Mediating Culture: Cultivating Socio-cultural Understanding of AI in Children through Participatory Design

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Figure 1: Drawings by children of answers to prompts about cats and dogs from Design Session 5

ABSTRACT

The surge in access to and awareness of Generative Artificial Intelligence (GenAI) such as *ChatGPT* has sparked discussion over the necessary technological literacies and competencies needed to effectively engage with these systems. In this context, we explore AI as a tool that mediates cultural understanding and *re*mediates human values – that are often influenced by biases and inequities. Using participatory design for learning with a group of 13 children (ages 8-13), we engaged in five co-design sessions featuring different modalities for socio-cultural approaches to AI literacy. We found that children were more aware of the cultural mediation aspect of AI when the content of the interaction aligned with their cultural background and context. This underscored the significance of aligning the representation of culture in these GenAI systems with people's socio-cultural ecosystems in modern technological literacies. We conclude with design principles for a more critical and holistic approach to AI literacy.

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CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**; • **Applied computing → Interactive learning environments**.

KEYWORDS

Cultural mediation, AI Literacy, Participatory design, Generative AI

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1 INTRODUCTION

Artificial Intelligence (AI) systems are increasingly integrated into our everyday socio-cultural experiences with technology. The increasingly active role Generative AI (GenAI) is playing in crafting cultural artifacts such as stories [74], artwork [3], news articles [91], and video games [86] is spurring debates on the nature of creativity, remix culture, and intellectual property [25]. Furthermore, GenAI systems are being integrated into technology for all ages and ability levels, such as the integration of the storytelling tool "Create with Alexa," which allows children to witness GenAI craft bespoke narratives reflective of the child's preferences, complete with illustrations, background music, and sound effects [47].

Given that GenAI and AI systems have become refined to a point where they are being used increasingly in public, creative, and casual ways, there is a need for AI literacy to address how these tools operate as part of the larger socio-technical ecosystem [10]. New technologies such as GenAI may be understood as what Brinkmann et al. [9] describe as *machine culture*, where AI not only interprets culture but also actively changes the way that culture evolves, drawing on the values of both the cultural data inputs and the designers of the AI model. This in turn can impact our ideologies and political policies [6], meaning that AI's impact on culture extends beyond immediate concerns like replications of human biases: it also suggests we are actively developing new ways to interpret the roles of information, art, and meaning-making in our culture, thereby influencing our collective perception of the world [25, 61]. Therefore, a question arises–what role does AI play as a *cultural tool*? In this work, we define a cultural tool as a technology that enables *mediation* [31], meaning a technology that allows for the transmission of symbolic messages between human agents and the environment [16]. More specifically, our work is interested in exploring the impact of AI not as a technical tool, manipulating cultural media objects, but a psychological one, that acts as a symbolic mediator of cultural concepts similar to other tools such as language [44]. Furthermore, electronic media has been suggested to perform mediation at both the individual level and at a mass cultural scale [53]. Therefore, we seek to also explore how users understand these larger social systems that create and disseminate these technologies.

From this socio-cultural perspective, Lev Vygotsky's work suggests that children offer a particularly apt way to understand cultural transmission, as they are active participants in cultural learning [44]. Children require more explicit scaffolding, typically from adults, to engage with and build an understanding of the cultural signs; yet, AI is unique in that it is a relatively new cultural tool that many adults are also still actively learning about and integrating into their lives [48]. Therefore, design methodologies such as participatory design (PD) offer a useful approach to simulate and elicit both child and adult perspectives on how AI technologies may mediate culture [101] and can inform more inclusive and culturally responsive technologies.

Considering this approach, we propose that the cultural mediation of AI is in dialogue with prior research on AI literacy. Recognizing the potential systemic and long-term impacts that AI systems may have on society, experts in AI education have suggested a series of essential competencies for navigating this evolving technological landscape. Notably, Long and Magerko define these competencies as the requisite skills for people to "*critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace*" [57, p. 2]. While recent research has explored methodologies for introducing children to the societal implications of AI systems [1, 19, 20, 57, 64] through the lens of computational thinking perspectives [17, 43, 46, 90] and the fairness aspect of the model's performance [12, 21, 50, 83], we build on prior work to investigate how children engage with AI systems as mediators of cultural understanding. With these new AI interfaces, it is also possible to draw on children's own funds of knowledge [67] to support their understanding of the inner workings of AI. To that end, we set out to answer the following research question:

- **RQ:** How do children (ages 8-13) explore their understanding of AI as a cultural tool through participation in co-design workshops around AI literacy?

We conducted five participatory design (PD) sessions [22] with 13 children (ages 7 - 13) from February 2023 to October 2023. Through the PD method of Cooperative Inquiry [22], we drew on adult-child design partnerships to understand how children interpreted and articulated the cultural implications of AI. Co-design activities ranged from using *ChatGPT* for creative writing to paper-and-pen simulation of AI classification, and aimed to elicit how children conceptualized ideas of AI as a cultural tool. Our findings revealed that children actively integrated AI into their cultural experiences, using it not only for creative endeavors but also as a lens through which they critically examined and navigated cultural biases within the technology. Furthermore, this suggests that children may understand AI as a tool that mediates cultural signs differently than themselves, critically interpreting these signs when they reflected on their own cultural experiences and funds of knowledge [67]. Based on our analysis of children's conversations, collaborations, and creative endeavors in our design sessions, our work contributes an empirical understanding of how the interactions of children with socio-cultural aspects of AI technologies help them understand AI as a cultural tool, connecting their experiences to the theory of *remediation* [5]. We emphasize AI's dual role as both a tool enabling the manipulation of cultural objects and a simulator of cultural symbols, and based upon our observations and this concept, we present a set of design principles for fostering children's understanding of AI as a cultural mediator. Lastly, we discuss design implications for AI education across different ages and contexts.

