Towards Understanding Children's Collaborative Interaction Patterns in Child-AI Co-creative Interfaces

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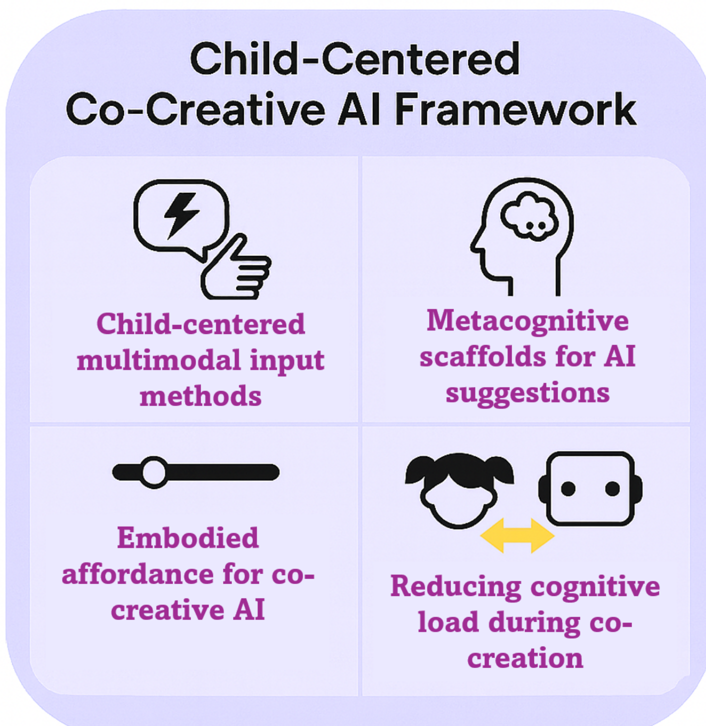

Figure 1: Child-Centered Co-Creative AI (CCAI, "Kai") Framework

Abstract

Children are increasingly using generative AI for co-creative activities, such as storytelling. While co-creativity is inherently about collaboration between children and AI, little is known about how children naturally engage, respond, and negotiate collaboration with AI. To address this gap, we conducted a participatory design study with children (ages 8–13) to examine the roles children and AI take and the strategies children use to align AI's output with

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their intent. Our findings introduce four novel child–AI collaboration profiles. We found that children were open to technical AI refinements (e.g., adding details to their drawings) as scaffolds for developing drawing skills, but resisted conceptual transformations (e.g., changing objects) that altered their original ideas. We introduce the Child-Centered Co-creative AI (CCAI, "Kai") framework, grounded in children's natural collaborative behaviors during co-creation with AI, to inform the design of future child–AI co-creativity interfaces.

CCS Concepts

• **Human-centered computing → Empirical studies in interaction design**.

Keywords

Human-AI Collaboration, Child-AI Interaction, Interaction Design, Co-Creativity, Collaboration

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1 Introduction

Generative AI (GenAI) is increasingly being integrated into a variety of co-creativity (collaborative creativity) interfaces for children, including storytelling, writing, and music [4, 12, 13, 21, 31, 32, 48, 61]. Co-creation is especially valuable for children because it mirrors how they already learn and create in social settings, through exploration, turn-taking, and building on others' ideas [16]. On one hand, this growing use of AI in children's creative interfaces holds promise for delivering personalized creative experiences and scaffolding [4]. For example, prior work has highlighted how having AI as a co-creative partner helped children with engagement and writer's block during the visual storytelling process [59]. On the other hand, it also raises concerns, as poorly designed interfaces may negatively affect children's creativity if technologies fail to accommodate their developmental needs and natural collaborative behaviors.

The design of child-AI co-creativity interfaces is made more challenging by the fact that children's expectations and natural collaboration behaviors are consistently shown to be different than those of adults [45, 54, 55]. Unlike adults, for whom creativity is more product-oriented and goal-focused [15, 23], for children, the process of carrying out creative tasks is often as important as the outcome [20]. This creative process (e.g., the act of drawing, building, or telling a story) exposes children to creative moments, referred to as "mini-c" creative experiences, or creative acts that are personally meaningful to the individual [2, 31]. Such moments have been shown to help build children's self-efficacy and confidence [2, 31]. If not designed with children's needs and natural behaviors in mind, the child–AI co-creativity interfaces risk reducing opportunities for children to engage in meaningful acts of creation, consequently impacting their creative confidence. Children are still developing cognitive flexibility and their ability to adapt to new perspectives [3]. This might shape how they receive AI contributions that diverge from their original ideas or mental models. Do children view such inputs as helpful prompts for exploration, or do they think of them as overstepping and resisting them? At the same time, autonomy and agency are central to children's socio-emotional development: feeling ownership over ideas and recognizing that their actions matter is essential to foster children's intrinsic motivation [33]. These developmental factors might shape where children "draw the line" in co-creation, what types of AI contributions they welcome, reject, or negotiate, and how they try to resolve misalignments with AI. However, little is known about these natural collaboration behaviors in child-AI co-creation.

Prior work in child–computer interaction has investigated children's mental models and interactions with GenAI [31, 59], but this work did not employ the lens of collaboration to study children's natural interaction behaviors during co-creation. For example, Newman et al. [31] focused on exploring children's perceptions of GenAI and its impact on their creativity and self-efficacy. This work positioned GenAI as a potential constructionist tool that acted as a co-creator, allowing children to focus on their larger creative intentions and experiences. However, it did not delve deeply into the different interaction design behaviors that shape co-creation [36], such as collaboration patterns, contribution types, and communication. In another study closer to our work, Zhang et al. [59] explored how GenAI could support children during storytelling by evaluating two child-AI collaborative strategies. In both strategies, the AI was positioned primarily as a generator of images, rather than a co-creator working with children on a shared product. In this prior work, Zhang et al. [59] issued a call for more research to systematically explore "deeper collaboration between children and AI". Our work takes a step towards addressing this gap by understanding various aspects of children's natural collaboration behaviors when co-creating visual stories with AI, such as collaboration profiles [41] and interaction strategies for establishing child-AI alignment. Prior research has shown that many co-creative systems fail to sustain engagement because the collaboration modes they support do not align with how users conceptualize co-creation [36]. If we understand how children naturally co-create with AI, we can design child-AI interfaces to more explicitly provide options to support the behaviors that children find natural.

In this paper, we draw on prior literature from Computer-Supported Collaborative Work (CSCW) [46, 54] to define natural collaboration behaviors as user interaction patterns, such as turn-taking, establishing joint attention, and mutual elaboration on ideas, that emerge when people collaborate with one another or with technology. In the context of human–AI interaction, studying these behaviors can help reveal how people expect AI interfaces to align with their existing, intuitive ways of collaborating, rather than requiring users to adapt their collaborative practices to the constraints of the technology's design. We further define natural co-creativity (or collaborative creativity) behaviors as the enactment of these natural collaboration behaviors in creative contexts, where children and AI co-create a shared artifact [36]. Examining these behaviors in the context of AI-based creativity support tools (CSTs) allows us to understand how children generate and refine ideas, take initiative, and respond to AI contributions as part of their creative process.

To understand how children naturally co-create with AI, we used Cooperative Inquiry (CI) [10], a child-centered Participatory Design (PD) method, and conducted four co-design sessions with an intergenerational group of seven children (ages 8–13). Our co-design sessions focused on intelligent co-creativity interfaces, with particular attention to interaction, technical (e.g., how to execute a task) co-creation, and conceptual (e.g., what task to execute next) co-creation. Each session involved different activities designed to elicit how children conceptualized intelligent creativity interfaces and how they behaved when AI co-created with them. We aimed to answer two research questions:

RQ1: In what ways do children naturally collaborate with AI during creative visual storytelling, particularly in terms of different collaboration profiles and the interaction strategies they use to establish child-AI alignment?

RQ2: What design implications do these collaboration behaviors have for the design of future child–AI co-creative interfaces?

We introduce four novel child–AI collaboration profiles, a set of seven AI contribution types with children's preferences, and a Child-Centered Co-Creative AI (CCAI, Kai) framework with 4 design dimensions. Our findings reveal distinct ways children co-create with AI and provide a new understanding of the AI contributions that children selectively welcome versus those they resist. For example, within the Child-Driver + AI-Refiner collaboration profile, children did not resist AI refinements such as detail enhancement, structure polishing, and shading because these built upon their original drawings. By contrast, in the Child-Initiator + AI-Transformer collaboration profile, children resisted many AI-driven transformations, particularly those that reoriented structures or altered the core of children's original ideas.

This paper makes three contributions to the SIGCHI community:

1. **A set of four child–AI collaboration profiles**: Independent, Child-Driver + AI-Refiner, AI-Inspirer, and Child-Initiator + AI-Transformer. Collaboration profiles [41] have been a useful analytic lens in HCI research on technology-enabled human-human collaboration; here, we extend this to the child-AI collaboration context. Future work can build on our collaboration profiles to assess which of them (or a combination) are effective in supporting children's creative self-efficacy.

2. We provide **new insights into how children perceive AI's contributions during co-creation**. This contribution addresses a critical gap in the literature by revealing children's natural co-creation behaviors and expectations with AI, and by clearly identifying the boundaries of when children welcome AI assistance and when they resist it. In total, we identified seven types of AI contributions, mapped them to children's preferences (Figure 10), and derived design implications from these findings.

3. **CCAI ("Kai") framework**, a prescriptive and empirically grounded design framework for child-AI co-creative tools (Figure 1) that centers (a) child-centered multimodal input methods, (b) metacognitive scaffolds for AI suggestions, (c) embodied affordance for co-creative AI, and (d) reducing cognitive load during co-creation. To the best of our knowledge, to date, our work is the first to prescribe a framework for child-AI co-creativity grounded in children's expectations and natural collaboration patterns with AI. Future work could validate and extend this framework with follow-up studies.

2 RELATED WORK

We situate our work within four research areas relevant to child-AI co-creativity interfaces: (1) collaboration and children's creativity; (2) interaction design for human-AI co-creativity; (3) child-AI co-creativity; and (4) participatory design methods.

2.1 Collaboration and Children's Creativity

Children's creative expression evolves with age [37]. Young preschoolers are often in the pre-conventional stage, producing imaginative stories and drawings that prioritize novelty over accuracy. By early elementary school, most transition to the conventional stage, becoming more attentive to realism and rules. At this stage, children also develop cognitive flexibility and perspective-taking [3], which may influence how they accept and engage with perspectives different from their own in collaborative creativity.

