StoryDrawer

A Child–AI Collaborative Drawing System to Support Children's Creative Visual Storytelling

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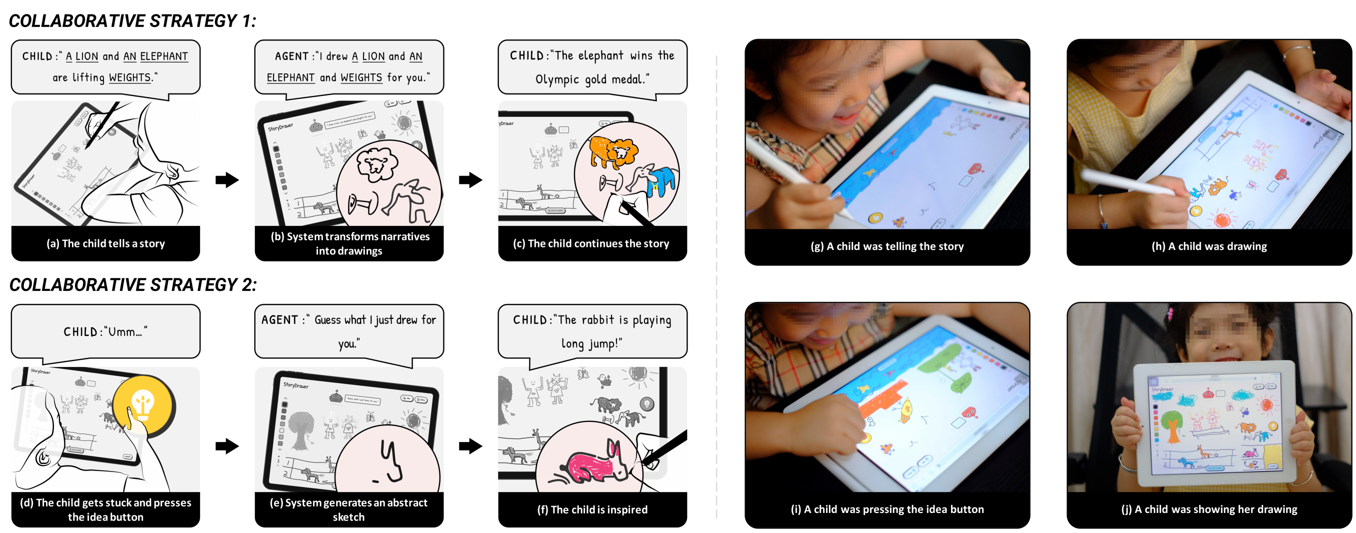

Figure 1: We introduced *StoryDrawer*, a co-creative drawing system embedded with a context-based voice agent and two collaborative strategies to support creative visual storytelling for children aged 6–10 years: (a-c) an example workflow of *Strategy 1* and (d-f) an example workflow of *Strategy 2*. Children interacted with *StoryDrawer*: (g) a child was telling the story; (h) a child was drawing; (i) a child was pressing the idea button; and (j) a child was showing her drawing.

ABSTRACT

Visual storytelling is a new approach to creative expression based on verbal and figural creativity. The keys to visual storytelling are narrating and drawing over a period of time, which can be beneficial but also demanding on creativity for children. Informed by need-finding investigations, we developed *StoryDrawer*, a co-creative system that supports visual storytelling for children aged 6–10 years through collaborative drawing between children and artificial intelligence (AI). The system includes a context-based voice agent and two AI-driven collaborative strategies: the real-time transformation of children's telling into drawings, and the generation of abstract sketches with semantic similarity to existing story content. We conducted a 2×2 study with 64 children to evaluate the efficacy of *StoryDrawer* by varying the two strategies in four conditions. The results suggest that *StoryDrawer* provoked participants' creative and elaborate ideas and contributed to their creative outcomes during an engaging visual storytelling experience.

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CCS CONCEPTS

• **Human-centered computing**; • **Human computer interaction (HCI)**; • **Interactive systems and tools**;

KEYWORDS

Visual storytelling, Drawing, Co-creative system, Child–AI collaboration, Creativity support tool, Children

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1 INTRODUCTION

Generally referred to as the ability to express feelings, thoughts, and ideas in a novel yet appropriate way [33], creative expression has been shown to play an essential role in enhancing cognitive skills, supporting literacy improvement, and facilitating creativity development [42, 48, 76]. It is commonly categorized into two forms: figural creativity (e.g., drawing, painting, sculpting) and verbal creativity (writing, storytelling, composition, discourse) [40]. Visual storytelling is a new form of creative expression that combines oral storytelling and narrative visualization and requires children to demonstrate their verbal and figural creativity.

Standardized creativity measures have previously demonstrated that as children progress from kindergarten to elementary school, their creativity drops. As evidenced by the Torrance Test of Creative Thinking (TTCT), there is a significant creativity slump in grade four (age: 8–10 years), which is referred to as the 'Fourth-Grade Slump' [79, 80]. Visual storytelling has been proved to be an effective way to cultivate creativity for this age-group [69]. When performing visual storytelling, children need to conceptualize storylines, draw series of story scenes, and tell the story at the same time [32].

Indeed, some barriers impede children's creative thinking in visual storytelling, causing unexpected interruptions and reducing their creativity. Through our formative investigation of children (N = 12) and their parents (N = 12), we reported three main challenges: (1) the parallel tasks of storytelling and drawing pose a multitasking burden on children; (2) children are prone to suddenly reach an impasse, which is usually called 'writer's block' [54]; and (3) children lack concentration and engagement. Inspired by our findings in the investigations, our motivation is to provide appropriate creativity support for children in visual storytelling.

One direction taken in creativity support tool (CST) research in human–computer interaction (HCI) has been to develop a co-creative system or to leverage human–artificial intelligence (AI) collaboration to facilitate creative thinking [25, 35, 51, 55, 65]. Co-creative systems usually allow an AI partner to participate in the cognitive mechanisms that humans go through when creating [27], such as divergent thinking [43, 58], convergent thinking [47], and sense-making [26]. Our research shared the same goal as that of prior research on co-creative CST, and we extended previous efforts by investigating how to design an AI partner to provide creativity support for children in visual storytelling based on cognitive theories of embodiment and visual thinking.

Building on related work and our formative investigation, we introduced *StoryDrawer* (Figure 1), a co-creative system embedded with an AI partner for children of 6–10 years to engage in visual storytelling through collaborative drawing. The AI partner was composed of a context-based voice agent and two novel collaborative strategies derived from embodiment and visual thinking. The collaborative strategies included (1) the real-time transformation of children's telling into drawings and (2) the generation of abstract sketches with semantic similarity to existing story content.

We conducted a 2×2 between-subject user study with 64 children by varying the two collaborative strategies in four conditions. Our quantitative results demonstrated that *StoryDrawer* with *Strategy 1* and/or *Strategy 2* significantly helped participants produce elaborated ideas and creative outcomes, and that participants engaged positively with the system. Our qualitative analysis revealed that *Strategy 1* helped children portray characters and enrich story details, and *Strategy 2* helped them make bold associations and create creative ideas. In addition, the qualitative results provided evidence that a positive relationship between the child and AI promoted engagement. Furthermore, we found that *Strategy 1* acted as a catalyst to enhance the efficacy of *Strategy 2* and suggested how *StoryDrawer* can be further improved.

This paper presents the following main contributions:

- We conducted a formative investigation of children and parents, suggesting that visual storytelling supporting tools should alleviate children's burden in parallel tasks, scaffold them to overcome writer's block, and increase their engagement.
- We developed a co-creative system, *StoryDrawer*, which provides a context-based voice agent and two AI-driven collaborative strategies to engage 6- to 10-year-old children in visual storytelling and provide creativity support.
- We verified the efficacy of the two collaborative strategies in children's creative performance and outcomes during visual storytelling through a 2×2 between-subject user study with quantitative and qualitative methods.