2 RELATED WORK

To understand how children (and others) approach and perceive the socio-cultural mediation of AI, we first consider existing theories on mediation and digital cultural tools. This section begins by examining these theoretical foundations, followed by a review of prior research focusing on AI literacy and design approaches for teaching AI competencies.

2.1 Mediation and Digital Cultural Tools

Education scholar Harry Daniels suggested that *mediation* can be understood as a process through which individuals are "*acted upon through social, cultural and historical factors*" [16, p. 36]. This process involves how our interactions with culture and cultural artifacts transform our mental models and understanding of the world. The concept of mediation traces its roots back to the learning theories of Lev Vygotsky [44], who proposed that culture had a central role in learning and that one's understanding of the world was constructed based on their interactions with external cultural symbols. These symbols are defined as *cultural tools*. Vygotsky further categorizes these tools into two distinct types: "technical tools," which manipulate the properties of external objects, and "psychological tools," directed towards inner understanding.

In the context of digital technology, and particularly the socio-technical systems such as popular social media tools, the distinction between technical and psychological tools becomes more complex. As an example, the work of the media theorist Lev Manovich explores the concept of "cultural software," which is a term he uses to describe software that support cultural actions such as creating, accessing, and sharing cultural artifacts. These technologies also include interactive cultural experiences and are, as Henry Jenkins posits, participatory in nature [39]. In essence, a cultural software is a cultural tool, but is often one that can, due to the nature of the digital medium, both manipulate digital objects and impact internal cognitive process. For example, a cultural software such as *Adobe Photoshop* operates external to the individual. It allows user to enact various technical tasks such as selecting colors or changing line thicknesses. Simultaneously, it also prompts a user to think about their creative expression and the way certain choices will impact a final product, effectively supporting their internal cognitive processes. These tools then, mediate how concepts such as "color" are understood both internally and externally. Software such as *Photoshop* also mediates our interpretations of images we view online, as photos can be changed and manipulated through the lens of the editor, instilling certain cultural values into the changes to the image (skin tone, thinness, removal of blemishes, and so on).

Continuing along similar lines, AI is seen by some as a mediator of cultural understanding but also as an active agent in shaping cultural evolution [9]. While historically new technology can often lead to cultural change [89], Brinkmann et al. [9] propose that AI's unique capacity lies in its potential to fundamentally transform the trajectory of cultural evolution. As an example, they suggest the ability of GenAI to recombine cultural concepts, raising questions of its potential to support new conceptions of art [9]. However, the role of AI in cultural products such as art and music is not readily agreed upon amongst technologists, artists, philosophers, and scholars [61], nor the general public [42]. Previous work has also suggested, that AI-mediated communication may lead to less trustworthiness [35, 55] as well as ethical concerns such as privacy and misinterpretation [94]. While it is apparent that AI does mediate aspects of broader popular culture in some form, the exact avenue for this is still emergent. In this work, we focus instead on how to scaffold understanding of the cultural mediation through participatory design, delving into how children understand AI in their own cultural context.

2.2 AI Literacy

AI literacy encompasses an understanding of AI concepts, practices and perspectives that enable learners to critically evaluate and utilize AI technologies [19, 57] while fostering considerations for AI ethics [57, 73, 84, 90]. Touretzky's five "big ideas" of AI – perception, representation & reasoning, learning, natural interaction and societal impact – provide a strong starting foundation for how to foster AI literacy [90]. Here, perception pertains to how computers interpret the world through sensors; representation and reasoning involve agents maintaining models of the world and utilizing them for logical thinking; learning involves computers gaining knowledge from data; natural interaction addresses the challenge AI developers encounter in creating agents that can interact seamlessly with humans; and societal impact refers to the potential effects of AI applications on society, both positive and negative [90]. Long et al. furthers this discussion of competencies by outlining AI literacy competencies (e.g. "*Recognize that humans play an important role in programming, choosing models, and fine-tuning AI systems.*"[57, p. 6]) and offering several design considerations for fostering AI literacy (e.g. "*Consider leveraging learners' interests (e.g. current issues, everyday experiences, or common pastimes like games or music*"[57, p. 9]) when designing AI literacy interventions. Additionally, Long et al. emphasize that from a HCI perspective, prioritizing design considerations such as explainability, leveraging learners' interests and contextualizing data among others can enhance the development and implementation of educational programs aimed at cultivating AI literacy [57]. We use the five "big ideas" [90] and Long's AI literacy competencies/design considerations [58] as guiding frameworks for our design research in this paper.

Furthermore, in recent years, researchers have introduced various educational resources aimed at different age groups to raise awareness about the societal implications of AI systems [37, 65]. For example, Melsion et al. [64] introduced an educational platform to teach pre-adolescents about gender bias in supervised machine learning. Payne [73] worked with young learners to emphasize the importance of training data in machine learning algorithms and helped them explore the potential repercussions of biased datasets on system outputs. Other scholars have addressed this topic from the lens of biases and power structures within the context of algorithmic fairness and demonstrated that children are capable of recognizing bias in their lives and technologies [14, 21, 50, 83].

Additionally, several scholars have also used constructionist approaches – where students actively build their own understanding, often through project based learning [72] – to integrate the technical concepts of AI systems with discussions about society and ethics [26, 75]. By connecting AI curricula with learner's existing expertise, constructionist projects foster a personally meaningful learning experience that allow learners to use their existing knowledge to challenge and question AI's decisions [15]. For example, in a study conducted by Castro and Desportes [13], learners examined the socio-technical aspects of AI as they created dance moves with a creative computing system, *danceON*. As students participated in their creation process with *danceON*, they discovered the implications of biased cultural assumptions about the human body embedded within AI systems [13]. Similarly, Register and Ko [77] had learners train basic machine learning models using personal data they had collected, followed by reflective exercises evaluating the applications and limitations of these models.