Collaboration is central to children's creativity, as idea generation and refinement are shaped by the social interactions and tools with which children engage [16]. Vygotsky's sociocultural theory emphasizes that creative thinking develops through collaboration, where partners scaffold each other's ideas within the Zone of Proximal Development [29, 40], which refers to the gap between what a learner can accomplish independently and what they can achieve with collaboration. Similarly, Sawyer and DeZutter's theory of distributed creativity highlights that novel ideas emerge through shared processes such as turn-taking, negotiation, and the use of artifacts rather than solely from individual minds [39]. Building on these perspectives, child–AI collaboration can be understood as another form of distributed creativity. Yet the presence of AI alone does not guarantee creative support; its effectiveness depends on how well we design child-AI collaboration interfaces to align with children's natural collaboration patterns and expectations. Not all child–AI collaborations are beneficial. While some AI contributions can support creativity, others risk undermining the small, personally meaningful "mini-c" acts that build children's self-efficacy and creative identity [2]. For example, a child's trial-and-error when deciding how to draw an expression is a mini-c opportunity for reflection; if AI instantly provides a polished solution, that moment of discovery may be lost. Davis et al. [7] extend this view by distinguishing between technical contributions (how to execute a task) and conceptual contributions (what task to pursue). This distinction highlights critical questions for child–AI co-creativity: what forms of support do children welcome, and how do they perceive AI's role as a collaborator? We use this lens to analyze children's natural collaboration behaviors with AI, capturing how children and AI distribute agency across technical and conceptual contributions and how children perceive this distribution. Based on our findings, we propose a set of seven AI contribution types with children's preferences that can be leveraged to design future child-AI interfaces.

2.2 Interaction Design for Human-AI Co-Creativity

Multiple studies have explored how to design effective human-AI co-creativity interfaces [35, 36, 43, 60]. Singh et al. [43], in a review of 62 co-creative systems across domains such as visual arts, design, and writing, emphasize two key design aspects: anticipating user needs and ensuring user control. Anticipating user needs involves understanding the types of contributions users expect from AI, especially when it acts as a proactive collaborator, so that interfaces can be designed to support or allow users to modulate those contributions. User control concerns how much influence users want over the co-creative process and whether they view AI as a partner or helper. Similarly, Moruzi and Margarido [30] proposed a user-centered co-creativity framework arguing that users should decide what role the AI plays in producing shared outputs. However, to design interfaces that enable such control, we must first understand what creative support users want AI to provide, and what they feel risks overstepping in the process. Our work takes a step in this direction through participatory design with children, examining how they envision AI's role in visual storytelling and uncovering the distinct roles children and AI assume during collaboration. Multiple human–AI co-creativity frameworks have been introduced in prior work to categorize AI's roles and contributions in co-creative processes [36, 60]. Rezwana and Maher [36] emphasized the importance of interaction design and proposed the COFI framework, which identifies four key dimensions of co-creative AI: collaboration style, communication style, creative process, and creative product. Analyzing 92 co-creative systems, they highlighted the need for shared mental models of contributions, noting that without clear communication about roles, co-creation risks becoming a "silent game." The COFI framework also characterizes AI contributions into four types: create new (introducing a new element), extend (building on a prior idea), transform (changing an element into something different), and refine (polishing or correcting). While this frameworks capture what the AI does, it does not consider the user's contributions alongside the roles and contributions the AI offers, which is critical for designing co-creative interfaces where users and AI work jointly.

Prior work in CSCW related to technology-supported human–human collaboration can offer a foundation for designing more effective human–AI co-creative systems [42]. One promising direction is to examine the collaboration profiles users adopt with AI, what we call their natural collaboration behaviors, and to design interfaces that intentionally support them. Shaer et al. [41, 42] defined collaboration profiles as verbal and physical patterns of how individuals collaborate on a shared task. For example, they identified profiles in technology-enabled learning, such as turn-takers, who share control by alternating contributions; driver–navigator pairs, where one participant leads the interaction while the other guides and scaffolds; and driver–passenger pairs, where one participant drives the activity while the other engages more passively with limited influence. Identifying these profiles enabled follow-up research to assess which patterns support effective collaboration and which do not. For instance, the turn-taker profile was shown to be particularly beneficial for fostering collaborative learning.

Building on the above-mentioned studies, we investigate the collaboration profiles children adopt when co-creating with AI. While prior frameworks categorize what the AI does [36, 60], they do not account for users' contributions alongside AI roles and mainly focus on adult users. Studies have shown that children's interaction and collaboration patterns with technology differ significantly from those of adults, in part because their cognitive, physical, and socio-emotional skills are still developing [45]. For example, children rely more on exploratory and exaggerated gestures [45], interpret system outputs as intentional or as socially meaningful [55], and are more likely to anthropomorphize AI systems [9]. This could lead to children approaching human–AI co-creativity with different mental models, contribution expectations, and interaction strategies than adults [45]. Our work extends prior work on AI roles during co-creativity to child–computer interaction. Through participatory design, we introduce four collaboration profiles that capture who initiates a contribution, whether the contribution is a refinement or transformation, and how children perceive and respond to different AI contributions. Just as identifying collaboration profiles in technology-supported human–human collaboration enabled follow-up research to evaluate which patterns best support learning, these child–AI collaboration profiles can provide a foundation for future work to assess which profiles foster creativity and self-efficacy among children.

2.3 Child-AI Co-Creativity

Multiple prior works have examined visual storytelling, which is an emerging form of creative expression that integrates verbal (narration) and figural (drawing) creativity, in the context of child–AI co-creativity [4, 12, 13, 21, 52, 56, 59, 61]. Lee et al. [26] designed an interface to support children and parents in rewriting stories with AI assistance, identifying key story dimensions users wanted to edit, such as character, setting, and action. However, this work did not deeply examine children's preferences for interacting with co-creative tools. Related to the current work, Zhang et al. [59] introduced StoryDrawer, a co-creativity interface evaluated with children ages 6–10. They tested two AI-driven strategies: (1) real-time transformation of children's verbal storytelling into drawings and (2) generation of abstract sketches related to story content. The findings showed that StoryDrawer fostered idea elaboration, but the creative product remained largely AI-driven rather than iteratively co-created with children. This limitation contrasts with the COFI framework, which positions working on a shared product as central to co-creativity [36]. Building on their findings, Zhang et al. [59] called for research into "deeper forms of child–AI collaboration". Our work addresses this gap by examining how children engage in visual storytelling with AI, in which both collaborators iteratively draw the story together.

More recently, Cai et al. [4] conducted a scoping review of 20 studies on child–AI co-creation and proposed six design considerations across dimensions such as balancing support and freedom, ethics, and peer/family collaboration. They emphasized the importance of participatory design approaches in which children themselves define what they consider appropriate in child–AI co-creativity. Similarly, Ojeda-Ramirez et al. [32] conducted a workshop with children aged 6–12 using Story AI, a narrative writing platform,

Table 1: Demographic characteristics of our child participants.

Participant ID	Age	Ethnicity
202	9	Asian/Black/African American
999	9	Asian American
888	8	Asian American
143	13	White/Asian/Roman
493	9	White/African American
666	8	White/Asian
113	11	White/Asian

and found that children preferred collaborating with the AI by selectively incorporating its outputs rather than relying on it entirely. While this study highlights children's tendency to filter AI contributions, it does not provide deeper insight into which types of contributions children accepted and why. Collectively, these studies underscore that children value AI as a co-creator. We advance this work by operationalizing child–AI collaboration through four collaboration profiles that make visible how children engage with AI and which contributions they value. We further translate insights from our study to propose CCAI ("Kai"), a framework with four design dimensions for creating child-AI creative interfaces: (a) child-centered multimodal input methods, (b) metacognitive scaffolds for AI suggestions, (c) embodied affordances for co-creative AI, and (d) reducing cognitive load during co-creation.

2.4 Participatory Design Methods and Techniques

For this study, we employed a child-centered form of Participatory Design (PD) called Cooperative Inquiry (CI) [10, 18, 31]. PD is an approach that involves users as active collaborators in the creation of new technologies [58]. CI specifically emphasizes building "as equal as possible" co-design partnerships between children and adults, distinguishing itself from methods where adults act merely as observers or facilitators [10]. Because meaningful co-design partnership with children requires trust, time, and familiarity [58], CI emphasizes practices such as child-adult relationship building, valuing ideas from all partners equally, lowering participation barriers through hands-on techniques, and sharing facilitation responsibilities. CI has been widely used to investigate children's perceptions of emerging technologies, including intelligent interfaces and augmented reality systems [31, 53, 55]. In this paper, we use *PD* to refer to the overarching methodological approach of engaging users as co-designers, and *co-design sessions* to refer to the specific collaborative activities where children and adults generate and iterate design concepts together. In addition to other design techniques [38], co-design sessions also involve children interacting with a prototype or system under development, using it as a design probe to explore preferences and brainstorm what they like and dislike about it through evaluation [38]. For our co-design activities, we used techniques such as Big Paper; Bags of Stuff; design probes; and Likes, Dislikes, and Design Ideas [51] (details in Design Sessions 3.2). We applied these techniques to investigate different aspects of collaboration in child–AI co-creative interfaces.

3 METHODS

Our co-design sessions (Table 1) focused on designing intelligent co-creativity interfaces, with particular attention to interaction and AI contributions through the lens of Davis et al.'s [7] distributed creativity framework, which distinguishes between technical and conceptual help. We employed the CI method with an existing intergenerational co-design group, *KidsTeam UW*, for two reasons [31]: (1) the children were already accustomed to working closely with adults through an ongoing collaborative relationship, which made them more comfortable expressing their ideas; and (2) the children had prior experience with multiple co-design techniques, allowing them to engage effectively in a range of design activities. We conducted four 90-minute sessions over four weeks, with one session scheduled per week. Each session involved a design activity selected for its potential to probe children's expectations and collaboration behaviors related to co-creativity interfaces. In our co-design sessions, adults participated not simply as facilitators, but as full design partners. They contributed ideas, asked clarifying questions, and built on children's suggestions, while leaving space for children to direct the design.

- Design Session 1 (DS1): Familiarization with Intelligent Creativity Support Tools: design your own child-AI creativity tool (Bags of Stuff, Big Paper)
- Design Session 2 (DS2): Interaction and Feedback: design ways to interact and communicate intent with a child-AI co-creativity interface (Bags of Stuff, Big Paper)
- Design Session 3 (DS3): Technical help: Children interacted with an existing co-creative AI drawing tool as a design probe and discussed their likes and dislikes regarding the types and levels of technical assistance (e.g., fixing lines, color-filling) they found useful when creating visual stories (design probe, Likes, Dislikes, Design Ideas).
- Design Session 4 (DS4): Conceptual help: Children used the same AI tool as in DS3 to explore how they wanted conceptual assistance (e.g., connecting story elements, suggesting changes) to be provided during story creation. They then discussed their likes and dislikes related to the tool's conceptual support (design probe, Likes, Dislikes, Design Ideas).

3.1 Participants

All our participants across four design sessions were members of an existing intergenerational co-design group, *KidsTeam UW*, which consists of child participants and adult researchers. The co-design group included seven children aged 8 to 13 years (average = 9.6 years), see Table 1. We included ethnicity data to ensure transparency regarding the diversity of our co-design group, aligning with inclusive design principles [5] and prior co-design studies [55]. Four of the children were identified as female, while three were identified as male. All participants filled out a demographics survey. The age group of our participants is consistent with prior Cooperative Inquiry studies [31, 55]. The majority of our participants had limited knowledge of what intelligent chatbots were or had rarely used them. Additionally, most participants reported never or rarely using digital creativity tools like Adobe Creative Suite or Canva. Our study protocol was approved by the institutional review boards of both the University of Washington (where the

Table 2: Prompts for Design Sessions.