2 RELATED WORK

2.1 Visual Storytelling in HCI

Visual storytelling is the telling of a story enhanced through the use of visual media (e.g., photography, drawings, illustrations, animations, and videos) [18]. The benefits of visual storytelling and how it fosters children's creativity have long been understood [32, 45, 57]. Phillips pointed out that visual storytelling has the ability to enhance knowledge and memory recall, support early creativity development, and expand creative potential in young children [69].

Visual storytelling typically consists of two activates: dictating a story and visualizing the narrates, which can be crossed or performed simultaneously. With the development of digital industry, many tools in HCI have been developed to help children visualize their stories. Most of these tools have chosen digital books [52], games [70], animations [22], or other mediums. For example, Yee et al. [22] utilized animation to investigate how visualizing mediates the creative storytelling process. They proved that animation benefits children's creativity, but it is too difficult for children to produce, like other digital materials, such as videos. Compared with these high-barrier mediums, drawing is one of the most familiar visualization activities for children; it is easier to perform and more intuitive. Furthermore, visual storytelling[1] that combines storytelling and drawing has been shown to be highly beneficial to children's creativity in a relatively child-friendly manner [83].

Although visual storytelling is beneficial and common for children, consciously practicing it is not an easy task. Previous studies informed that children's creativity could be disturbed during visual storytelling [6, 17], yielding an incoherent creative process. Therefore, in this study, we explored what hinders children's creativity through a formative study to adopt appropriate methods to provide creativity support.

2.2 Embodiment and Visual Thinking

2.2.1 Embodiment in Interactive Visual Storytelling. Embodiment theory argues that human cognition is rooted in perception, action, and interaction with the environment [82]. Davis et al. [27] proposed a subcategory of embodied cognition referred to as embodied creativity, which claims that the cognitive mechanisms involved in creativity, such as idea generation, conceptual combination, and mental imagery, are facilitated by interaction with the environment. For example, designers use sketches as external structures to prime their idea generation [59]. The same is true for visual storytelling: children conceive stories while drawing. Differently, multitasking (i.e., draw-and-tell) can be difficult for children, who are limited by their immature cognitive and attention resources [23].

Since Marshall's 2001 work [61] solidifying embodied interaction as a key theme in HCI, much research has been conducted on embodiment for children's interactive storytelling technologies [7, 21, 22, 34, 60]. For example, Chu et al. [20] studied the effects of visual contextual structures on children's imagination in a digital-augmented space contextualized by a background image. Another example within this line of research is Zarei et al.'s work [87] on a virtual reality system to embody cognitive processes in children's storytelling. They provided a series of visual elements, including characters, props, and background, to help children create externalized representations before telling a story. These efforts, however, have ignored the improvisational nature of visual storytelling. The creation process of external structures (drawing) is preset. To embrace improvisations, we allowed children to draw when narrating stories, which introduced the multitasking burden. Wilson indicates we can off-load cognitive burden onto the environment or tools as one of the six views of embodied cognition [84]. Inspired by this concept, we proposed the first collaborative strategy to alleviate children's cognitive load on multitasking: the real-time transformation of children's telling into drawings.

2.2.2 Visual Thinking for Creativity Support. Visual thinking, derived from perceptual psychology, is related to the cognitive process of creatively and actively understanding and organizing the perception of environment [9]. Arnheim has stated that the visual perception is strongly identified with creative thinking and goes before language [8]. In visual storytelling, visual thinking occurs after embodiment and usually consists of three activities: idea-sketching, seeing, and imagining [62]. Visual stimuli, such as visual metaphors, figural fragments, and abstract sketches [37, 38, 81], have been shown to enhance visual thinking. They serve as new, yet incomplete, ideas for triggering analogies when seeing and promoting associations when imagining. The Test for Creative Thinking–Drawing Production (TCT-DP) [81], one of the most popular creativity assessment tools, uses figural fragments to elicit children's figural creativity. Much prior work in CST also has leveraged visual stimuli to promote ideation [51, 58], accelerate discovery [14], and improve creative collaboration [75]. We expanded on previous research by considering how to design and provide visual stimuli for children to facilitate their visual thinking during visual storytelling.

Conceptual shift [24] is a cognitive mechanism based on visual thinking to aid the creative process of analogical reasoning. Computational modeling to make conceptual shifts can be used to analyze and extract visual and semantic features from users' inputs [49, 50]. Aligning with the literary traditions of storytelling, we applied semantic similarity [49] to design inspired visual stimuli and proposed a second collaborative strategy: the generation of abstract sketches with semantic similarity to existing story content.

2.3 Child-AI Collaboration

In the field of Child–Computer Interaction (CCI), AI previously was used as a learning partner or playmate to foster positive behaviors, such as curiosity [39], growth mindset [68], persistence, and attentiveness [11]. In a similar theme, we explored whether a collaborative AI partner could foster creativity in young children.

Several studies have looked at ways of using child–AI collaboration to stimulate children's creativity. For example, Jibo [28] is a tangible robot that offered creativity scaffolding by demonstrating different creative behaviors. Ali et al. [2, 3] leveraged mechanisms of social emulation to encourage children to learn figural creativity from a virtual agent. In addition, Agostinelli et al. [1] designed a collaborative AI peer that applied a human-in-the-loop approach to develop children's creative problem-solving skills. They ignored, however, the cognitive mechanisms of children in creative activities and did not provide targeted support.

The presence of AI partners generally can take two forms: tangible robots or virtual agents. DragonBots, Misty, Yolo, and Nao [4, 16, 56] are examples of tangible robots that are standalone and inaccessible. Alternatively, virtual agents, such as Bio Sketchbook [88], StoryCoder [29], and WordBot [36], can run on accessible hardware like tablet computers. We choose the virtual agent because it can be embedded in digital painting applications which provide various features to support children in creating narrative drawings. The AI partner can directly recognize what children is drawing without the need for peripherals such as cameras on tangible robots [58].

Voice interfaces are a prevalent interactive method used in virtual agents. Pantoja et al. [67] have demonstrated that voice agents can help children maintain attention. One example is MiniBird [77], a voice agent that enhances children's participation in codesign tasks.

[1]In this paper, we define visual storytelling as a creative expression combining oral telling and narrative drawing.

Our work extended previous research on context-based voice agents [12, 86], in which languages or utterances are designed according to information derived from the context or previous discourses. The key to *StoryDrawer* was to take information from children's drawing or verbal descriptions and to integrate it into the voice agent's responses.

3 FORMATIVE INVESTIGATION

As detailed, visual storytelling has been proved to be an effective way to promote creativity; yet, some barriers hinder children's creative thinking in visual storytelling. Therefore, we engaged in a formative investigation to (1) identify the challenges that interfere with children's creative performance in visual storytelling and (2) inform design opportunities that address these challenges using child–AI collaboration.

3.1 Method

We recruited 12 parents (7 females, 5 males) and 12 children of ages 6–10 (M = 7.83, SD = 1.21; 4 females, 8 males). We included one parent for each child. We chose this age-group because of the fourth-grade slump phenomenon [79] and Kim [53] and Sawyer et al. [72]'s recommendations to encourage creativity prior to this period. In addition, we interviewed parents rather than educators because visual storytelling often takes place at home and is part of home education [31]. All children have the experience of creating visual stories in the company of their parents at home.

First, we conducted a visual storytelling workshop with these children. For COVID-19 reasons, the workshop was held in a classroom on a university campus rather than the children's own home. Participants were provided drawing tools like crayons and papers and were asked to create a visual story (i.e., to narrate an oral story and create a narrative drawing) with no restrictions on the theme. A research assistant took notes on notable children's behaviors and was required not to say anything suggestive. The storytelling process for each child lasted 20 min and was video-recorded. We also audiotaped their voices and collected their drawings.