While prior work has demonstrated a need to define competencies needed for AI literacy and its connection to design, as well as a need for educational resources that help children connect these competencies to their everyday lives; our work builds on this approach by supporting children to question and recognize the role that AI systems play in mediating cultural understanding, including drawing a connection to how the amplification of certain cultural ideologies are mediated through technology.

3 METHODS

Building upon previous literature in both AI literacy and the mediation potentials of digital tools, we use participatory design methods to investigate how children comprehend AI and its role as a cultural tool. This section details our methodology, including our use of Cooperative Inquiry, participants, descriptions of our design sessions, and data analysis.

3.1 Cooperative Inquiry

We employed a participatory design (PD) method called Cooperative Inquiry (CI) [22, 23, 101], which positions children as active partners with adult researchers in co-designing new technologies [23, 29, 101]. CI has been shown to support constructionist learning [22] and foster the development of conceptual models [99] and pedagogical strategies [80, 81] that inform design implications. Additionally, prior research suggests that CI empowers children to express abstract and complex ideas more concretely by facilitating discussions and prompting reflection [22, 81]. CI has proven valuable in studying various aspects of children's experiences, including their perceptions of security and privacy [45, 100], studies on gender and sexuality [52], examinations of family finances [97], and investigations into the role of creativity [2]. We similarly employ CI as a means of enabling children to question and recognize the role that AI systems play in mediating cultural understanding. Additionally, we aim to encourage children to share their thoughts about AI through collaborative design processes, fostering dialectical engagement [62] and creative expression [41].

3.2 Participants

We conducted our study with the co-design group **KidsTeam UW**. KidsTeam UW includes adult design team members (researchers, graduate and undergraduate research assistants) and N=13 child participants living in Seattle, United States. The co-design group meets twice a week over the course of the school year, as well as for a one week camp in summer. Children who participate may come to one or both of these weekly sessions. Due to this, not all participants are present in all sessions. For the purposes of this work, child participants are denoted with the prefix 'P' (*e.g.*, "P7 said..."). The demographic information of these participants is included in Table 1. Child participants were recruited through mailing lists, posters, and snowball sampling. Participants, once recruited, participate throughout the school year. We obtained parental consent and child assent for all participants, and our university's Institutional Review Board reviewed and approved the research.

3.3 Design Sessions

KidsTeam UW meets twice weekly in a designated space on a university campus. Every KidsTeam UW session consists of: **Snack Time** (15 minutes) to foster relationships with the children; **Circle Time** (15 minutes) with a warm up activity in which adult facilitators ask a "Question of the Day" to prime children for the design activity; **Design Time**, wherein children co-design with adult facilitators in groups (45 minutes); and finally, **Discussion Time** (15 minutes), wherein groups present their final designs and the whole team reflects on the design experience. We held five such co-design sessions (denoted with "DS") over the course of eight months, between February to October 2023.

During these sessions, we adhered to the four dimensions of equal and equitable design partnerships [101]. Each group included multiple children and two or more adult facilitators, to allow for adult and children collaboration and foster a dynamic where children could inspire each other while still receiving individual guidance from the adult facilitators [98, 101]. To mitigate potential power imbalances and influence of children's responses on each other, facilitators were trained to encourage equal participation, ensuring that every child felt their input was valued, thereby promoting an environment where children felt comfortable expressing unique thoughts without undue influence from their peers or the adults [98, 101]. Adult facilitators were also trained to navigate discussions in a way that minimized dominant behavior by any single participant and to foster collective idea generation where contributions were built upon rather than overshadowed [98, 101].

The warm-up questions prompted children to share their personal experiences with AI and were intended to create an inclusive environment in which all participants felt comfortable voicing their perspectives. During the design activities, five to eight adult facilitators acted as design partners for each 90-minute session. Children and adult facilitators collaborated in groups of three to four as they participated in four design activities focused on the socio-cultural aspects of AI. These activities included: (1) Exploring children's initial experiences with GenAI tools; (2) Examining how children interpret the use of AI for classification; and (3) Investigating how children perceive their thinking in contrast to AI outputs. Table 2 presents the learning goals of the sessions, along with an overview of the design objectives for these interactions.

3.3.1 DS1 (February 2023): Using ChatGPT 3.5 for Creative Writing.

We first introduced kids to *ChatGPT 3.5* (henceforth referred to as *ChatGPT*) as a cultural technology via a familiar school exercise: creative writing. Children were encouraged to prompt *ChatGPT* to generate various genres of writing, such as poems, song lyrics, short stories, movie scripts, and plays. DS1 aligns with the learning goal of understanding AI as cultural tool as it allows children to interact with *ChatGPT* in the context of creating cultural artifacts. Children were given the freedom to prompt the AI system in ways that were personally meaningful to them, with no specific topics provided. This open-ended approach allows for a more organic interaction and also aligns with the design goal of understanding children's initial experiences with GenAI tools. During the session, we used a CI activity called *Likes, Dislikes, and Design Ideas*, in which co-designers wrote out children's responses to each of these categories on a sticky note. This approach has been commonly employed in