Design session (DS)	Design questions	Design activity
DS1	Design something that helps you be creative in telling stories you imagine?	Design a creative AI partner [*Big Paper and Bags of Stuff*]
DS2	How would you want to communicate your story idea to a computer? What is the weirdest way you can think of communicating with a computer?	Act out how you would communicate different story concepts (e.g., character, action, setting) to a computer [*Acting out, Big Paper, and Bags of Stuff*]
DS3	What kind of help does a child need when giving drawing input for storytelling?	In a design probe, create a story panel from a given prompt, and discuss likes, dislikes, and design ideas for technical help [*Design probe, Likes, Dislikes, and Design Ideas*]
DS4	What parts of telling a story do you find hardest? Which parts of the story creation would you like the AI to help you with?	In a design probe, create a set of story panels from a given prompt, and discuss likes, dislikes, and design ideas for conceptual help [*Design probe, Likes, Dislikes, and Design Ideas*]

sessions occurred) and the University of Illinois Chicago, and a data sharing agreement was approved by both institutions.

3.2 Design Sessions

We conducted four design sessions, each lasting 90 minutes, with a maximum of one session per week. Each session was divided into the following phases: Snack Time (15 minutes), social time; Circle Time (15 minutes), presenting the question of the day to introduce adults and children to the design activity; Design Time (45 minutes), during which children and adults were divided into small groups to complete the design activity using PD techniques; and Discussion Time (15 minutes), during which the group was reconstituted to present finished designs and reflect on common themes from the design activity. During Circle Time and Discussion Time, adult researchers posed several direct questions to children in a group interview format to encourage reflection on the design activities. We structured the sessions so that children could become familiar with the concept of Creativity Support Tools (we used the term "AI Partner for Creativity Support" in the sessions) before participating in the sessions related to interaction, technical, and conceptual help for visual storytelling.

As the co-design group, we had adults and children working together on design activities. During the Design Time, participants were divided into groups. The groups were different each time so that everyone had the chance to work with different people in each session. Each group was made up of two or three children and two or three adult researchers. While a high adult-to-child ratio might imply a risk of power imbalances in one-off studies, in this context, it was necessary to lower participation barriers [58]. This ratio ensured that all children's ideas were heard, documented, and supported, particularly for tasks requiring dexterity (e.g., typing prompts, note-taking, or capturing design artifacts). Many of the participating children have worked with our team for months or years, which helps reduce the power imbalances often present in adult-child interactions [58]. Because of this long-term design partnership, children were comfortable voicing their opinions and disagreeing with adults, a pattern consistent with prior CI research [58]. This relational foundation enabled balanced, collaborative design work throughout the study.

To better accommodate both some of the authors (first and last) as well as children who might have extenuating circumstances such as parental illness, transportation issues, and so on, sessions were conducted in a synchronous hybrid modality. This format has been used in this design group for the past several years, drawing on previous work in remote co-design [22, 25]. Children attending in a hybrid capacity join via Zoom and are assigned to groups just like the in-person attendees. Although hybrid participation was present, all children and adult design partners had already worked together in person for months. Because strong social bonds already existed [58], the hybrid format functioned as a seamless extension of our in-person practice rather than a disruption. Adult researchers ensured remote children remained included through screen sharing, camera views, and coordination of physical artifacts. We observed that this setup did not negatively impact the children's creativity; remote participants contributed to brainstorming and drawing with the same level of agency as those in the room. All sessions were audio and video recorded; the adult facilitators collected field notes and pictures of the design artifacts.

3.2.1 Design Session 1: Design a Co-Creative AI partner for Storytelling (DS1). : In the first session, we introduced children to the concept of AI tools for creativity. The design activity involved using Bags of Stuff and Big Paper to create their own prototype of an AI-based creativity support tool. Bags of Stuff is a low-tech prototyping method where participants use large bags filled with craft materials to create prototypes in groups [51]. Big Paper is a low-fidelity prototyping method in which design groups collaborate on a large shared sheet of paper [51].

3.2.2 Design Session 2: Interaction and Feedback (DS2). In the second session, we elicited how children would want to communicate different aspects of their stories to an AI storytelling interface. To encourage ideas beyond familiar methods like touch or drag-and-drop, the activity asked children to act out how they would interact with the system. Children were divided into four groups, each with at least one adult facilitator, and provided with Bags of Stuff and

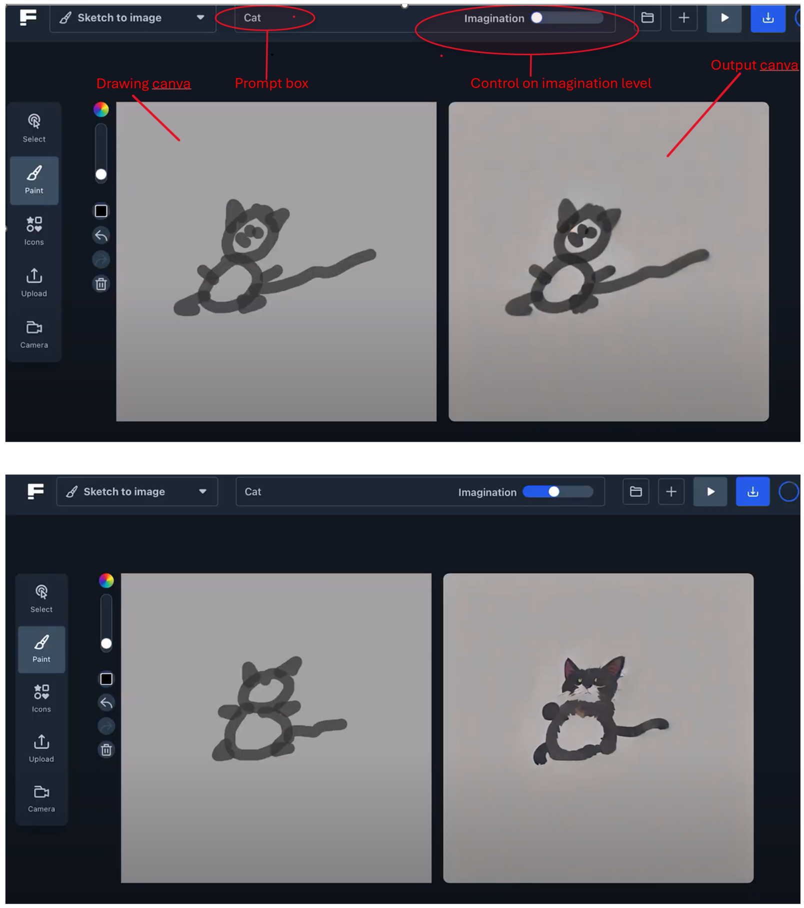

Figure 2: Screen capture of the Pikaso Freep!ck [14] tool used during DS3 and DS4, showing imagination level 0 (top) and imagination level 48 (bottom). The left panel is where children can draw, and the right panel is the AI output panel, which varies in fidelity based on the selected imagination level.

Big Paper. The facilitator asked the children to choose one story component among those presented during Circle Time: character, action, and setting. Then, children were asked to demonstrate how they would communicate that component to a computer.

3.2.3 Design Session 3: Technical Help (DS3). In the third session, we aimed to uncover the nature of technical help children might need with the drawing (i.e., figural creativity [59]) aspect of visual storytelling. The design probe activity consisted of children interacting with an online tool called Pikaso Freep!ck [14] (Fig. 2), which presents an interface split into two panels. On the left-hand side, children could draw using tools provided, and a text box allowed them to enter prompts. The intelligent algorithms in the interface then combined the text prompts with the children's drawings to produce updated AI-generated drawings that included AI contributions layered on top of the original work or an updated version of the children's drawing. A sliding bar from 0 to 100 (Fig. 2, see label on top right) enabled children to adjust the "Imagination Level" (IL), which controlled the extent to which the AI modified the drawing and inserted its own ideas. To start with, children were asked to select a prompt from a provided set ("A baby lion eating an apple," "A bee flying on a flower," or "A dragon sleeping in a field of flowers") or to create their own. They then used Pikaso while experimenting with different ILs. Both during and after completing the design activity, children were asked to share their likes and dislikes about how the interface provided help, and what they would modify.

3.2.4 Design Session 4: Conceptual Help (DS4). For the final session, we continued exploring children's preferences for AI's support, this time focusing on conceptual or idea-related forms of help. Similar to DS3, during the design activity, we employed the design probe technique as part of our PD approach: children interacted with Pikaso Freep!ck as a group on either a tablet or desktop to create a storyboard with multiple panels. At the beginning, we instructed children to use an imagination level between 0 and 30, and later asked them to increase it to a value between 30 and 70. Both during and after the activity, we asked what they found to be the hardest part of creating a story and whether they preferred a tool that directly changed pictures or suggested modifications. Children were also asked to reflect on how they might reprogram the imagination level slider and how they would modify the drawing tool.

In DS3 and DS4, adult designers, adult designers familiarized themselves with the Freep!ck AI drawing tool in advance. Given that the goal of these sessions was to probe children's preferences for technical and conceptual help during collaboration with AI, we explained the overall plan but intentionally gave children the lead. Adults primarily asked probing questions to advance the story, take notes, and provided technical troubleshooting. They contributed ideas (e.g., suggesting how to rewrite a prompt) or demonstrated tool features only when explicitly asked; for instance, there were moments when children asked adults to draw or demonstrate something. This approach ensured that children remained in control of the creative process.

We selected Freep!ck for two primary reasons. First, it provided an intuitive interface that combined both text and drawing inputs, allowing children to engage in visual storytelling using both text and figurative drawing. Second, the tool offered an easy-to-test mechanism for varying the level of AI contribution through a slider control. This feature gave children a straightforward way to modulate the level of AI participation in their creative process. By using an interface that allowed children to manipulate collaboration through a simple drag gesture, we ensured that our analysis remained focused on how children perceived and negotiated AI's role in co-creation, rather than on usability barriers or interface complexity.

3.3 Data Analysis

As in prior PD work with children [31, 55], the first author transcribed and wrote memos from the design session videos, screen recordings, prototype images, and questionnaires from the four sessions. Excluding snack time, we collected approximately 720 minutes of video recordings. Transcriptions were completed verbatim, while memos were created by listening to 15-minute intervals of the recordings (for DS3 and DS4, both the design session and iPad screen recordings were reviewed) and noting anything the researcher considered relevant to our research questions.