After the workshop, we conducted one-on-one semistructured interviews with the participants and their parents individually. We asked children about the stories they just told and reasons for some of the behaviors observed by our research assistant. As for parents, we tried to understand how they accompanied their children to tell visual stories at home, the difficulties encountered, and their solutions. The interviews lasted 14–24 min (M = 19.17, SD = 3.31) for children and 26–33 min (M = 30.42, SD = 1.98) for parents. The interviewer took notes on the participants' responses and asked targeted follow-up questions throughout the interview, and the audio recordings were transcribed for later analysis. Finally, the participants and their parents were compensated with a souvenir worth $10.

All data were recorded and analyzed with parental consent. We applied thematic analysis [15] to analyze the recorded videos and the interview transcripts. Videos were coded for different behaviors indicating that children were experiencing difficulties, including rarely drawing, rarely storytelling, and short or long pauses in the task. Interview transcripts were coded for possible causes and potential solutions to these behaviors. We expected to determine whether children become creatively blocked or encounter engagement issues, and to identify other unexpected challenges children face in visual storytelling. Two researchers individually coded these data using NVivo and over several meeting discussions to converge the findings into themes.

3.2 Key Findings and Design Implications

We briefly report three high-level themes with corresponding design implications that reflected the challenges children face when visual storytelling in this section.

3.2.1 Parallel Task. For most children, we found the parallel tasks of telling and drawing to be difficult. Only six children could balance narrating and drawing, whereas the rest could focus on only one of the tasks. One reason is that multitasking disrupted their creative thoughts in visual storytelling. For example, three participants tended to forget what they had just told when they were drawing, resulting in some inconsistencies in their stories. One child kept drawing during the process, and he told us, "I have to focus on one thing. If I tell the story, I can't draw." Another reason is that children's drawing skills impeded the creation of stories. One child talked all the time, rarely drew, and even asked our research assistant to draw for him. He told us that he did not want to draw because "I can't draw well". In addition, we found that when children could not draw an object, they tended to abandon the storyline associated with it. This made them waste opportunities to develop their stories. Based on previous work and our observations, we aim to design an AI partner to (1) reduce the difficulty of multitasking (draw-and-tell) in the visual storytelling process and (2) compensate for the lack of children's drawing skills.

3.2.2 Writer's Block. We observed that the children sometimes suddenly got stuck and made stammering noises, as if they were about to speak out but could not. This phenomenon, commonly known by practitioners as writer's block or 'artist's block' [54], occurred in every participant. Specifically, children suddenly found themselves at an impasse, unable to think of the next step they should take to continue the creative process. We counted the number of writer's block occurrences, averaging 3.42 (SD = 1.38) times per child. When writer's block occurred, a few participants could overcome it after a period of thought, but others felt overwhelmed and frustrated. One participant told us: "I felt very nervous" when she was creatively blocked. One of the directions to fix the writer's block is to provide stimuli that can provoke creative thinking [66]. Together, to address challenges of writer's block, we aim to design stimuli that both match the visual storytelling scenario and stimulate children's creativity.

3.2.3 Engagement. Previous research has demonstrated that high levels of engagement enhance children's creative behaviors [71]. We found that the children easily lost their attention during visual storytelling. For example, we observed two children wandering off in the workshop, one spinning his pen unconsciously, and the other scribbling on the paper. As one of the parents said, "The most serious difficulty is getting them to focus" in visual storytelling at home. We asked parents how they generally address this issue; one parent told us, "I usually ask him what he's drawing to get his attention back to the storytelling." Another parent noted that

Figure 2: The user interface of *StoryDrawer* includes (a) Voice Agent Dialog Box, (b) Drawing Tools, (c) Canvas, (d) Idea Button, and (e) Speak Button. To interact with their drawings, users can (f) rotate, (g) move, or (h) zoom sketches by touch gestures like dragging, rotating, or pinching.

when two children played together, their attention became more focused. Expanding on previous work and approaches we found in the interviews, we aim to promote engagement by designing a voice agent to talk with children and ask them questions about their creations.

3.3 Design Goals

On the basis of prior work and our findings in the investigations, we derived three major goals for the design of an AI partner to support visual storytelling: Goal 1 shares the burden of multitasking by helping children to draw their stories; Goal 2 provides visual stimuli to facilitate children's visual thinking and mitigate the effects of writer's block; and Goal 3 designs a voice agent to elicit more active participation from children in an inquiry manner based on their stories and drawings.

4 STORYDRAWER

On the basis of these three design goals, we built *StoryDrawer* (Figure 2), a co-creative system embedded with a context-based voice agent and two AI-driven collaborative strategies, to engage children of ages 6–10 in visual storytelling and to provide creativity support.

4.1 How to Use This System

StoryDrawer is employed on an iPad[2]. Children use Apple pencils[3] to draw or erase on the canvas (Figure 2(c)) and switch colors or adjust line weights in the drawing tools area (Figure 2(b)). The system also allows children to move, rotate, or zoom sketches by touch gestures like dragging, rotating, and pinching (Figure 2(f), 2(g), and 2(h)). Users press the speak button (Figure 2(e)) to communicate with the voice agent, and the dialog box displays the agent's words in real time (Figure 2(a)).

When children press the speak button (Figure 2(e)) and narrate a storyline, the system transforms what they say into drawings based on *Strategy 1* (Section 4.2.1) and utters a context-based response (to be discussed in Section 4.3). Children are free to modify the generated drawings or continue their stories. If the system cannot draw an object, the agent would ask children to help draw it to keep the flow going seamlessly.

> CHILD: A little rabbit and a little turtle took part in the race at the field day.
>
> AGENT: [drawing a rabbit and a turtle] Good. I drew a rabbit and a turtle for you. What's next?

In addition, users can press the idea button (Figure 2(d)) to trigger *Strategy 2* for inspiration. The agent would provide an abstract doodle as a prompt and encourage children to guess what it represents. Next, children draw and convert the abstract prompt into a meaningful goal object. The agent then recognizes what children have drawn and speaks a response.

> CHILD: [pressing the idea button] Umm . . .
>
> AGENT: [drawing a visual stimulus] Look. Guess what I just drew for you. Please complete it as you like.
>
> CHILD: [drawing more strokes to convert the visual stimulus to a cat]
>
> AGENT: Great. A cat here. What's it doing in your story?

Children click the complete button to signal they are done telling the story. Upon finishing, their story and drawing are saved to the database for future listening and recalling.

4.2 Collaborative Strategy: Goals 1 and 2

Inspired by the theory of embodiment [27, 82] and visual thinking [9, 24], we designed two collaborative strategies to engage AI in children's cognitive mechanisms when performing visual storytelling (Figure 3).

4.2.1 Strategy 1: Real-Time Transformation of Children's Telling into Drawings (Goal 1). It is difficult for children to manage the parallel tasks of telling and drawing, which provides a significant barrier to

[2] A tablet computer designed, developed and marketed by Apple Inc.
[3] A line of wireless stylus pen accessories designed and developed by Apple Inc. for use with supported iPads.

Figure 3: The system pipelines of *StoryDrawer*: (a) when the child narrates "There were two pink flowers on the roadside," the system extracts three keywords— "two," "pink," and "flower"—and draws two pink flowers in real time; (b) after the child presses the idea button, *StoryDrawer* generates an initial sketch and prompts children to convert the sketch into a meaningful goal object like a cat.

creative thinking in visual storytelling. Inspired by voice interfaces, our system applies a voice-driven drawing interaction. Specifically, as children narrate a storyline, the system recognizes entities (such as characters, colors, and numbers) from their voices and generates the corresponding number and color of the characters' sketches on the screen. For example, when the child says, "There were two pink flowers on the roadside," the system extracts three keywords—"two," "pink," and "flower"—and draws two pink flowers in real time. Sketches generated from one sentence are placed next to each other and appear randomly in a blank area on the canvas. Children can freely move, color, or modify the generated sketches as needed. The pipeline of *Strategy 1* is shown in Figure 3(a).