Name	Gender	Ethnicity	Age	Sessions
P1	Male	Asian/White	8	1, 2, 3, 4, 5
P2	Male	Hispanic/Latino	10	1, 2, 3, 4, 5
P3	Female	Asian/White	13	1, 2, 3, 4
P4	Female	White	9	1, 4, 5,
P5	Female	Asian/Black	9	3, 5
P6	Male	Asian/Black	9	1, 2, 3, 5
P7	Male	Asian/White	9	1, 2, 4, 5
P8	Male	Asian/White	13	1
P9	Male	Black	10	1
P10	Female	Asian/White	13	1, 2, 4
P11	Male	White	10	1, 2
P12	Male	White	8	1, 2
P13	Female	Black/White	9	5

Table 1: Demographic characteristics of our child participants

Learning Goal	Design Goal	Design Session(s)
Gain an understanding of AI as a cultural tool.	Explore children's initial experiences with GenAI Tools	DS1; DS2
Investigate how AI makes assumptions about cultural concepts.	Examine how children interpret the use of AI for classification	DS3
Explore the concept of AI as a model of learning.	Investigate how children perceive their thinking in contrast to human thinking.	DS4; DS5

Table 2: Summary of Goals during Design Sessions

CI to discover children's perceptions of current technologies and their suggestions for changes [29].

3.3.2 DS2 (March 2023): Creating Storybooks with DALL·E 2 and ChatGPT. During our second design session, children co-authored digital storybooks using AI-generated visuals and text. We chose storybooks as a design activity as prior work in AI literacy indicates that storytelling may be a useful way to engage children in their understanding of AI systems [96]. Participants were provided with access to *DALL·E 2* (henceforth referred to as *DALL·E*) for generating pictures and to *ChatGPT* for generating text. Adult co-designers explained the capabilities of *DALL·E*, highlighting the ways in which it could be used in tandem with *ChatGPT* to support the creation of storybooks wherein the text was accompanied by what the design team of kids and adults deemed a suitable image. The design activity began by children brainstorming ideas for their stories followed by prompting *ChatGPT* to initiate the creation of a fantasy narrative. Children were encouraged to experiment with *DALL·E* by prompting it with various subjects, descriptions, and art styles, such as pixel art. Children then used the images produced by *DALL·E* and the text produced by *ChatGPT* to create a storybook in Google Slides. Adult co-designers encouraged children to reflect on their decision-making processes, considering whether to use *ChatGPT* or *DALL·E* first, how to determine the selection of a story, and select corresponding illustrations. Similar to DS1, the goal was to encourage the children to create their own storybooks with a high degree of flexibility in constructing narratives and to have them consider how AI might intersect with their cultural experiences.

3.3.3 DS3 (March 2023): AI Classification with Word Cloud Interface. During our third design session, children used craft materials like modeling clay, pipe cleaners, and construction paper to create tangible artifacts to test AI's adaptability to interpret and classify physical inputs across different mediums. In contrast to the digital artifacts created with *ChatGPT* and *DALL·E* in previous sessions, the introduction of physical artifacts in this design session serves a dual purpose. First, it provides children with the opportunity to produce physical objects that carry cultural significance for them. These tangible artifacts act as unique inputs for the AI model to classify, allowing for a more personalized and hands-on interaction with technology. Second, it underscores the idea that culture (and what might be impacted or interpreted by AI) is not solely confined to the digital realm; it extends into the tangible, real-world creations of individuals. At the beginning of the session, children and adults created their artifacts from the provided craft materials. After creating the artifacts, children then interacted with a real-time word cloud interface (Fig.2) which was designed and developed by the researchers. This tool allows immediate interaction between the participant and an AI model by capturing and processing images in real-time as they are received from a webcam's video stream. The tool then uses CLIP,[1] an AI model capable of quantifying the association between an image and a corresponding text, to automatically retrieve the ten words with the highest probability of matching the webcam image. These top words of the model's classification

[1]Specifically CLIP-ViT-Base-Patch32.

Figure 2: The wordcloud interface on the left includes ① a webcam stream and ② a collapsible menu for entering metadata such as participant ID. ③ On the right side of the interface, a word cloud is displaying the output of the computation.

results are then visually presented to the end user in a word cloud, as shown in (Fig.2), which refreshes every 2 seconds.

The association between the image from the webcam stream and each of the words in the model's vocabulary is computed by obtaining the matrix-vector product of the normalized image embedding with the normalized text embeddings, which is equivalent to the cosine similarity between the image embedding and each text embedding corresponding to a word in the vocabulary. Cosine similarities are proportional to logits in CLIP [76], such that the highest cosine similarities indicate the words the model would be most likely to use to classify the image. The system greedily returns the ten largest cosine similarity values and associated words and uses them as input to a word cloud function, which renders the words visually such that they are proportional in size to their cosine similarities. The only form of interaction with this interface is through the webcam, which simplifies the process for users by eliminating the need to master more complicated input methods.

DS3 was structured towards the learning goal of understanding AI assumptions during classification, with the design goal of exploring how children perceive and interpret the use of AI in the context of classifying tangible artifacts. The design of this interface facilitates fluid experimentation [79] and hypothesis generation, as it does not inform users about the reasons behind the displayed words in the word cloud. Consequently, users can experiment with the interface and formulate their own theories about how the AI responds to specific changes and its underlying mechanisms.

3.3.4 DS4 (July 2023): Paper and Pen Simulation of AI Classification. During our fourth design session, children and adults assumed the role of an AI classification model to explore the intricacies of bias and cultural representation. We elected for this activity to be analog (using markers and paper) so that children could reflect on how their own biases influenced their choice of rules for the system. The design activity was comprised of three parts: generating training data, generating rules, and fine-tuning. During the training data section, all participants had 20 seconds to draw a dog and then 20 more seconds to draw a cat. All of the drawn pictures were then placed on two parts of a whiteboard, with one part corresponding to dog images, and the other corresponding to cat images. During the rules generation section, design groups of four children and two or three adults then each worked to develop a set of five classification rules–a set of characteristics that described the data based on the children's observations–that would result in the cat pictures being classified as cats and the dog pictures being classified as dogs. The fine-tuning phase involved an adult who assumed the role of the AI. The adult in the simulation could only respond using four distinct classification options:

(1) "This is a dog."
(2) "This is a cat."
(3) "This is a dog or a cat."
(4) "I have no idea what this is!"