We analyzed the data using affinity diagramming, a well-established method for organizing large-scale qualitative data [6, 47]. This bottom-up, inductive approach involved iteratively defining, refining, and grouping individual data points (notes) into broader themes [47]. To construct the affinity diagram, we used MiroBoard, an online whiteboard platform for remote collaboration. Each statement from our memos and transcripts was represented as a digital sticky note. The first and last authors iteratively organized these notes into themes through several group discussions. To do so, the first and last authors met for two rounds of group discussions, each lasting 60-90 minutes. Before the first discussion, the first author created an initial round of themes by reviewing the transcripts and memos for each session. These themes included content both related to child-AI collaboration and other non-child-AI collaboration themes, such as how children worked with adults, their views on AI in general, and its limitations. During the discussion meetings, authors discussed themes related to interaction episodes, compared interpretations, and looked at videos when needed to gather more context. During these discussions, when discrepancies in interpretation arose, for example, when a sticky note did not go in depth about an interaction episode or how children reacted when AI updated their ideas, the first and last authors revisited the data videos, discussed the underlying behaviors observed, and came to an agreement. Then, during a third meeting with a larger research group including all authors, the emerging themes were shared for feedback and refinement. In line with prior work [27], since our goal was to generate a rich, qualitative account of children's natural child-AI collaboration behaviors rather than to establish a codebook for quantitative reliability testing, we did not compute inter-coder reliability statistics such as Cohen's Kappa.

In this paper, we report the themes related to children's expectations and natural collaboration behaviors with AI during co-creation, illustrating each theme with examples from the design sessions (DS1–DS4). We next present our findings.

4 FINDINGS

The goal of our analysis was to understand how children naturally collaborate with AI. We structure our findings as (4.1) child-AI collaboration profiles, (4.2) child-AI alignment: interaction patterns and challenges, and (4.3) collaborative brainstorming. We use the insights discussed in these findings as an empirical grounding to create the CCAI framework (Figure 1, described later in the Discussion section 5.1) to inform the design of future child-AI creativity interfaces.

4.1 Child-AI collaboration profiles

We identified four collaboration profiles across our data that capture children's natural co-creative behaviors with AI: Independent, Child-Driver + AI-Refiner, AI as inspirer, and Child-Initiator + AI-Transformer. These profiles categorize child–AI collaboration based on the types of contribution: initiators, who introduce new ideas; refiners, who make small improvements while preserving the original idea; and transformers, who make major changes that extend or alter the direction of the idea. While future work can further evaluate the efficacy of these profiles in supporting children's creativity, here we focus on describing them as foundational insights into how children naturally collaborate with AI. Attending to these natural behaviors is important for designing co-creative systems that can flexibly support the diverse ways children collaborate with AI.

4.1.1 Independent Use. One of the collaboration profiles we observed was independent use, where children generated and refined visual representations of their ideas entirely on their own without asking for or considering AI input during the storytelling process. In this profile, we saw children often erase and redraw their sketches multiple times; they sometimes voiced frustration with their own drawings but insisted on not using AI assistance, especially during the early phases of sketching out their vision. For instance, in DS3, G2, one child was drawing a lion for the prompt "baby lion eating an apple." With the imagination level set to 0 (no AI help), the child first drew the body of the lion (Figure 3, a), then said, "*na* . . . " and restarted the drawing by experimenting with new shapes for the face and body (Figure 3, b). Another child, observing this, asked, *"Can AI draw something completely out of shape?"* but did not take AI's input and continued drawing independently. The child

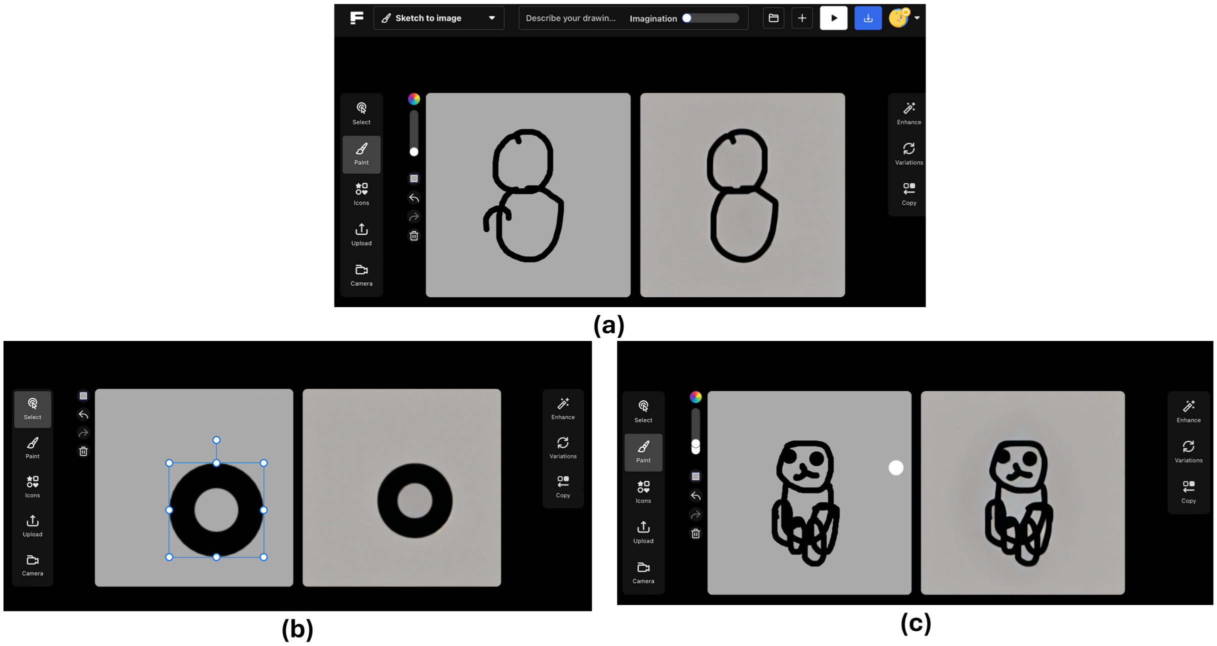

Figure 3: Screenshot from DS3: G2 creating a drawing for the prompt 'baby lion eating an apple.' The child begins with (a), then erases it and redraws using shapes (b). The revised baby lion drawing, completed without AI assistance (IL = 0; the AI panel shows the same drawing as the child's drawing with no additions), is shown in (c).

eventually redrew the same structure (Figure 3, c), remarking, "*It's the worst drawing I have ever made*." When prompted by an adult designer about whether she wanted help from AI, she responded, "*Not necessarily … nothing for the drawing*." This example highlights how children engaged in iterative cycles of self-correction, sketching, evaluating, and revising to match their mental vision, particularly during the early phases of story creation when they were still clarifying what they wanted to depict.

During our design sessions, we also saw that even when AI suggestions were available, children sometimes chose to disregard them if they did not like what AI suggested. For instance, a child in DS4, G1, drew "*the dolphin swimming around*" with imagination level set to 25. Although the AI suggested an alternate dolphin orientation, the child ignored the AI's contribution and continued their own drawing. Overall, **this finding illustrates that children viewed collaboration with AI as optional and not as something they would want to do for all parts of creative storytelling**. They valued maintaining a zone of independence, deciding when to exclude AI and prioritizing their own cycles of refinement and self-correction, in line with Piaget's constructivist view [50] about how children actively build knowledge through cycles of trial and experimentation.

4.1.2 Child-Driver + AI-Refiner. Another common collaboration profile we observed during the design sessions was the child as the driver and the AI as the refiner. In this profile, children proposed the initial idea. They performed any major transformations to visualize and extend the idea, while AI added refinements to the existing drawing without changing the core concept. Here, we highlight instances of how the AI contributed to refinement and how children received these contributions. Overall, in our data, we saw three types of AI refinements: **detail**, **structure**, and **shading**.

One prominent type of AI contribution during co-creation was detail refinement, where the system enhanced children's original sketches by adding elements such as eyes, fins, teeth, or fur texture. These detailed refinements were generally received positively, with children rarely undoing them or commenting negatively. This example illustrates how the AI added details to children's drawings while maintaining the general tone of what children drew: in DS3, G2, a child was drawing a visual for the prompt "baby lion eating an apple". As seen in Figure 4, the child first outlined the baby lion's body structure (imagination level set to 48). Building on the original body structure, AI added face details (Figure 4, a). However, the child was initially not satisfied with the alignment of face details added by the AI to the lion's face structure in Figure 4, a: "*It's not very good though; it is not fully lining the picture*". But as the child added more details of the face in their drawing by adding a mouth, AI adjusted its details to better align face details with the mouth the child added. Figure 4, b shows the child adding a mouth to the lion, and corresponding details that were added by the AI to the face to make it look closer to a baby lion, such as eyes and fur-like texture that were missing in the child's original drawing. Encouraged by these enhancements, the child continued drawing, adding color to the lion's leg (Figure 4, c). After the child filled in color in their drawing, AI added more refined details to the lion's face and legs, such as toe fingers and colored fur texture, about which the children were excited and said "*nice*".

In our data, we also saw children respond positively to body **structure** refinements and **shading** refinements. When asked what

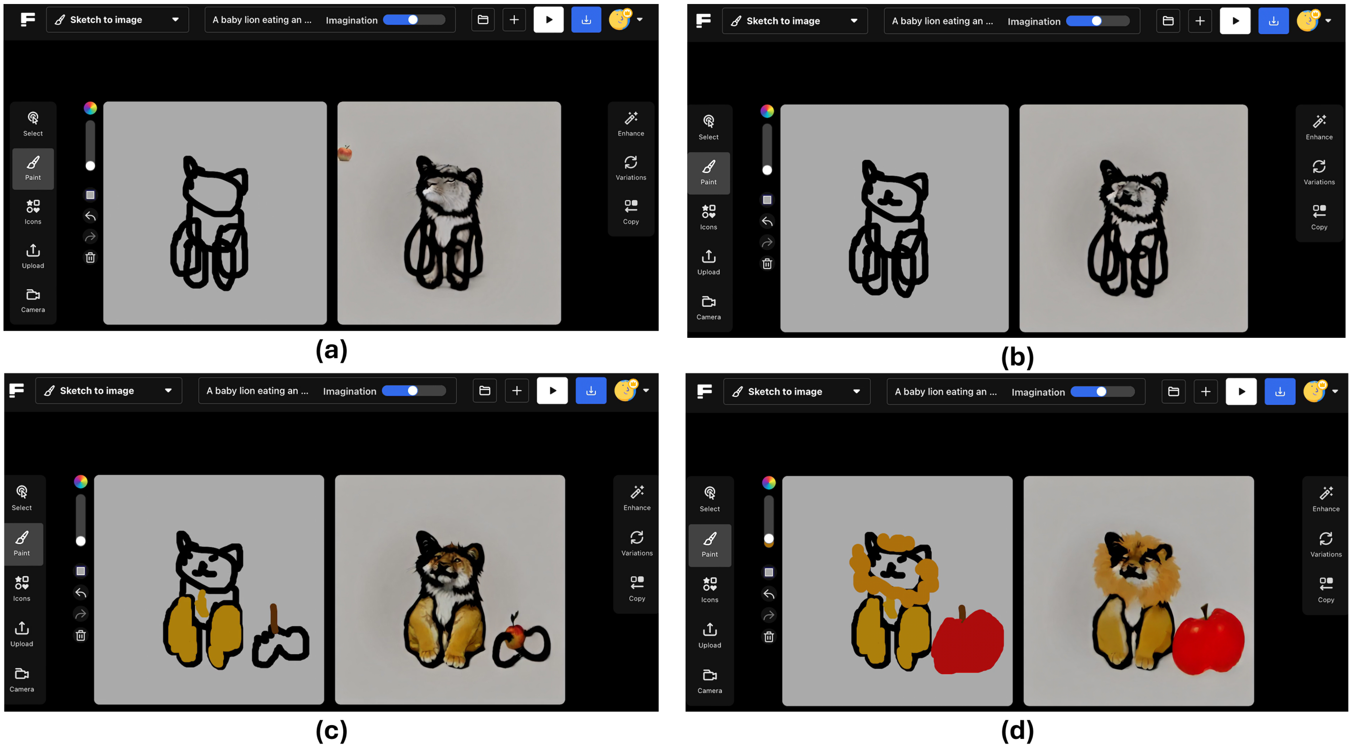

Figure 4: Example of detail refinements added by the AI during Child-Driver + AI-Refiner collaboration profile, (a) and (b): the AI added facial details to children's drawings. (c) and (d): the AI added refinement details to the lion's toes and fur.