Theories of embodied cognition have suggested that external representations such as sketches help people to think [78]. By transforming children's narratives into sketches, we offload children's drawing tasks onto the system. This method eases children's cognitive load and frees cognitive resources for other creative reasoning tasks [46, 73]. For example, it facilitates mental projection, allowing children to directly anchor their mental story imagery in the generated sketches instead of drawing first.

Strategy 1 implements a voice-driven sketching algorithm consisting of a natural language processing (NLP) module and a sketch generation module. The NLP module enables speech recognition and translation into English text with the Google Speech-to-Text API[4] and the Google Translation API[5]. Then, the NLP module applies NLTK[6] (a Python package for NLP) to extract entities, including nouns, colors and numbers, from the text. Finally, the sketch generation module retrieves the corresponding category in the Quick Draw! dataset[7] to generate sketches of corresponding quantity and color. The Quick Draw! dataset contains a collection of 345 different categories of sketches, with thousands of variants in each category.

[4]https://cloud.google.com/speech-to-text
[5]https://cloud.google.com/translate
[6]https://www.nltk.org/
[7]https://quickdraw.withgoogle.com/data

4.2.2 Strategy 2: Generation of Abstract Sketches with Semantic Similarity to Existing Story Content (Goal 2). When encountering writer's block, children get frustrated and experience a creative slump. Inspired by Karimi et al.'s work [49, 50], we utilized the conceptual shift mechanism of semantic similarity to generate abstract sketches to provoke children's creativity. After children press the idea button (Figure 2(d)), *StoryDrawer* generates an initial sketch with semantic similarity to the existing user's sketches and prompts children to associate, draw, and convert the sketch into a meaningful goal object (Figure 3(b)). The system then identifies the category from children's completed sketches and encourages them to continue the narrative (Section 4.3).

This collaborative drawing method supports various aspects of creative thinking. First, children are encouraged to demonstrate divergent thinking, attempting to imagine how to build on a draft sketch to create a complete figure. It also supports users' associational fluency by associating the starting prompts with the target objects [13]. The collaborative mechanism also requires children to elaborate on ideas as they complete the prompts [80]. For example, they need to complete the target character's face, dress, posture, expression and even movement.

We used the word2vec word embeddings [64] trained on the Google News corpus[8] to compute semantic similarity. Semantic similarity measures the cosine distance between two feature word vectors [49]. We pretrained 100 Sketch-RNN models [44] of different categories and collected their names in a target list. We also collected the nouns that appear in children's stories as an existing list. When *Strategy 2* is triggered, the system selects one model from the targeted list by calculating its semantic similarity to the existing list. The selected model then generates a sketch on the canvas. Note that the generated sketch should not only be abstract enough to provoke imagination but also suggestive enough to trigger association. We adjusted the temperature parameter (1.3) while training the modes to satisfy the trade-off requirements.

[8]https://code.google.com/archive/p/word2vec/

4.3 Context-Based Voice Agent: Goal 3

The context-based voice agent is designed to improve children's engagement. The response from the voice agent consists of three parts: positive utterances, context-based utterances, and substantive utterances. A positive utterance is a short verbal response to acknowledge what the children said. For example, "Good," "I like it," "It's great," and so on. A context-based utterance is a response that incorporates information from children's stories or drawings in preset patterns. For example, "I drew a turtle and a rabbit for you." The 'turtle' and 'rabbit' comprise the information obtained from children's narratives, and "I drew a [slot][9] for you" is a pattern. Another example of this response is "I see you drew a lion." The 'lion' is information obtained from children's sketches, and "I see you drew a [slot]" is another pattern. Moreover, a substantive utterance [56] elicits more users' narratives by expressing expectations. For example, "I'd like to know more" and "What's it doing?"

We use Baidu Text-to-Speech API[10] for speech synthesis. The voice agent extracts context information (mainly characters) from children's speech and identifies categories from children's sketches. The NLP module is in charge of entity extraction, and we trained a YOLOv3[11] model on the Quick Draw! dataset across 345 categories to detect new objects in drawings. When children narrate or draw a new object, the agent provides a response, such as "It's great. I see you drew a bear. What's it doing?"

5 HYPOTHESES

Strategy 1 transforms children's narratives into drawings to ease their multitasking load, while *Strategy 2* provides abstract sketches as prompts to provoke children's creativity when they are stuck. To verify the achievement of Goal 1 and Goal 2, we examined how these two collaborative strategies affected children's creative performance. Children's creative performance reflects the efficacy of these two strategies in helping children overcome the burden of multitasking and writer's block. For stories told by children, we adopted two metrics from prior research [85] (i.e., idea fluency and idea elaboration) to measure children's creative thinking reflected in storytelling [80]. Idea fluency is indicated by the number of creative ideas, and idea elaboration is indicated by the number of additional details subsequently provided after a creative idea. In addition to oral stories, children also create drawings during the visual storytelling process. Adapting from the narrative drawing analysis method [19], the creativity reflected in drawing is measured by the number of characters and scenes. Furthermore, Amabile [5] has suggested that children's creativity can be measured through expert ratings on their creative outcomes (stories and drawings). Therefore, we made the following hypotheses:

- H1 (*Strategy 1*): *Strategy 1* significantly improves children's idea fluency (H1a), idea elaboration (H1b), drawing creativity (H1c), and the expert ratings on stories (H1d) and drawings (H1e) in visual storytelling.
- H2 (*Strategy 2*): *Strategy 2* significantly improves children's idea fluency (H2a), idea elaboration (H2b), drawing creativity (H2c), and the expert ratings on stories (H2d) and drawings (H2e) in visual storytelling.

Finally, to verify the achievement of Goal 3, we measured the level of children's engagement through the Giggle Gauge engagement metric [30], which has been validated with children in our target age-range and assesses engagement in terms of perceptions such as challenge, interest, and endurability.

6 EVALUATION

To test these hypotheses, we conducted a 2×2 between-subject controlled trial with 64 children aged 6–10 years. All children used the *StoryDrawer* system, and the independent variables were whether or not the system implemented the two collaborative strategies. The dependent variables included idea fluency, idea elaboration, drawing creativity, expert ratings on stories and drawings, and the level of children's engagement. We designed four experimental conditions to explore the effect of the independent variables on the dependent variables. We kept *StoryDrawer*'s user interface, basic drawing functions (such as the color switcher and touch gestures), and the voice agent intact to control variables, and all variables are given in Table 1

- No strategies (S1-S2-): *StoryDrawer* without implementing either strategy.
- Only *Strategy 1* (S1+S2-): *StoryDrawer* with implementing *Strategy 1*.
- Only *Strategy 2* (S1-S2+): *StoryDrawer* with implementing *Strategy 2*.
- *Strategy 1* and *Strategy 2* (S1+S2+): *StoryDrawer* with implementing *Strategy 1* and *Strategy 2*.

6.1 Participants

We recruited 64 participants aged 6–10 years for this study (34 female, 30 males). The average age was 8.19 (SD = 1.14). These participants were newly recruited for the 2×2 between-subject evaluation, which differed from those in the formative investigation. All participants were native Mandarin speakers. They were familiar with how to use the iPad and had experiences with visual storytelling. To recruit participants, authors posted announcements on their personal social media accounts and distributed flyers at local libraries, primary schools, and community centers throughout the metropolitan region where the study took place.