The responses were determined based on how well a set of randomly sampled images of dogs and cats matched the classification rules created by each group during the earlier stages of the activity. Three rounds of fine tuning were conducted. The first round featured images of real animals, the second round included pictures of dogs and cats represented by food or drawings, and the third round incorporated the most abstract images, such as expressionistic paintings or the cartoon character *Catdog*. A sample image from each round can be viewed in (Fig.3). Following each round of fine-tuning, design teams had the opportunity to refine their rules. This could involve removing a rule, altering the wording of a rule, or adding a new rule, allowing for an iterative process of improvement and adjustment in response to the evolving challenges posed by different types of images. The use of cultural concepts like drawings of dogs and cats in the activity allows participants to reflect on how cultural factors might influence the design of AI models. This aligns with the learning goal that the data used for training AI models often carries cultural connotations and biases, and these can impact the system's outputs.

3.3.5 DS5 (October 2023): Paper and Pen Simulation of AI Classification with Prompts. In our fifth design session, children were asked to put themselves in the shoes of someone using an AI model and generate prompts that would reveal potential issues or challenges with the established rules. The group started the design session by reviewing pictures of cats and dogs from the previous sessions, and created a new set of rules. After this, children were asked to consider different scenarios and create prompts that fell into three distinct categories:

(1) **Optimal Rule Application:** Create a prompt that demonstrates the effective application of the rules, showcasing how well the rules guide the AI in accurately generating an image.

(a) Sample Image Round 1 **(b) Sample Image Round 2** **(c) Sample Image Round 3**

Figure 3: Sample Images used for "Fine-Tuning" in DS5

(2) **Rule Limitation:** Create a prompt that the existing rules could not effectively handle or interpret. This could highlight limitations in the rule set and provide insights into areas that might require improvement.
(3) **Ambiguity Challenge:** Create a prompt that intentionally makes it challenging to determine if the resulting model should depict a dog or a cat. This helps explore potential misunderstandings or ambiguities that may arise during the AI's decision-making process.

By creating prompts and envisioning scenarios, children engage with the AI model in a way that reflects their understanding of cultural nuances and expectations. The design goal was to reveal the extent to which children incorporate cultural elements into their interactions with AI. The three categories of prompts in the simulation directly address potential misclassification scenarios. It also aligns with the learning goal that misclassifications and limitations may arise from biases present in the rule set, and the prompts generated by children can identify these issues.

3.4 Data Collection

For all design sessions, our team utilized built-in webcams on desktop computers to create video and screen recordings of the sessions using *Zoom*, a video conferencing software. Depending on the number of design groups for each session, this resulted in a total of one to four cameras recording, and we collected a total of 643 minutes of video. In addition to the videos, we saved the images, text, slide decks, and any other digital artifacts produced by participants during the sessions to serve as triangulating data. We also photographed physical artifacts created during the sessions, such as those constructed using modeling clay and pipe cleaners during DS3. Finally, we collaboratively drafted memos describing the thoughts and experiences of children and adult co-designers using *Google Slides* at the end of each session.

3.5 Data Analysis

We employed a combined inductive and deductive qualitative approach for data analysis [87]. As a first step, we created analytical memos through consolidating the videos and design artifacts. This process involved undergraduate or master's student research assistants working with KidsTeam UW who acted as primary and secondary reviewers. The analytic memos were created first by one volunteer who watched the assigned recorded video and recorded a narrative summary of what occurred in 5-minute intervals. The primary reviewer was instructed to document collaborations and interactions between adults and children, including direct quotes related to the study's research questions. Once the primary reviewers finished their memos, another research assistant acted as a secondary reviewer and replicated the process, ensuring the accuracy of the primary reviewers' work and adding supplementary comments as necessary. After creating and reviewing the analytic memos, both the primary and secondary reviewers engaged in open coding, suggesting potential codes such as "Human Bias" and "Limitations of AI."

Based on the suggested codes and a review of relevant literature related to AI literacy [12, 57], co-design, mediation, and digital cultural tools the first authors created an initial codebook with four main code categories: 1) children's mental models; 2) mediated learning; 3) affect and emotion; and 4) critical perspectives of AI. Each code category had subcategories, as reflected in Table 3. Memos were created in a word processor and then moved to Atlas.ti for qualitative coding purposes. Primary coders assigned codes to specific vignettes and interactions, while secondary coders checked the codes with +1 for agreements or -1 for disagreements, explaining their reasoning. Coding disagreements were raised to the group and resolved and the codebook was iteratively discussed and updated until consensus was achieved [7, 34].

4 FINDINGS

We present our findings in three major themes: (1) children's perspective of AI as a cultural tool for both creation and cultural reinterpretation; (2) children's understanding of data's role in AI-mediated culture, and (3) the role of human mediation in understanding AI as a cultural tool. We present descriptions of co-design sessions and direct quotes from the children portraying these themes.

4.1 Children's Perspective of AI as a Cultural Tool

In our design sessions, children recognized GenAI's capacity to generate cultural artifacts, viewing it as a potential tool for cultural creation. However, children faced challenges in interpreting AI's role in cultural mediation when the presented cultural concepts deviated from their pre-existing understanding.