help children wished for, a child replied, "*I wished it had corrected my lines*," suggesting that structural correction was a valued form of support. In DS4, G1 (Figure 5 a, b), a child drew a dolphin, and the AI subtly adjusted the body structure and curves to resemble a real dolphin more closely. The child did not resist or undo these edits. Later, in the same group, we saw the AI helping with shading details, where a child drew a shark and filled in colors, and the AI added details of teeth and shading on the face of the shark (Figure 5, c). The AI continued the drawing, making it look more realistic while maintaining the tone of the child's drawing rather than completely changing the picture. Across these examples, we saw that children did not show resistance to AI refinements where AI did not overwrite the tone of children's drawings, whether lion, shark, or dolphin, but instead built upon their original sketches. **These findings illustrate that refinements to detail, structure, and shading were perceived as supportive enhancements rather than intrusive changes, provided that the AI maintained the tone of children's original sketch.**

Our findings also highlighted that AI refinements sometimes introduced **interpretive errors**, where the system misread a child's drawing and refined it into something unintended. For example, when a child drew a cloud, the AI interpreted it as froth, which surprised the child: "*What… maybe it does not know it's a sky… it thinks it's froth… .*" The child then redrew the clouds in blue to clarify their intent. While the child appreciated other refinements made by the AI, they disliked the conversion of the cloud into froth. Because the AI refinements were applied globally, children could not indicate that a specific change, such as interpreting a cloud as froth, was incorrect. Instead, they had to undo the entire set of refinements, even if they were happy with some of the other edits. **This finding suggests the need to enable children to select or reject AI refinements at the object level (i.e., specific objects within a drawing) in addition to a global level (i.e., the entire drawing)**.

4.1.3 *AI as inspirer.*

We saw instances during the design sessions where the AI directly or indirectly inspired children's visual drawings of the story prompt. Our interface included an imagination level slider that children could use to modulate how much additional imagination the AI added to their drawings. For example, in DS4, G1, children used the slider to explore alternatives for the text prompt "the bee returns to her beehive" (Figure 6, a-c). As they browsed the AI's interpretations, they reacted with comments such as "*fleet of bees*" and "*it has a big butt*." This example illustrates how the slider, as an interface affordance, allowed children to flexibly invite more or fewer AI contributions, helping them explore diverse visual interpretations of their prompt. We also observed instances where AI indirectly inspired children's independent drawings, even when they were not actively seeking its input. In DS3, G1, for instance, when the children entered the text prompt "gun," the AI immediately generated a drawing of a gun before the child had

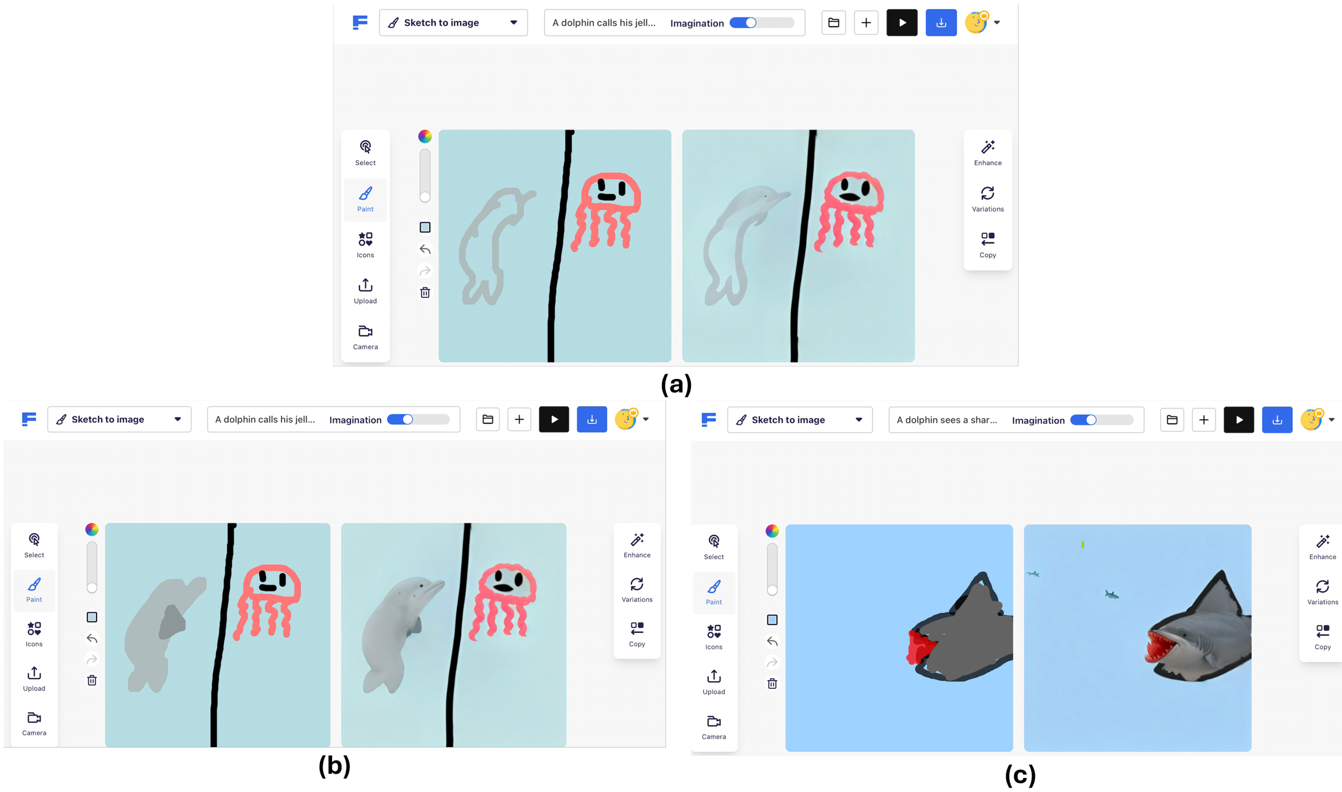

Figure 5: Examples of structural and shading refinements added by the AI during the Child-Driver + AI-Refiner collaboration profile are shown. (a) and (b): The AI added structural changes and shading to the dolphin; (c): The AI added shading refinements to the shark.

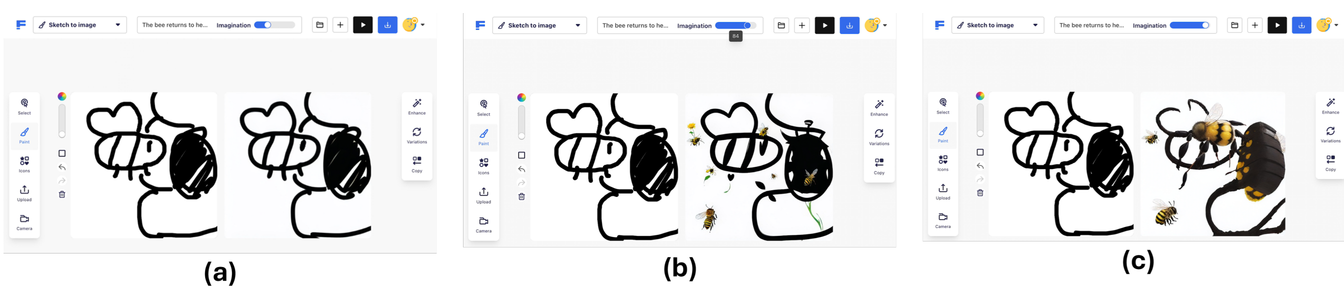

Figure 6: Example of children using the imagination slider to explore different interpretations of their prompt 'bee returning to the beehive', with imagination levels set at <40, 84, and 100, shown in (a–c), respectively.

begun sketching. The children took inspiration from the AI's depiction of the gun's structure but proceeded to draw it on their own. Although the interface was not intentionally designed to inspire children in this way, the presence of a separate AI drawing space and the feature of auto-visualizing prompts sometimes influenced what children drew independently. **This example shows how the timing of AI suggestions appearing before children had even started sketching unintentionally shaped their ideas, underscoring the importance of carefully designing when and how AI input is introduced in co-creative systems**.

4.1.4 Child-Initiator + AI-Transformer. During our sessions, another way we saw children co-creating with AI was through a role in which children proposed an initial sketch, but at higher imagination levels, the AI transformed it by adding new ideas. Transformation is different from refinement, in that it extends or changes the original idea. Overall, we saw four types of transformations during our design sessions: **content expansion**, **structure reorientation**, **style shift**, and **cross-concept blending**. Children perceived some of the AI transformations as positive and others as not.

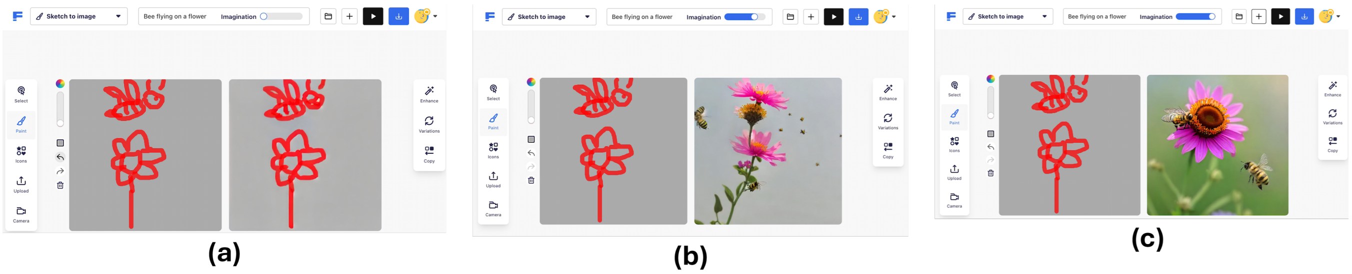

Figure 7: Example of content expansion, re-orientation, and style shift AI transformations (a–c, respectively) from the Child-Initiator + AI-Transformer collaboration profile.