6.2 Procedure

6.2.1 Pretest. We brought all participants to a same classroom to eliminate the differences introduced by settings. The participants' writing apprehension and creativity were pretested to drive a quasi-random assignment into groups across four conditions. Based on Autman and Kelly's Writing Apprehension questionnaire [10], our writing apprehension test consisted of six items in 5-point Likert scales. We assessed participants' creativity using the Torrance Test of Creative Thinking (TTCT), a paper-based evaluation for creative thinking that featured two sets of assessment activities: verbal creativity test and figural creativity test [80]. To avoid literacy barriers of young participants, one research assistant dictated every question. As shown in Table 2, all participants' age, gender,

[9]The *[slot]* indicates that there is a location reserved for context information.
[10]https://ai.baidu.com/tech/speech/tts
[11]https://pjreddie.com/darknet/yolo/

Table 1: Variables across the four conditions.

Conditions	*Strategy 1*	*Strategy 2*	User Interface	Basic Drawing Functions	Voice Agent
S1-S2-	No	No	Yes	Yes	Yes
S1+S2-	Yes	No	Yes	Yes	Yes
S1-S2+	No	Yes	Yes	Yes	Yes
S1+S2+	Yes	Yes	Yes	Yes	Yes

Table 2: 64 participants were divided into balanced groups based on their gender, age, writing apprehension scores and TTCT scores.

Conditions	N	ID Range	Gender	Age	Writing Apprehension Scores	TTCT Scores
S1-S2-	16	C01-16	F = 9, M = 7	8.13 ± 1.20	22.38 ± 3.38	43.22 ± 3.23
S1+S2-	16	C17-32	F = 8, M = 8	8.25 ± 1.00	22.38 ± 3.72	43.76 ± 5.57
S1-S2+	16	C33-48	F = 8, M = 8	8.25 ± 1.00	22.13 ± 1.20	42.63 ± 4.01
S1+S2+	16	C49-64	F = 9, M = 7	8.13 ± 1.41	22.25 ± 3.82	43.12 ± 3.65

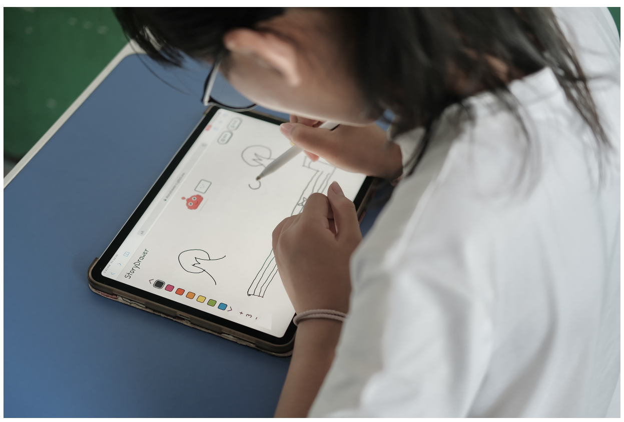

Figure 4: A child participant was interacting with *StoryDrawer* installed on an iPad in a classroom.

writing apprehension, and creativity scores were balanced across all conditions.

6.2.2 During Task. After one week following the pretest, participants were invited back to perform the study one by one (Figure 4). At the beginning, a research assistant explained to each participant how to use the system and allowed him/her to practice for 5 min. Then, the participant was given a story theme ('Forest Sports') on which to base their story. To balance the difficulty of story creation, we fixed the theme and set a same time restriction across four conditions. The participants needed to create a visual story—that is, they had to narrate an oral story and create a narrative drawing—within 20 min using the system according to the assigned conditions. The whole process was recorded and transcribed with the consent of the children's parents.

6.2.3 Post-Test. After storytelling, the participants filled out a post-questionnaire to rate their engagement levels during their interaction with the system. Finally, they were engaged in a short semistructured interview about the user experience and system usability, covering such questions as "Can *StoryDrawer* help you think of something new?" "What do you think *StoryDrawer*'s role is (e.g., partner, tool)?" and "Will you use *StoryDrawer* again for visual storytelling?" All participants were given a toy worth $10 as compensation. The procedure for one participant is shown in Figure 5

6.3 Measures

Five main types of data were collected: story transcriptions, narrative drawings, expert ratings, engagement questionnaires, and video recordings. Table 3 summarizes the collected data and the measures used in the evaluation. For each rubric-based measure, two research assistants first coded 10% of the data (six participants, chosen randomly by a random-number generator) and met to ascertain agreement before independently coding all of the data. We performed an inter-rater reliability analysis and achieved a final intercoder agreement of more than 90%.

6.3.1 Story Transcriptions. For coding of the story transcriptions, we adopted two concepts form prior approaches to measure children's creative performance: idea fluency and idea elaboration [85]. Idea fluency was indicated by the number of creative ideas per minute in children's spoken narratives [85]. A creative idea contains one character and its corresponding action in its utterance. For example, "The frog is swimming" contained one idea (frog as the character and swimming as its corresponding action). Idea elaboration was indicated by the amount of idea elaboration per minute in spoken narratives [85]. Idea elaboration refers to additional details (e.g., when, where, why, etc.) subsequently provided after a creative idea. For example, "The crane jumps very high because it can fly" describes the height of the jump and provides a reason (and thus scored two points).

6.3.2 Narrative Drawings. Following the narrative drawing analysis method from Sharon and Francis's work [19], we coded each participant's narrative drawing and evaluated their creative performance. Drawing creativity was indicated by the total number of characters and scenes in narrative drawings [19]. Characters refer

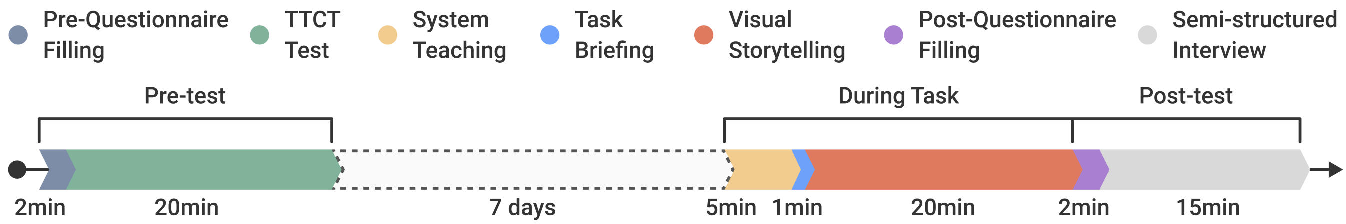

Figure 5: The flow chart for one participant. Notice that the procedure was kept consistent across the four conditions.

Table 3: Summary of the collected data and the measures used in the evaluation.

Data	Measure	Description
Story Transcriptions	Idea Fluency	Idea fluency was indicated by the number of creative ideas per minute in children's spoken narratives [85].
	Idea Elaboration	Idea elaboration was indicated by the amount of idea elaboration per minute in children's spoken narratives [85].
Narrative Drawings	Drawing Creativity	Drawing creativity was indicated by the total number of characters and scenes in children's narrative drawings [19].
Expert Ratings	Expert Ratings on Stories	Expert ratings on children's stories were performed under Amabile's [5] consensual creativity assessment technique.
	Expert Ratings on Drawings	Expert ratings on children's drawings were performed under Amabile's [5] consensual creativity assessment technique.
Engagement Questionnaires	Giggle Gauge Instrument	Giggle Gauge self-report instrument [30] assesses children's engagement in seven terms of perceptions on a 4-point scale.
Video Recordings	Open Coding and Affinity Diagramming	Three researchers first coded key clips individually and met to achieve consensus [15]. The codes were then discussed by the research team and arranged into themes [74].

to the different actors, animals or other roles shown in the drawing. Scenes refer to the story frames formed by different combinations of characters in different environments. For example, if there are several animals playing basketball, this is one scene.

6.3.3 Expert Ratings. Under Amabile's [5] consensual creativity assessment technique, children's spoken narratives and drawings were rated by three primary school educators with at least three-year pedagogical experience. Based on the statement provided ("The story is creative" or "The drawing is creative"), the educators rated their agreement on the level of creativity in each participant's story or drawing on a five-point Likert scale. The interjudge reliability was high, yielding intraclass correlation coefficients of 0.94 ($p < .001$) for stories and 0.89 ($p < .001$) for drawings.