Code	Subcode	Example Coding
Critical Perspective of AI	*detection of bias in AI*	"AI makes assumptions and sometimes says something is true when it is not."
	reflection of AI	"How does it come up with words that are context?
	production of AI	An adult asks how the AI knew how to draw a bird, and P1 says that "it is able to look it up online."
	limitations of AI	They notice that *DALL·E* prompts have word limits.
Affect and Emotion	*likes*	P6 gave *ChatGPT* thumbs up "because no other technology like it exists and it sounded like a 4th grader wrote it."
	dislikes	"The images are not in the same style and do not really reflect the given prompt."
	strong emotions about AI	"This is technology at its highest peak."
Mediated Learning	*use of artifact for learning*	They notice that the grammar and spelling in the art are not legible.
	child - child	P4 thinks this story is better than the first one. P1 joins them, and they discuss how the stories differ.
	child - adult	An adult asks about missing *DALL·E* features: P3 says "appropriateness, also an English dictionary", P6 wants "a style picker to maintain consistency."
Mental Model	*description of AI*	"AI can detect it's a Rice Krispies treat because it's a chip."

Table 3: Examples of Codes and Subcodes

4.1.1 Using GenAI to Reinterpret Existing Cultural Content. In both DS1 and DS2, children actively participated in creative writing exercises and crafting storybooks using GenAI. There were many examples of children demonstrating a keen awareness of GenAI's ability to generate responses by combining pre-existing cultural content. For instance, during DS1, when asked to generate creative writing using *ChatGPT*, P2 and P1 prompted the system to create a poem by blending two poems—one inspired by *The Legend of Zelda* and another by *Minecraft*. In a separate example, P7 prompted *ChatGPT* to craft a *Mario* and *Luigi* script featuring *James Charles*, an American youtuber and makeup artist, as *Mario* and *Tyler1*, an American online streamer, as *Luigi*. Similarly, P2 prompted *ChatGPT* to create a movie script with *Zelda* and *Dwayne the Rock Johnson*. The prevalence of video game characters such as *Zelda*, *Minecraft*, *Mario*, and *Luigi* in all these examples indicate how video games serve as influential cultural touchstones for children. These instances highlight how children actively chose to merge content from popular video games and cultural references that were meaningful to them to reinterpret and generate something entirely new and extend it beyond mere consumption.

The use of GenAI to reinterpret popular culture was also evident in DS2, where children used both *ChatGPT* and *DALL·E* to create their own storybooks. For example, P1 and P2 wanted to create a story about the movie *Back to the Future,* and they used *DALL·E* to generate a picture using the prompt, *"A talking Delorean [sic] saying in english 'I have a friends called Marty who drove me [from] time to time' in action style."* However, P2 did not like the results, re-prompting *DALL·E* to prompt "*a car says let's go home but the trap was done*." They note that the car in the pictures is not actually a *Delorean*. They continue to prompt, and suggest "*The delorean becomes president in a digital art style*." The iterative process of refining the prompt to better match their vision highlights the children's desire to accurately represent and reinterpret a specific cultural reference. Both children liked the results as shown in Figure 4, with P2 saying "*I like the second one since it has like a clock in his hand. And that that means the computer understands that it's supposed to be Back to the Future*. P2's comment reflects an understanding and appreciation for subtle details associated with "*Back to the Future*." Through their experiences, the children learned not only how to refine their prompts, but some of the potential limitations of AI systems to interpret their requests.

4.1.2 Comparison of GenAI Produced Artifacts to Personal Knowledge. During DS1 and DS2, children showed critical reflection of AI mediated representations by comparing the GenAI produced artifacts to their pre-existing cultural knowledge. For example, in DS1 when P10 prompted *ChatGPT* to "*write a short story about Ayato Kamisato from Genshin Impact*" – a popular video game – after reading the story, P10 described both factual mistakes and misinterpretations of character motivation in the *ChatGPT* generated text. *ChatGPT*'s story stated that *Ayato* is the youngest son in his family (the "*Kamisato clan*"), which P10 noted is incorrect. More fundamentally, P10 noted that *ChatGPT*'s story presented Ayato in a way that was inconsistent with P10's expectations of the character, saying "*he would never [do that]*." P10's identification of factual mistakes and misinterpretations in the initial story, such as *Ayato* being the youngest son instead of the only son and the elder sibling, highlights her awareness about the model's vulnerability to inaccuracies and misunderstandings, drawing on her own knowledge. When P10 further prompted *ChatGPT* to revise the story, adding the context that Ayato is the only son and the elder sibling, *ChatGPT*'s output then began with "*Ayato Kamisato was the only son of the*

Kamisato clan, and as the elder sibling..." Observing this immediate responsiveness to P10's input, P7 noted that AI models like *ChatGPT* "*change without hesitation, or they change without thinking*," reflecting how children's interactions with *ChatGPT* changed their perception of the model from a thinking machine to a technology primarily dependent on human input and human preferences.

Furthermore, in DS2, P3 prompted *DALL·E* to generate "*a detective girl named Lisa with special powers in anime style, specifically in the style of Saiki K*" for her storybook. Despite P3's specific request for images in the style of *Saiki K*, she realized that the generated images did not resemble that particular anime style. Additionally, P3 noticed that *DALL·E* did not remember her previous prompt details. This made her realize that *DALL·E* did not have a "*memory*" leading to potential issues with understanding character references, such as the name "*Lisa.*" Throughout the design session, despite P3's attempts to guide the model by specifying the desired animation style, she expressed difficulty in keeping image styles consistent for her storybook.