As an example, in DS3, G1, children began by sketching (at imagination level 0) the outline of a bee and a flower to depict 'a bee flying on a flower.' At this stage, they appeared satisfied with their drawing and did not seek AI assistance (Figure 7, a). When the adult designer asked, "*Is there anything you need help with, or are you satisfied with the drawing?*" the child responded, "*Yes*" (again, signaling that AI was seen as optional during the initial phase of visual idea depiction, as discussed in 4.1.1). However, we later saw the group experimenting with higher imagination levels, and the AI began expanding the content beyond what the children had intended. After raising the imagination level to 77, the AI, as a co-creator transformed the drawing by **content expansion**, adding two additional flowers beyond what the child had drawn, and multiple bees around the original flower (Figure 7, b). This content expansion surprised the children: "*wah, it's a little too high* [imagination level]", illustrating that children resisted and did not prefer AI-driven content expansions during co-creation. Then, while exploring, children increased the imagination level to 100 (Figure 7, c). At this point, the AI completely restructured the drawing (**structure re-orientation**), altering how the flower was positioned and how the bee was approaching it. In addition, the AI shifted the style to a more realistic rendering (**style shift**). Although the children initially expressed surprise at these transformations, they quickly judged them as excessive by saying, '*Look at the evolution, it's sprouting a flower ... it changed a lot*' and '*it's too much*.' These reactions **illustrated how children considered it an intrusion rather than support when the AI's contributions altered the drawing substantially from their original intent**.

However, **some transformations that combined two distinct concepts into something novel, beyond what children had thought of, were well received because they were seen as imaginative extensions rather than intrusions**. In DS3, G1, for instance, children appreciated when the AI blended "Among Us" with the flower prompt to generate a completely new drawing, an outcome they would not have thought of themselves. The child said, "I want to draw an Among Us character." Children drew an Among Us character but used the text prompt "a bee flying on a flower." The AI combined the child's Among Us drawing with a flower from the text prompt, to which the children excitedly said, "*It's an Among Us flower*". The adult researcher asked, "*If it gave you an Among Us flower, would you want that?*" The child replied, "*Yeah, that's cool*". On being asked "*What do you like about it [the AI]?*", a child in DS3, G2 mentioned they liked how "*liked the random it [the AI] is.*"

4.2 Child-AI Alignment: Interaction Patterns and Challenges

During our analysis, another theme we saw was the challenges children faced when trying to align the AI's outputs with their mental models. To manage this alignment gap, children sometimes employed explicit strategies, while at other times their natural ways of communicating introduced new alignment gaps. We identified two interaction strategies: (1) alignment through text prompt editing and (2) alignment through drawing-based instructions; and two interaction patterns that often created alignment gaps: (3) underspecified prompts and terminology, and (4) object relations.

4.2.1 Alignment through Text Prompt Editing. We saw multiple instances during our analysis where children made minor text adjustments and provided follow-up conversational prompts to obtain a desired result. As an example of **small text adjustments**, in DS3, G2, we saw a child drawing a comic-style dragon on a field of flowers, but the AI kept generating a realistic-style dragon. To better align the AI to the drawing style children had in mind, the child edited the text prompt gradually, adding or changing some words each time to obtain the intended output. The initial prompt was "A dragon lying in a flower field." They then changed it into "A Gyarados (meaning: a water/flying type dragon-looking Pokémon) lying in a flower field" (editing), hoping it would generate a cartoon-style representation of a water dragon. When this attempt failed, the child opted for "A cartoon dragon lying in a flower field" (adding). The child then tried "A Pokémon dragon lying in a flower field", which was then changed to "A dragon lying in a flower field in Pokémon style". Instead of just repeating the same prompt, this example shows children playing around with words to explore how minor changes in prompts impacted the AI's way of thinking. In addition to editing the text prompt, we also saw children providing **follow-up conversational prompts** to the interface to achieve a specific result. They differ from prompt editing because they do not involve modifying a previous prompt, but rather involve using a series of complete and self-contained prompts that add information. For instance, in DS3, G2, we saw that if the AI did not add the desired scales to a created dragon, children would input "add scales" as a new prompt, expecting it to be a conversation and for the AI to remember the last prompt. **This**

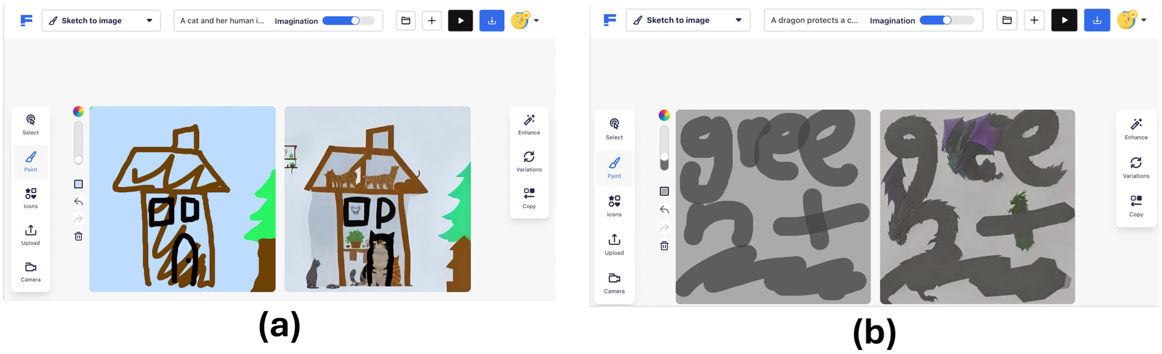

Figure 8: Visual interaction strategies used by children to communicate intent to the AI for supporting child–AI alignment.

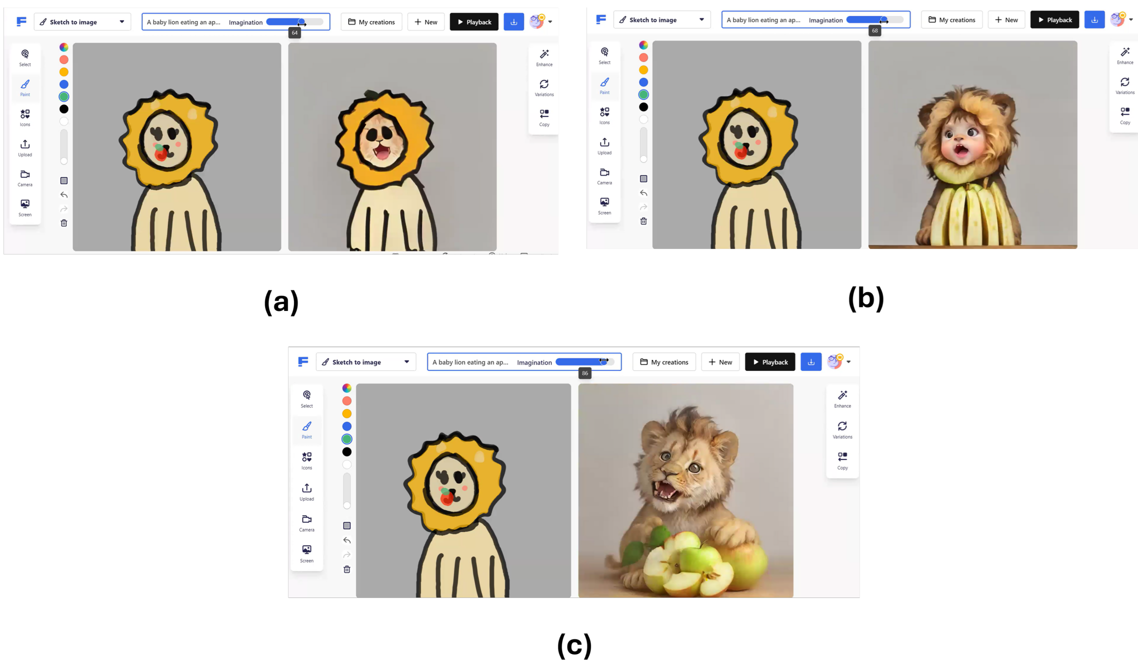

Figure 9: Example of child-AI misalignment for object relations.

example illustrates children's tendency to consistently try to align the AI to the drawing they intended to make, rather than easily giving up or going with the AI's interpretation. During alignment, children tended to use reference words like "Pokémon style" or "Gyarados" to better communicate with the AI what their intentions were, rather than describing the style under discussion.

4.2.2 Alignment through Drawing-Based Instructions. During our analysis, we saw children trying to communicate their intentions to the AI visually while drawing. For example, in DS3, G1, a child scribbled over part of the drawing to indicate their intention to discard that specific section (Figure 8, left). In addition to using the text box for prompts, children wrote textual instructions directly in the drawing area, expecting the AI to interpret them as commands. For instance, one child wrote 'green' in the drawing area to signal that the AI should use green for the cash they were trying to draw (Figure 8, right). However, during the study, the AI ignored these visual communication cues and treated them as part of the drawing. We also saw children using drawing as a medium to emphasize which parts they wanted the AI to keep updating. One such interaction method for emphasis was bolding: children repeatedly darkened specific parts of their drawing when the AI seemed to ignore or misinterpret them. For example, in DS4, G1, children drew a dolphin swimming alongside a shark and a jellyfish. Since the AI failed to render the jellyfish's expression as happy, the children insisted on the smile by bolding it until the AI finally included it in the output. **Overall, children used drawing-based cues, such as scribbling, bolding, and writing text in the drawing area,**

not just to create content, but to signal their intentions and nudge the AI to better align with their mental models.

4.2.3 Underspecified prompts and terminology. During our analysis, we observed two types of children's natural interaction behaviors that created alignment challenges. The first was their tendency to write very short text prompts that often lacked story objects or verbs. For example, one child simply wrote "*fight*" without specifying who was fighting. In such cases, the adult facilitator had to intervene: "*Make the prompt more specific*," suggesting the addition of a verb or object. This illustrates that **children frequently relied on shorthand prompts and required external scaffolding to clarify context or action**. The second tendency was children's assumption that the AI would understand terminology tied to their peer culture or specific contexts. For instance, one child entered the prompt "*Among Us*." In response, the system produced a drawing unrelated to the child's mental model of the game. The child remarked: "*AI does not know much about Among Us*." showing that **although AI processed the surface-level text, it did not consider the child's underlying mental model** of what Among Us means to them.