6.3.4 Engagement Questionnaires. We evaluated participants' engagement level utilizing the Giggle Gauge self-report instrument [30], which has been validated with children in our target age range and assesses engagement in terms of perceptions such as challenge, aesthetic, feedback, and endurability, on a 4-point scale.

6.3.5 Video Recordings. We applied open coding to analyze the recorded video of participants' creation process [15]. We focused on children's creative behaviors and child-AI collaborative patterns under different strategies and relationships between children and the AI partner. Three researchers first watched the recorded video repeatedly, coded key clips individually, and met to achieve consensus on the generated codes. The codes were then discussed by the research team using affinity diagramming [74] over multiple sessions of thematic analysis to uncover themes of various levels. We report the uncovering themes in Section 7.2.

7 RESULTS

7.1 Quantitative Analysis

We obtained measures for the quantitative analysis in our experiment from six metrics referring to idea fluency, idea elaboration, drawing creativity, expert ratings on stories, expert ratings on drawings, and children's engagement level (Table 3). For each dimension of the metrics, we illustrated the data distribution by bar charts, as shown in Figure 6

7.1.1 Idea Fluency. As shown in Table 4, we did not find a statistically significant main effect of *Strategy 1* on idea fluency ($H(1) = 2.428$, $p = 0.119 > 0.05$); H1a was rejected. A statistically significant main effect of *Strategy 2* was found ($H(1) = 24.433$, $p < 0.001$); H2a was accepted. To exploit the interactions between *Strategy 1* and *Strategy 2*, we conducted a Welch's t-test and found a statistical difference ($t(16) = -2.146$, $p = 0.043 < 0.05$) between the condition with both strategies ($M = 2.84$, $SD = 1.18$) and with only *Strategy 2* ($M = 2.12$, $SD = 0.62$), that is, with the influence of *Strategy 1*, the efficacy of *Strategy 2* became more significant (Figure 6(a)).

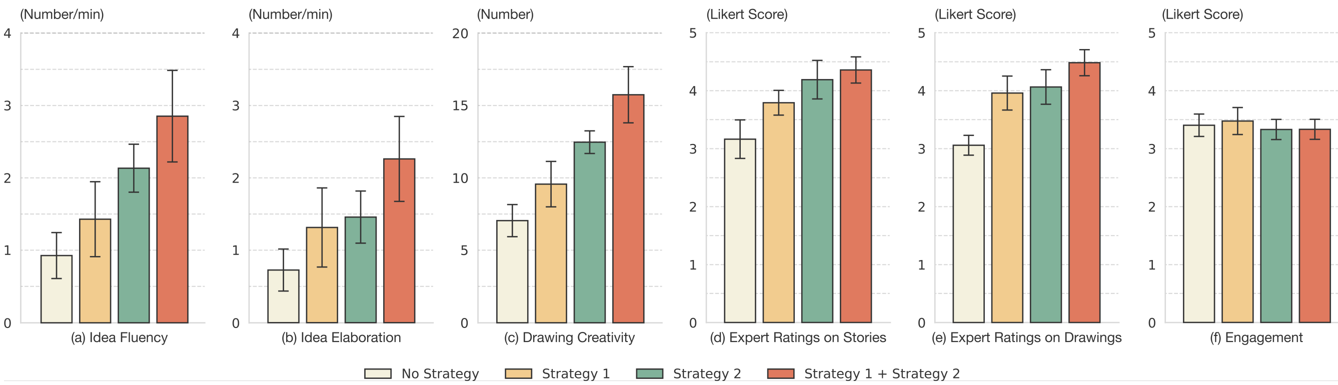

Figure 6: Bar charts illustrate the data distribution of (a) idea fluency, (b) idea elaboration, (c) drawing creativity, (d) expert ratings on stories, (e) expert ratings on drawings, and (f) engagement across the four conditions. Error bars represent 95% confidence intervals (CIs).

Table 4: The statistical metrics on participants' creative performance across the four conditions, where the two-way Kruskal-Wallis test p-values ($*$: p < .050, $**$: p < .010, $***$: p < .001) are reported.

Metrics	Distribution (M ± SD)				Statistics			Hypotheses
	S1-S2-	S1+S2-	S1-S2+	S1+S2+	Case	H (1)	p	
Idea Fluency	0.92 ± 0.59	1.42 ± 0.97	2.12 ± 0.62	2.84 ± 1.18	S1	2.428	.119	H1a rejected
					S2	24.433	.001***	H2a accepted
Idea Elaboration	0.72 ± 0.54	1.31 ± 1.02	1.45 ± 0.67	2.25 ± 1.10	S1	6.651	.010**	H1b accepted
					S2	11.824	.001**	H2b accepted
Drawing Creativity	7.00 ± 2.07	9.50 ± 2.92	12.38 ± 1.46	15.63 ± 3.61	S1	7.862	.005**	H1c accepted
					S2	36.147	.001***	H2c accepted
Expert Ratings on Stories	3.15 ± 0.62	3.77 ± 0.40	4.17 ± 0.62	4.33 ± 0.42	S1	4.431	.035*	H1d accepted
					S2	24.431	.001***	H2d accepted
Expert Ratings on Drawings	3.04 ± 0.32	3.94 ± 0.55	4.04 ± 0.56	4.46 ± 0.42	S1	13.364	.001***	H1e accepted
					S2	20.787	.001***	H2e accepted

7.1.2 Idea Elaboration. As shown in Table 4, we found a statistically significant main effect of *Strategy 1* (H (1) = 6.651, p < 0.010) and a statistically significant main effect of *Strategy 2* (H (1) = 11.824, p < 0.001) on idea elaboration; H1b and H2b were accepted. Participants elaborated with more details using *Strategy 1* (M = 1.31, SD = 1.02) or using *Strategy 2* (M = 1.45, SD = 0.67) than in the S1-S2- condition (M = 0.72, SD = 0.54). Although we did not observe any interaction between *Strategy 1* and *Strategy 2*, the influence of combined factors was most evident (M = 2.25, SD = 1.10) (Figure 6(b)).

7.1.3 Drawing Creativity. As shown in Table 4, we found a statistically significant main effect of *Strategy 1* (H (1) = 7.862, p = 0.005 < 0.01) and a statistically significant main effect of *Strategy 2* (H (1) = 36.147, p < 0.001) on drawing creativity; H1c and H2c were accepted, that is, with *Strategy 1* or *Strategy 2*, the participant produced a more creative narrative drawing during visual storytelling. Notably, as shown in Figure 6(c), the number of characters and scenes in the drawing with combined factors was the highest (M = 15.63, SD = 3.61).

7.1.4 Expert Ratings. We ran follow-up two-way Kruskal-Wallis tests considering the effect of *Strategy 1* and *Strategy 2* on expert ratings. As shown in Table 4, we found a statistically significant main effect of *Strategy 1* (H (1) = 4.431, p = 0.035 < 0.05) and a statistically significant main effect of *Strategy 2* (H (1) = 24.431, p < 0.001) on expert ratings for stories; H1d and H2d were accepted. As for expert ratings on drawings, the main effect of *Strategy 1* was statistically significant (H (1) = 13.364, p < 0.001); H1e was accepted. We also found a statistically significant main effect of *Strategy 2* (H (1) = 20.787, p < 0.001); H2e was accepted. Thus, H2 was fully accepted.