Another example of children's comparison of their cultural understanding to AI cultural representations occurred during DS1, where children were collaborating on creative writing with *ChatGPT.* P4, P3, and an adult prompted *ChatGPT* to "*write a song about Flaming Hot Cheetos.*" The lyrics were originally generated in English, to which P3 requested a rendition in Korean, inspiring P4 to seek a translation into Russian. Building on this exploration of linguistic representation in *ChatGPT*, the adult co-designer prompted the group to talk through the differences and similarities both in the language and the ways that different cultures were represented in the song. As the group proceeded compare the resulting songs, they noted variations in length and expression of the songs. P4 pointed out that the song generated is "*Russian but they don't have meaning, just random Russian words.*" Additionally, P3 says "*it's not so good, since it put Japanese and Korean together as the same word side by side.*" We see this as a form of dialectical engagement [62], where children first identified how language and cultural elements that were represented in *ChatGPT* differed from their pre-existing cultural knowledge, identified conflicting aspects of their understandings, and then synthesized their own beliefs via these conflicts.

4.1.3 Summary Analysis. In exploring children's use of GenAI for creative processes, we saw that children exhibited a nuanced understanding of its potential for generating cultural artifacts as well as the potential pitfalls. Children actively utilized GenAI's capabilities to merge and reinterpret pre-existing cultural content. Examples from both the creative writing and storybook creation sessions demonstrated the children's adeptness in combining elements from popular video games and cultural references, such as *Zelda*, *Minecraft*, *Mario*, and *Back to the Future*, to create novel and personalized narratives. In comparing GenAI produced artifacts to their pre-existing cultural knowledge, children displayed discernment and awareness, pointing out issues with the outputs. Instances of factual inaccuracies or misinterpretations by GenAI prompted critical reflections, as seen in the case of *Ayato Kamisato* from *Genshin Impact* in the creative writing session and the stylistic inconsistencies in *DALL·E*'s anime-style images in the storybook creation session.

4.2 Children Understand Data's Role in AI-Mediated Culture

In our study, children emphasized the significance of selecting and representing cultural data. They engaged in an iterative process of refining their understanding of how AI classification is influenced by training data. Children also identified training data as a limiting factor in AI-mediated culture, understanding that the choice of training data, algorithmic rules, and fine-tuning processes shape how AI mediates cultural concepts.

4.2.1 Data Acts as a Limitation in AI-Mediated Representation. Over the course of our sessions, children came to see data as a limiting factor in what types of cultural concepts AI could represent. For example, during DS4, children were asked to make the "classification rules" for AI to distinguish between a cat or dog based on drawn pictures of cats and dogs by children. When creating the rules, the children started with simple observations, like noting that cats have a nose and a body. However, as the discussion progressed, a more detailed rule was suggested by P10, stating that "*cats have a round head.*" This rule was challenged by P1, who pointed out that it might be incorrect because "*the ears still connect,*" referencing specific images in Figure 5a. Throughout the discussions, the children seemed to reflect on the significance of having diverse and representative training data for AI. They realized that the AI's ability to grasp cultural concepts, like the distinguishing characteristics of cats and dogs, relies on the variety and richness of the data it encounters during its training. This growing awareness of data's importance also persisted into DS5. In one instance, when children were asked to come up with a prompt that the group generated rules for classification couldn't handle (i.e. a prompt that asked for a picture of neither a dog nor cat) P13 pointed out to use "*a bird on a sunny day*" as "*all [AI] knows is cats and dogs?*" This quote from P13 emphasizes the understanding of AI's difficulty to classify something different (like a bird on a sunny day) when their AI model has only been trained on examples of cats and dogs.

Children noted the importance of training data not only included what might happen when certain features (such as of cats and dogs) get left out, but also how AI might approach biases based on what attributes were highlighted. For example, during a group discussion in DS4, an adult raised a question about whether including eyelashes in a drawing would inherently imply the gender of the bear that P3 was drawing. To this, P3 responded with a simple "*Yeah*," indicating agreement with the idea that including eyelashes could imply the gender of the bear. The adult then extended the discussion by drawing a parallel to AI and its ability to distinguish between genders. The adult suggested that it might be challenging for an AI to differentiate between a boy and a girl, and seeked P3's input on this matter. In response, P3 expressed the view that it can be difficult because "*there are always exceptions*" to general rules or patterns. These moments highlight how children identified the importance of connected bias and training data. When children were able to see the process of data creation, selection, and how these choices translated into rules, they showed critical understanding around how training data and wording of rules can can lead to limitations in AI-mediated representation.

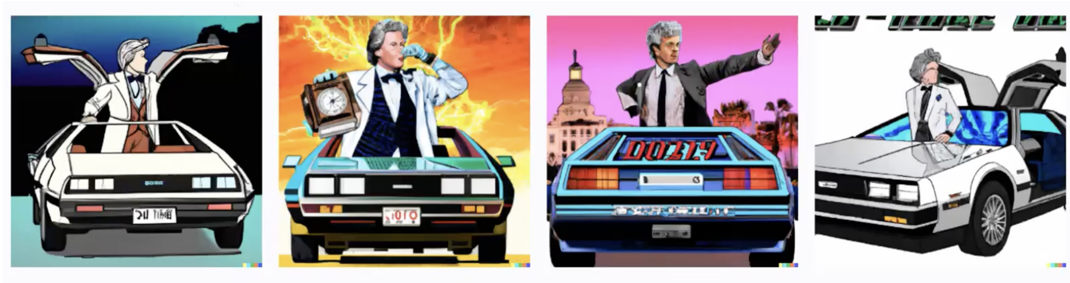
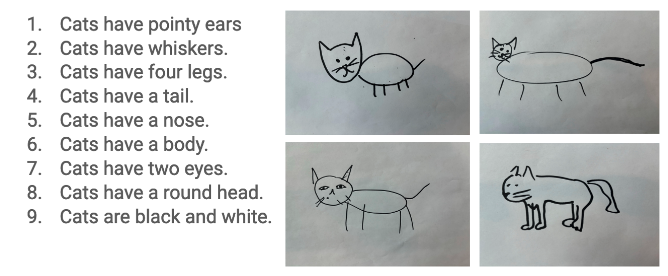
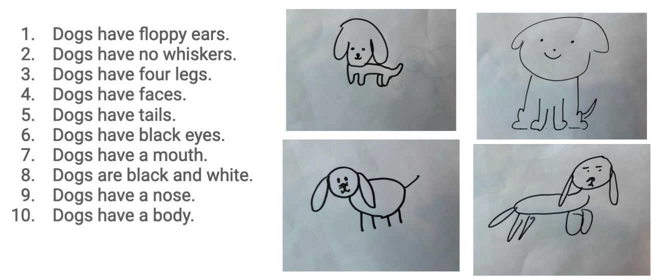