4.2.4 Object relations. Another example of child-AI misalignment we saw during our design session was AI ignoring the relationship between story objects that the child specified when visually depicting them through drawing. For example, in DS4, G3 child drew a visual for the prompt 'a baby lion eating an apple' and increased the imagination level to see how the AI would help. In response, the AI replaced the apple with the lion's mouth (Figure 9, a), ignoring the apple in the drawing completely. When the imagination level was changed again, the AI focused primarily on the objects in the prompt (lion, apple) while giving minimal attention to the relationship between them (the act of eating). It converted the drawing into a person in a lion outfit (Figure 9, b); instead of *eating* an apple, the person was carrying slices of apple. Frustrated, the child exclaimed: '*...What is AI doing to my beautiful baby lion! … It's a person…*' When the imagination level was increased further, the AI ignored the child's original drawing and produced a generic image of a lion and an apple (Figure 9, c). Overall, this example shows misalignment where the AI often included the correct objects ("baby lion" and "apple") from children's prompts, but ignored the intended relationships between them ("seating"). **Children expected that writing actions like 'eating' would produce a literal depiction of the scene, but the AI treated prompts probabilistically and seemed to focus only on object presence, leaving children frustrated and sometimes feeling a loss of agency**.

4.3 Collaborative brainstorming

In addition to interactions with AI, we saw how children collaborated with other children and adult designers in their co-design groups to expand their thinking about conceptual story ideas. During our analysis, we often saw adult designers stepping in and prompting children to extend their stories or consider new relational elements. For example, in DS4, G1, after a child drew a dolphin, the adult asked: '*Is that when it meets the shark?*' When the child introduced a jellyfish, the adult followed up: *'How are the dolphin and jellyfish related, and how are they both connected to the shark*?' These prompts helped children elaborate on the narrative connections between characters and continue their story in a cohesive manner. During our sessions, we also saw children brainstorming and drawing together to complete the story panels. For example, in DS4, G3, two children took turns adding elements to a shared story drawing. One child began by drawing a cat, followed by the other adding a house. During this turn-based drawing, children discussed spatial placement of objects ('*Is the house behind the cat or next to it?*') and later negotiated sequencing ('*Draw the house first because it's in the background*'). These examples show the nature of collaborative discussion that helped children during story conceptualization and pushed them to elaborate relationships and think about how to visually depict a scene. **Although AI support during our design sessions did not provide such opportunities for reflective discussion, the above-mentioned examples suggest design opportunities where an AI co-creator could move beyond generating outputs to also act as a conversational partner who prompts children to consider relationships between story elements in real-time and discuss spatial elements of drawing.**

5 DISCUSSION

We conducted participatory design sessions with children to examine how they naturally collaborate with AI during co-creation and what types of contributions they accept or reject. Based on our analysis, we identified four collaboration profiles (Independent, Child-Driver + AI-Refiner, AI as Inspirer, and Child-Initiator + AI-Transformer) and seven types of AI contributions (Figure 10) along with children's preferences for each (**RQ1**). The four collaboration profiles we observed were not rigid roles that children and AI consistently stayed in, but rather were temporary states that they moved in and out of. For example, a child might begin in the Independent profile while sketching an initial idea and then shift into the Child-Driver + AI-Refiner when seeking detail enhancements. Thus, collaboration profiles should be seen less as fixed categories and more as dynamic collaboration patterns. This underscores the importance of designing co-creative AI interfaces that flexibly support transitions across profiles rather than locking children into one mode of interaction. Our findings build on prior work in child–child collaboration technologies, extending it into the context of child–AI collaboration. For example, Woodward et al. [54] examined collaboration styles around tabletops (e.g., dominant–submissive, divided dominant, balanced, independent, or verbally controlling) and argued for explicitly considering these natural behaviors when designing collaborative technologies for children. Similarly, our four collaboration profiles categorize child–AI collaboration based on the nature of contributions from both children and AI and provide a foundation for future work to assess which collaboration profiles might best support children's self-efficacy and mini-c creative moments.

Prior work by Pu et al. [34] used participatory design to examine the challenges and needs of students aged 14–17 when integrating AI into school contexts. One of their key findings was that students preferred personalized hints to direct answers. Although their participants were older than ours (ages 7–13) and their work was not situated in a creativity context, yet we observed a similar

Category	Definition	Examples from Data	Children's response
AI refinements: Small, detail-oriented changes that preserved the child's overall structure or concept. Children generally accepted or selectively adopted these.			
Detail Enhancement	AI adds small details (eyes, textures, colors) while preserving structure.	AI added eyes, fur texture, and toe shapes to a child's lion sketch. [DS3, G2]	😊 Welcomed as supportive, children said "*nice*" when details aligned with their drawing outline.
Structure Refinement	AI subtly improves outlines or proportions.	AI refined dolphin outline, smoothing body curves. [DS4, G1]	😊 Accepted as helpful; child wished AI could '… *correct lines …*'.
Shading and Textures Refinement	AI adds shading or slight realism within the child's drawing style.	AI added teeth and shading to a shark drawing. [DS4, G1]	😊 It was not met with resistance, since it did not overwrite the child's intent.
AI transformations: Major structural or relational changes that altered the child's intent or story direction. Often resisted or rolled back by children.			
Content Expansion	AI adds new objects not drawn by the child.	AI sprouted extra flowers and multiple bees at high imagination. [DS3, G1]	😣 Rejected when additions felt unnecessary; children said it was '*too much*.'
Structural Reorientation	AI alters the layout/structure of story objects.	At Imagination 100, AI repositioned the bee and flower, changing the composition. [DS3, G1]	😣 Children were surprised but often rolled back the imagination slider to regain control.
Style Shift	AI changes sketch to a cartoony or realistic style.	AI made the drawing look either too cartoony or too realistic. [DS3, G1]	😣 Viewed negatively when it diverged from the intended tone: "*Sometimes it is too cartoony*."
Cross-Concept Blending	AI merges two distinct concepts to create novelty.	Combined 'Among Us' with a flower to create a hybrid figure. [DS3, G1]	😊 Appreciated as 'cool': children liked it when AI pushed imagination.

Figure 10: Types of AI Refinements and Transformations and Children's preferences during Child–AI Visual Storytelling

pattern among younger children. Children in our study preferred AI contributions that extended or refined what they had already created rather than those that overlooked their original ideas. Our findings go further by identifying seven distinct AI contribution types along with children's preferences for each (Figure 10), showing that children selectively accepted contributions that preserved and respected their original ideas. Newman et al. [31] conducted a co-design study with children to explore the potential of GenAI as a creativity support tool and found that children who struggled to intuitively express their creative goals to AI also struggled to create with GenAI and evaluate its output. Our findings add to this prior work by highlighting two natural child behaviors that should be considered to enable children to more easily communicate their creative goals to GenAI: (1) children often wrote very short text prompts that lacked key story objects or verbs, and (2) children frequently assumed that the AI would understand terminology tied to their peer culture or specific contexts. Designing GenAI systems that recognize, scaffold, and respond to these natural communication tendencies could help children articulate their creative goals more naturally and reduce alignment breakdowns.

Our findings highlight design opportunities and challenges for supporting child-AI creative collaboration. To translate these insights into actionable design guidance, we propose the Child-Centered Co-Creative AI (CCAI, "Kai") framework (Figure 1), which synthesizes our empirical findings with relevant child development theories. We first present the CCAI framework (Section 5.1) and then outline design implications derived from our study, explicitly connecting each implication to one or more dimensions of the framework (Section 5.2).

5.1 Child-centered Co-creative AI (CCAI, "kai") Framework

The CCAI framework (Figure 1) organizes design for child–AI co-creativity around four key dimensions: (1) child-centered multimodal input methods, (2) metacognitive scaffolds for AI suggestions, (3) embodied affordance for co-creative AI, and (4) reducing cognitive load during co-creation. These dimensions capture both the developmental needs of children and the interaction patterns we observed in our co-design study. Existing human–AI co-creativity frameworks such as COFI [36] have been invaluable for describing roles, agency, and levels of automation between humans and AI. The CCAI framework builds on these by extending them with insights into children's natural behaviors and developmental needs. The four dimensions reflect both our empirical observations and child development theories. This framework is not intended to be comprehensive or final, but rather a starting point to open a discussion about what additional perspectives are needed to adapt existing human–AI interaction research for children in ways that actively support their creativity.

The first dimension of our framework is **child-centered multimodal input methods**. Prior work has noted communication as a key factor in supporting human–AI co-creation [36], where users and AI have a shared understanding of goals and actions. Children are still developing literacy skills and often rely on visual symbolic representations and gestures to externalize complex ideas [17]. For example, in our analysis, we saw children using shorthand prompts (e.g., 'fight,' 'Among Us') or visual communication cues (e.g., bolding and scribbling) to communicate and align the AI with their intentions (Section 4.2.2). Hence, it is important for future child–AI co-creativity interfaces to support children in expressing their intentions visually (e.g., through gestures or drawings) during the creative process. To achieve this, future work should consider leveraging child-centered gesture and drawing recognition algorithms [1]. Prior work shows that children gesture and draw differently from adults [1], underscoring the need to use recognition algorithms tailored to children's developmental communication practices when designing child-AI co-creativity interfaces. A design prompt question related to this dimension for future designers is:

Design prompt: Does the interface provide children with child-centered multimodal ways to express ideas, rather than relying only on text?

A second dimension is **metacognitive scaffolds for AI suggestions**. Children are still developing executive functioning, the ability to reflect on and evaluate creative outputs [8]. Prior work has highlighted the importance of supporting children's metacognitive thinking during the creativity process with AI, where they critically evaluate the output rather than passively accepting or rejecting it [32]. In our study, we saw moments where children clearly articulated why an AI output did or did not fit their intent (e.g., "too cartoony," "this isn't what I meant"), demonstrating the reasoning behind their acceptance or rejection of the AI's suggestions. On the other hand, we also observed instances where children accepted or rejected AI suggestions with minimal explicit reflection. Given the importance of higher-order metacognitive thinking during human–AI creativity [32], interfaces can scaffold reflection by prompting children with simple evaluative questions (e.g., "What part of the AI's contribution matches (or does not match) your story?"). However, designers should carefully consider how reflective prompts are framed so that they respect children's autonomy and their need to pursue their own ideas without requiring explicit reasoning. This is because the lack of verbalized reasoning when children reject AI suggestions does not always mean limited metacognition; it may reflect their intrinsic motivation or natural resistance to external influence [3] to stay true to their original ideas, no matter the alternate suggestion. Hence, we recommend that the nature of reflective prompts embedded within child-AI creative interfaces should match children's actions. When children reject an AI suggestion, prompts should remain simple and non-pressuring, for example, offering "I just feel like keeping my idea" as one possible option among the many reasons a child may choose to stay with their original concept. This affirms ownership without requiring justification. When children do accept an AI suggestion, the interface can invite slightly deeper reflection (e.g., "What did you like about this idea?" or "How does this make your drawing better or different?"), helping children notice how new elements fit into their creative vision while still keeping them in control. This form of reflective scaffolding provides gentle, optional opportunities for reflection, where, instead of categorizing AI output as "right" or "wrong", a natural tendency due to their fixed thinking