7.1.5 Engagement. We used two-way Kruskal-Wallis tests to determine whether a significant difference was elicited in the level of engagement across four conditions. We did not find a statistically significant main effect of *Strategy 1* (H (1) = 0.248, p = 0.618 > 0.05) or *Strategy 2* (H (1) = 1.996, p = 0.158 > 0.05), that is, collaborative strategies did not significantly contribute to increasing children's engagement. Notably, the mean scores of the four conditions were all greater than 3.0 (Figure 6(f)), indicating a "moderate" level of engagement [30]. The result was as expected, given that all four

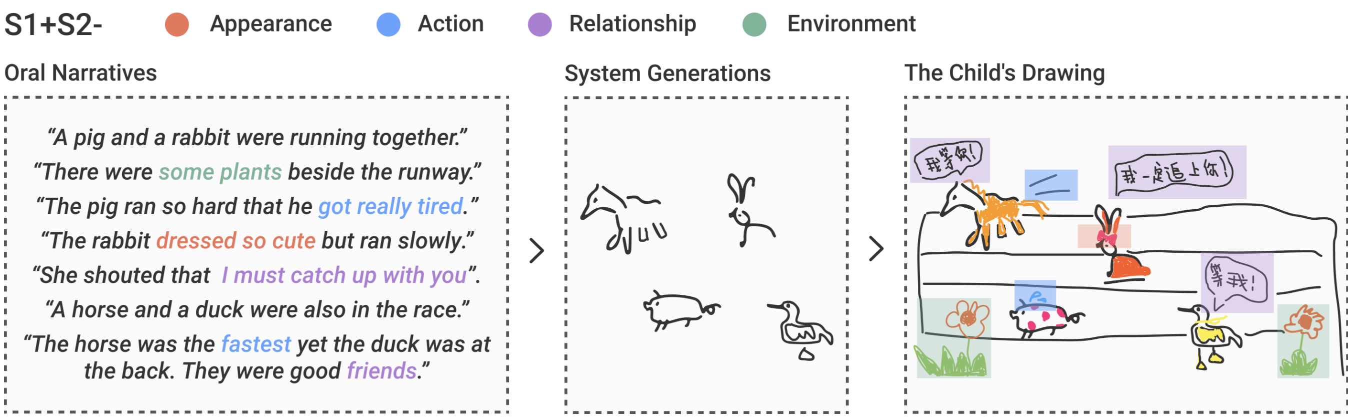

Figure 7: The oral narratives (abridged version) and the drawing from C28 in S1+S2-. The story details were about appearances, actions, relationships, and environments.

conditions had implemented the context-based voice agent. However, we found that the challenge subscore was relatively low in condition S1-S2+ (M = 2.96, SD = 1.12) and S1+S2+ (M = 2.89, SD = 0.97). This was because of the additional associative tasks of abstract sketches that children needed to perform with the involvement of *Strategy 2*.

In summary, our quantitative analysis demonstrated that *Strategy 1* significantly facilitated the participants' creative performance, especially more detailed spoken narratives and more creative drawings, indicating that participants could overcome the burden of multitasking. We found that *Strategy 2* significantly improved children's creative performance in the storytelling process, including the number of ideas and elaborations, that is, *Strategy 2* helped children to overcome writer's block to develop a greater number of elaborate ideas. We also found that all four conditions with the voice agent achieved moderate levels of engagement.

7.2 Qualitative Analysis

Our qualitative analysis revealed three main themes arising in participants' creation process: more creative details inspired by *Strategy 1*, more creative ideas inspired by *Strategy 2*, and positive child-AI relationships promoting engagement. We describe each of these in turn.

7.2.1 More Creative Details Inspired by Strategy 1. We found that children were able to create more story details when inspired by *Strategy 1*. Specifically, children usually conceptualize the story details in terms of four aspects: appearances (such as costumes and jewelry), actions (such as symbols indicating speed), relationships (such as dialogue content), and environments (such as runways and plants). As shown in Figure 7, the story drawing of one child in S1+S2- depicts an animal race: "A pig and a rabbit were running together . . ." The *StoryDrawer* system generates the story's characters (i.e., 'pig' and 'rabbit'), and the child recreated more details based on the system generations, such as "the pig ran so hard that he got really tired" and "the rabbit was dressed so cute but ran slowly". However, the animal race drawing in S1-S2- (Figure 8) shows fewer details; the child simply colored each runner and drew a runway.

In general, inspired by *Strategy 1*, children could create more details about the characters or the environment to continue their narratives. *Strategy 1* drove the children to "keep thinking about whether something else could be added" (C28, the same meaning expressed by C30, C57, and C63) by sharing the burden on multitasking, which played an active role in portraying the characters and enriching the storylines.

7.2.2 More Creative Ideas Inspired by Strategy 2. We found children made bold associations when inspired by *Strategy 2*, which led to many creative stories. We identified four collaborative patterns between children and AI with *Strategy 2*. When the system generated an abstract sketch, the children would (a) convert the prompt into one goal character or object; (b) draw the prompt into multiple goal characters or objects; (c) discard the sketch and redraw a new character or object next to it; or (d) associate a scene from the abstract sketch (Figure 9). These collaborative patterns all helped children create new ideas in visual storytelling. Comparing the drawings in Figure 8 and Figure 9, it is obvious that the drawing in Figure 9 contains more characters and scenes.

Strategy 2 stimulated children to observe more carefully and to associate more actively. They began to discover things they previously had not noticed (such as the robot image) and were creatively inspired to develop associations. As shown in Figure 9, C39 associated an abstract sketch with the robot and made it 'join the running race'. Another sketch reminded the child of a rabbit, and instead of adding it to the existing storyline, the child developed a new storyline about a 'carrot-pulling race'. More associations promoted children's divergent thinking and helped them to overcome writer's block. When we asked the children how they felt about *Strategy 2*, C56 said, "Sketches just pop up! It's a surprise!" This sense of surprise also alleviated the anxiety children experienced when they suffered from writer's block.

7.2.3 Positive Child-AI Relationships Promoting Engagement. Although the participants could not talk freely with the voice agent, most children still saw it as a partner and developed friendships. Some of them (e.g., C3, C11, C14, C20, C28) asked about the voice agent's preferences and talked about their daily lives (the agent

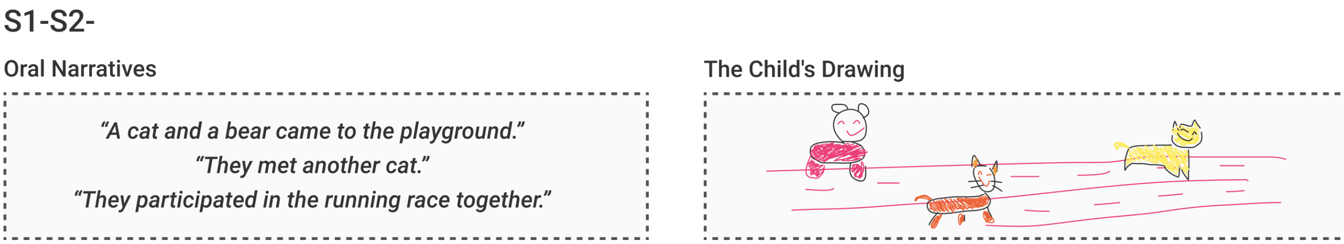

Figure 8: The oral narratives (abridged version) and the drawing from C11 in S1-S2-.

