childhood (3-8 year old)	[62] [63] [11] [61] [59] [4] [64] [35]
Middle Childhood (9-12 year old)	[24] [15] [62] [63] [29] [11] [60] [37] [59] [30] [4] [35]
Adolescence (13-18 year old)†	[2] [30]
Unspecified	[51] [6] [65] [33]

Table 1: Age groups and referenced papers. † As per COPPA guidelines.

Co-Creative Activity	Papers
Story writing/Storytelling	[24] [62] [11] [61] [37] [33] [59] [30] [35]
Other types of writing	[29] (poem) [15] (theater) [10] (video scripts)
Visual Creation	[51] [62] [63] [65] [2] [60] [37] [4] [35]
Music creation	[37]
Character Creation	[6] [64] [35]
Programming	[11]
Family Creation	[33] [30] [35]

Table 2: Co-Creative Activities and referenced papers.

Model Used	Papers
GPT models (ChatGPT/GPT-3/GPT-4)	[24] [65] [11] [61] [37] [33] [59] [30] [10]
Dall.E	[24] [37]
Stable Diffusion	[6] [11]
Midjourney	[64] [35]
Generative Adversarial Network (GAN)	[51] [2]
Recurrent Neural Network (RNN)	[62] [4]
Latent Consistent Model (LCM)	[63] [65]
Rule-based	[15] [29]
Others	[62] Quick,Draw dataset [37] Magenta for music [33] ChatGLM
Not specified	[60]

Table 3: Models used and referenced papers.

AI's role	Definition	Papers
Generator	Minimal constraint on what AI can do. Children provide a broad prompt, and AI fills in the rest.	[24] [6] [65] [37] [10]
Facilitator	AI does not directly contribute to the final artifact but scaffolds the child's creativity by encouraging reflection, brainstorming, or clarification.	[63] [29] [11] [61] [59] [30] [4] [35] [10]
Collaborator	AI is a visible co-creator. Both the AI's and the child's contributions are reflected in the final work.	[51] [62] [61] [33] [59] [4] [35]
Enhancer	AI works from a child-generated base, adjusting, augmenting or transforming it — not creating from scratch. E.g., transform detailed and complete description/writing to art, drawing to 3D.	[62] [63] [11] [60] [59] [64] [35]

Table 4: AI's roles in the Child-AI Co-creation and referenced papers.