[3], children can selectively integrate AI contributions that feel meaningful while preserving their creative autonomy. A design prompt related to this dimension is:

> *Design prompt: Does the interface help children pause and think, "Do I like this and why?" instead of treating AI's output as simply right or wrong?*

A third dimension is **embodied affordance for co-creative AI**. Prior work in child–computer interaction has emphasized the need for simple and accessible interface designs. For example, Soni et al. [45] proposed a framework of guidelines for children's touch-screen technologies, showing that easy-to-use menus and settings reduce cognitive load and make systems more approachable for young users. In our study on child–AI co-creativity, we found that the imagination-level slider served as an embodied affordance that allowed children to directly control how much the AI contributed using a drag gesture (Section 4); they raised it to explore alternatives and lowered it when the AI overstepped. The slider made AI's role visible, tangible, and easy to adjust in real time, framing collaboration as something children could manipulate directly, rather than something hidden under complex menus. One drawback of the slider was that it let children apply AI's contributions globally to the entire sketch. However, we observed children wanting to refine AI contributions in local or specific parts of a drawing, while keeping the rest intact (Section 4.1.2). For example, when the AI misinterpreted froth for cloud, children wanted to redo that contribution while keeping the other AI contributions intact. Because the interface lacked localized controls, they were forced to regenerate the entire image, which caused frustration. This highlights a design gap: while global embodied affordances like sliders help children manage overall collaboration, they also need object-level embodied affordances such as selective accept/reject or localized sliders—to support finer-grained control. Designing co-creative systems for children should therefore include embodied affordances at both global and local levels: sliders, or interactive scales that make AI's role visible and adjustable across the whole canvas, as well as object-level controls. A design prompt related to this dimension is:

> *Design prompt: Can children see and easily manipulate how much the AI is contributing, and adjust or revise the contributions at both global and object-centric level?*

Finally, our framework incorporates **reducing cognitive load during co-creation**. Collaborative Cognitive Load Theory (CCLT) offers a useful lens for child–AI co-creativity by highlighting how different types of cognitive load shape collaboration [24]. Creative storytelling is naturally complex for children; they have to juggle characters, actions, sequencing, relationships, and style. This places a high intrinsic load on children. In our sessions, adult facilitators helped distribute this load by asking reflective questions such as 'Is the shark facing the dolphin?' or 'What is the dragon protecting?' (Section 4.3). At the same time, we observed frequent extraneous load created by child-AI misalignments. For example, when prompted with "a baby lion eating an apple," the AI often rendered a lion and an apple but ignored the relational action of eating or misinterpreted a child's drawing of the cloud as 'froth' or failed (Sections 4.1.2 and 4.3). These breakdowns consumed children's effort in correction rather than creation. Future child–AI interfaces should aim to minimize cognitive load by supporting children's natural input and collaboration behaviors. By reducing both intrinsic and extraneous demands, these interfaces can free children's working memory to prioritize imaginative expression and preserve mini-c creative moments. The collaboration profiles we identified provide a foundation for this goal, offering patterns that designers can use to better align system behavior with children's expectations.

5.2 Design Implications

Next, we present design implications based on our findings and connect them to dimension(s) of the CCAI framework.

5.2.1 Err Towards Refinement over Substitution. In our findings, we saw that children did not resist AI refinements that could be assimilated into the existing structure and tone of their drawings (e.g., detail, shading, or structural corrections). However, they resisted major transformations that altered their original ideas, such as re-orienting structures or expanding content. As shown in Figure 10, we identified seven types of AI contributions along with children's preferences for each. One explanation for this behavior comes from a constructivist perspective (Piaget), which suggests that children in the concrete operational stage are learning to coordinate multiple aspects of a task—such as form, detail, and style [28]. From this lens, children valued AI contributions that expanded their imagination or scaffolded sub-skills they were still developing (e.g., adding refinement details). This perspective of children valuing sub-skills they had not yet mastered aligns with the dimension of the CCAI framework focused on reducing cognitive load during co-creation. By providing incremental assistance (e.g., polishing details or correcting structure) without replacing children's core ideas, refinements helped manage intrinsic cognitive load [24] associated with the figural creativity task and operated within Vygotsky's Zone of Proximal Development (ZPD) [40]. From an interaction design perspective, children's collaborative behaviors point to the need for child-centered creative AI models that prioritize enhancement over replacement. Such systems should support children's sketches through complementary refinements while preserving their creative tone and intent. **We recommend that designers consider creating co-creative interfaces that avoid pushing toward "perfect" or overly realistic outputs. Instead, focus on ways to preserve the child's style and authorship, offering refinements as collaborative suggestions rather than substitutions. For example, when AI adds refinements, have it mimic the child's existing line style, stroke thickness, or coloring style, instead of generating a polished or hyper-realistic version**.

5.2.2 Support Children's Visual Communication Practices during Co-creation. Vygotsky mentioned that children use semiotic tools (language, drawings, gestures) to externalize their thinking [17]. We found that in addition to expressing a story through drawing, children also used similar semiotic tools (e.g., drawings) as a symbolic language to communicate their intentions with AI. For example, they used scribbling to communicate the part of the drawing they would like to delete (e.g., scribbling on a house drawing to delete it, Section 4.2.2) or bolding to emphasize parts of a character they want AI to take a note of (e.g., bolding a dolphin's smile to ensure the AI takes note of it, Section 4.2.2). This finding that children used scribbles and bolding as communication signals and Vygotsky's theory on semiotic tools informed the child-centered multimodal input methods dimension of the CCAI framework. Thus, based on this finding, **we recommend that future human–AI co-creative interfaces consider the dual purpose of drawing and avoid dismissing scribbles or text-in-drawing as noise**. Instead, they should recognize these as children's attempts at communication with AI and respond to them meaningfully to support an effective collaborative process.

5.2.3 Support Transformations that Expand Children's Creative Vision. In our analysis, we observed that children resisted AI contributions when they were repetitive or incremental and changed their original idea (e.g., adding more of the same objects they had already drawn, Section 4.1.4). In contrast, they welcomed AI's role as a collaborator when it introduced novel transformations that combined different concepts children had mentioned in surprising but meaningful ways (as discussed for the Among Us + Flower example in Section 4.1.4). These moments reflect a collaboration pattern in which children positioned the AI as an imaginative partner that could extend their thinking, rather than as a tool that overwrote or replaced their ideas. This expectation aligns with Vygotsky's theory of imaginative play [44], where creative partners co-construct meaning by combining elements in unexpected but meaningful ways. At the same time, this implication connects to the metacognitive scaffolds for AI suggestions dimension of the CCAI framework: for children to benefit from AI's divergent ideas, **interfaces should scaffold reflection, prompting them to pause and evaluate whether a transformation expands or undermines their creative intent**. For example, an interface could briefly present both the child's original drawing and the transformed version side by side with a prompt such as "What do you like about each one?" to help children articulate why an AI idea feels inspiring or not.

5.2.4 Consider using AI to encourage children to elaborate on story relationships. During co-design sessions, we observed that children's collaborative storytelling often benefited from the presence of peers and adult facilitators. Adults frequently posed reflective questions (e.g., 'How is the dolphin and jellyfish related to the shark?') that encouraged children to elaborate on relationships, while peers prompted one another to negotiate sequencing or spatial placement (e.g., 'Is the house behind the cat or next to it?'). These prompts helped children extend their ideas, maintain story coherence, and practice turn-taking. In line with the metacognitive scaffolds for AI suggestions dimension of the CCAI framework, future child–AI systems could consider incorporating collaborative brainstorming affordances that mimic the supportive roles adults and peers played in our sessions. By doing so, AI's role would expand beyond refinement and transformation to scaffolding distributed creativity, helping children co-construct stories with the AI.

6 LIMITATIONS AND FUTURE WORK

The goal of our study was to present a rich qualitative analysis of children's recurrent natural collaboration behaviors when co-creating visual stories with AI, aiming for theoretical rather than statistical generalization [57]. While our sample size (n=7) may seem small, it is consistent with previous PD and CI research with children [11, 18, 19, 55, 58]. Our contributions are intended as a starting point for understanding how children collaborate with AI. We see these findings as foundational insights that should be expanded and validated through future work. For example, future studies can build on our insights to test how our themes hold across different populations and whether collaboration patterns differ with children's age. Although children in our study used a one creativity tool, they engaged with it across two 60-minute sessions (DS3 and DS4), allowing us to closely examine the technical and conceptual contributions from AI that children accepted, rejected, or negotiated. The child-AI collaborative interaction patterns we analyzed in our study are not tied to specific interface features; rather, they capture children's natural behaviors and responses to broader categories of AI contribution, which could be found in any other child-AI creativity interface, such as when the AI updated part of a drawing, filled in missing elements, or proposed alternative ideas. Because the recurrent behaviors we identified represent fundamental collaboration dynamics between children and creative AI, rather than reactions to a single interface implementation, we believe our findings can theoretically generalize and provide actionable insights for designing future child–AI co-creative systems. Future work can extend this analysis to aspects of child-AI collaboration other than the nature of contributions and collaboration profiles, such as child-AI communication strategies or task division negotiation [43]. Another factor is that our participants were members of an established co-design group with prior exposure to intelligent tools and generative AI. Future work with children less experienced with AI will be valuable for understanding how prior exposure shapes expectations, mental models, and behaviors with co-creation. In this work, our goal was to understand how children collaborated with AI to create a story and how their ideas improvised during this co-creation process. This aligns with prior work by Trajkova et al.[49], which notes that "[creative] choices are shaped by the interplay between in-the-moment influences between the self, partner [a collaborative partner, which could be AI], and the environment [digital or physical environment], a set of generative strategies, and heuristics for a successful collaboration." Hence, we did not capture children's full initial ideas at the outset, but instead observed how their concepts unfolded during co-creation with AI and how closely their final sketches aligned (or diverged) from their emerging intentions. Future research could incorporate methods that capture children's initial intentions, such as pre-sketch prompts or early articulations of their ideas, to more directly examine fidelity and divergence over the course of AI-supported co-creation. Our study contributes collaboration profiles and a conceptual framework that capture how children naturally co-create with AI. These contributions provide a starting point for future research to assess which forms of collaboration are most effective in supporting children's creativity. Future work can also extend and validate our CCAI framework by conducting interviews and focus groups with larger and more diverse populations, as well as by designing and evaluating prototypes grounded in the framework.

7 CONCLUSION

We conducted four co-design sessions with a group of seven children to explore how they co-create with AI in creative storytelling. From these sessions, we introduced a set of collaboration profiles, identified seven types of AI contributions along with children's preferences for each, and developed the CCAI framework, which brings a child-development perspective to designing future co-creative AI interfaces. We found that children's preference for AI contributions depended on how much the AI valued their ideas. Our findings inform the design of future child–AI co-creative interfaces that scaffold creativity while preserving children's agency.

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