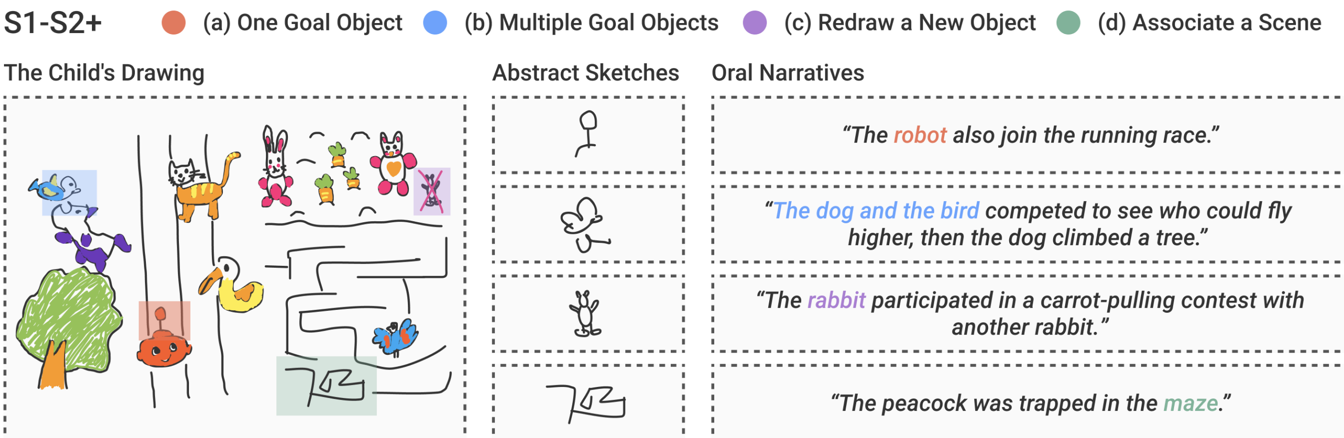

Figure 9: The oral narratives (abridged version) and the drawing from C39 in S1-S2+. Based on the generated abstract sketches, children would (a) convert into one goal character or object, (b) draw into multiple goal characters or objects, (c) redraw a new character or object, or (d) associate a scene from the prompt.

could not answer). Children's comments indicated a positive relationship. For example, C54 said, "I love *StoryDrawer*, and I want my best friend to meet it" (this idea was also expressed by C14, C37, and C61). In addition, children would communicate with the AI partner in a timely and polite manner, which indicated a high level of engagement [63]. For example, the children frequently used positive words, such as "thank you" and "you draw so well," to reply to the agent. In addition, a few participants used the system as a tool. These children talked with the voice agent in a directive tone, such as "draw me a green tree". Notably, those participants who developed friendships with the agent were more proactive in using the collaborative strategies, reflecting an engaging experience.

8 DISCUSSION

Our experiment demonstrated that *StoryDrawer* combined with *Strategy 1* and/or *Strategy 2* significantly helped participants produce elaborate ideas and creative outcomes, and that participants engaged positively with the voice agent. Our qualitative analysis revealed that children collaborated with *Strategy 1* to portray characters and enrich story details, and with *Strategy 2*, they made bold associations and created creative ideas. In addition, we found that children who had a positive relationship with the voice agent showed high levels of engagement. *Strategy 1*, however, did not contribute to the idea fluency (H1a was rejected). In this section, we explain why H1a was rejected and discuss children's preferences on strategies. We also identify the limitations and future work of our research.

8.1 Strategy 1 as a Catalyst for Strategy 2

Strategy 1 is based on embodiment theory, and *Strategy 2* is based on visual thinking. We found that *Strategy 1* did not significantly increase the number of ideas (idea fluency) when implemented alone. Because *Strategy 1* is based on children's telling of drawing objects, it is possible that it did not yet directly provide inspirations. Notably, we found that when coupled with *Strategy 1*, *Strategy 2* had a more pronounced effect on idea fluency (see Section 7.1.1). Idea fluency was reported as one of the criteria on divergent thinking [41]. Hence, we expected *Strategy 1* to be a significant catalyst for *Strategy 2* on children's divergent thinking.

Strategy 1 helped children build external representations (i.e., sketches). According to embodied creativity [27], the mechanisms involved in creativity, such as idea generation, conceptual combination, visual thinking, and mental imagery, depend on and are facilitated by interaction with the external representations. In addition, theories of distributed cognition [46, 73] also describe the externalizations that can free cognitive resources for other creative reasoning tasks. As described earlier, *Strategy 1* further promoted visual thinking in *Strategy 2* by helping children draw and externalize, releasing their cognitive resources to make associations and divergent thinking.

8.2 Children Behavioral Patterns and Preferences

Children's ways to drive the storylines are different in S1+S2+, which can be reflected in their strategy preference and their creative process. We derived two behavioral patterns: narrative first storytelling (e.g., C49-50, C52, C55-56, C63-64) and drawing first storytelling (e.g., C51, C53-54, C58, C60-62).

Children who preferred developing their stories by narrating used *Strategy 1* more frequently. They were concerned with how oral storytelling could drive the presentation of their drawings. In addition, they tapped the idea button only when they encountered writer's block. We found in their stories that, given the theme of 'Forest Sports', they tended to focus on one or two competitions or scenes, from which many interesting storylines emerged. For example, C52 told a story about a swimming race and its award ceremony; C56's story involved a tree-climbing competition.

In contrast, children who adopted the drawing first behavioral pattern used *Strategy 2* more often. They preferred developing their stories by enriching elements in their drawing. They actively triggered *Strategy 2* for abstract sketches, even though their thinking was fluent and they did not encounter writer's block. Besides, they welcomed the ability to arrange characters in different scenes. Their stories contained more competitions, but their narratives for each competition were shorter. For example, C58 recounted six different sporting events, each with different participants; however, she did not expand her descriptions of the subsequent development of each event, such as the outcome of the competition.

In fact, despite children's differences in behavioral tendency, both strategies contributed to their creative performance. Thus, we cannot completely separate or prioritize narrating and drawing, which are interrelated during visual storytelling.

8.3 Limitations and Future Work

As with any research project, this work had several limitations. First, *Strategy 1* helped children draw only the characters or objects in their stories, not the scenes or settings. Second, the system occasionally makes errors in recognizing children's sketches, which affects the user experience. Third, the collaborative strategies allowed AI to intervene in children's cognitive mechanisms, but we did not measure the level of support at the cognitive level. Because our study focused on creativity support, our measurements focused on children's creative performance and creative outcomes. Further study on cognitive aspects, however, may help us understand the deeper collaboration between children and AI. Fourth, our study lacked long-term observations of children's creativity development in the context of *StoryDrawer*.

These limitations revealed many exciting directions for future work. We hope to iterate the algorithm of *Strategy 1* to help children draw more than just characters or objects and to improve the accuracy of the sketch detection algorithm. As for *Strategy 2*, we will attempt to provide multisensory prompts other than visuals, such as sounds or smells, that can inspire children's creativity. We also plan to explore the impact of *StoryDrawer* at the cognitive level as well as the long-term influence on children's creativity development in home contexts. In addition, a further study of engagement is scheduled to be added to extend the contribution of this paper beyond creativity support.

Participants and their parents in the evaluation shared their expectations and suggestions for the system, including more unrestricted conversations and diverse interactions. For example, the output story could be played with animations if the drawing process and the trajectory of the child's moving sketches could be recorded. In addition, the characters could change their actions, colors, or positions as children narrate their stories. Finally, the impact of social interactions on creativity when multiple children and an AI partner co-create visual stories is also a direction worth exploring.

9 CONCLUSION

In this work, we presented *StoryDrawer*, a co-creative system that supports visual storytelling for children (age: 6–10 years) through child–AI collaborative drawing. We conducted a formative investigation through a workshop and interviews to understand the challenges children faced and to elicit design goals. On the basis of our findings and the design goals, we designed two AI-driven collaborative strategies with a context-based voice agent for *StoryDrawer*. These strategies were as follows: (1) the real-time transformation of children's telling into drawings and (2) the generation of abstract sketches with semantic similarity to existing story content. Results from our 2×2 between-subjects evaluations with 64 children demonstrated that *StoryDrawer* with the two collaborative strategies and the voice agent provided an engaging experience for children, helped them to produce creative and elaborate ideas, and contributed to their creative outcomes. We also identified improvements to be made to the system, including planned future work in diverse interactions and longitudinal testing.

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