Figure 4: Pictures generated by *DALL·E* for a story about the movie *Back to the Future* in DS2



(a) Rules about Cats



(b) Rules about Dogs

Figure 5: Rules created for DS5 about how to identify cats and dogs

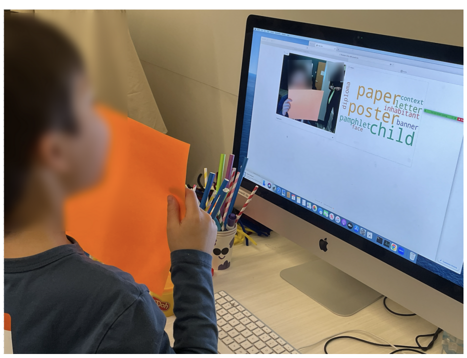
4.2.2 Data as a Design Feature for Access to Culturally Mediated Representation. While DS4 focused on helping children understand how AI models learn from data, DS3 focused on the design aspect of enabling AI to respond effectively to end users. During our third design session, children engaged in crafting tangible artifacts using materials like modeling clay, pipe cleaners, and construction paper. These artifacts (Fig.6) served as inputs for the word cloud classification interface (Fig.2), displaying the top ten probable words based on their inputs in real time. To construct the initial word cloud list, we used the Affective Norms for English Words (ANEW) lexicon [8], and after manual review by the first and second authors, we curated a final list of 300 words. The curation process involved removing words perceived as potentially harmful and retaining those with cultural significance. Therefore, in this case, regardless of the model's pre-training and envisioned capabilities during theoretical sessions, the AI's outputs were governed by the human-imposed restrictions of our word list. For instance, during the design session, P10 placed a small spider figure in front of the camera, expecting the word "*spider*" in the text box. However, the generated words included "*hand*" and "*finger*" but not "*spider*." Similarly, P1 created a "*UFO*" using blue modeling clay, but the outputs were descriptive words such as "*green*" and "*blue*" instead. This discrepancy occurred because the system could not access certain constructs such as UFO and spider, as they were not members of our word list.

During the design session, children recognized the system's restricted vocabulary, prompting an exploration into how changes in the testing environment influenced AI responses (Fig.7) . P10 exemplified this process when the word cloud interface mis-classified her yellow flower that she has created using a pipe cleaner. In order to eliminate potential distractions in the background, P10 strategically placed a white paper as a background and held her flower close to the camera. The system, this time, classified her artifact as a butterfly, sparking curiosity in P10 and P1 about the factors influencing AI's classification. In response, they began questioning how the features of their artifacts such as colors and shapes influenced the recognition process. As a first step, they decided to test if the AI could recognize the color yellow accurately. Through trial and error, with adult guidance, they explored various methods, from showing yellow paper with the word "*yellow*" written on it to presenting yellow objects such as P1's yellow jacket and a yellow post-it board. Despite their efforts, when the AI failed to output the word "*yellow*," P10 stated that ' '*yellow is not in the AI's output list.*" When asked, how do you think the AI works?, P10 responded, "*It has a list of words that are searched. The images from the search are then compared to the camera footage and the images that are closest appear.*"

4.2.3 Summary Analysis. Our findings show that children have a perceptible understanding of the role of data in AI-mediated culture. They recognized the significance of diverse and representative training datasets in influencing AI's capability to accurately reflect and interpret cultural concepts. For instance, when distinguishing between cats and dogs, children demonstrated an awareness of the complexity of AI classification rules and the potential biases that could arise from the choice of data. Furthermore, children

Figure 6: Physical Artifacts made by children to test different classifications generated by the wordcloud interface in DS3

(a) A child holding a crafted object to test AI's classification.



(b) A child observing the differences in classification when holding up a piece of paper instead of a crafted object

Figure 7: Children prompting the wordcloud system with different types of objects in DS3

understood the impact of data choices on AI responses [13, 15]. Faced with the human-imposed restrictions of a predefined word list for word cloud classification, children experimented with creating artifacts and explored how changes in the testing environment influenced AI responses.

4.3 Role of Human Mediators in Supporting Understanding of AI as a Cultural Tool

During our design sessions, children made use of their peers and adults to support their internal understanding of cultural concepts and how these concepts were represented by AI systems.

4.3.1 Peer Mediation. Peer mediation often involved children collaborating to either solve a problem or refine their conceptual understanding of AI. For example, during a creative writing session, P11 and P7 prompted *ChatGPT* with, "*Recreate the scene in Star Wars when Anakin Skywalker says, 'You underestimate my power'*," but in response, *ChatGPT* only provided an explanation, not a creative story. So, P11 and P7 revised the request to, "*Can you provide me with an alternative version of the scene in Star Wars when Anakin Skywalker says, 'You underestimate my power?'*" Despite the clarification, *ChatGPT* still provided "*exact summaries*" from the movie. Recognizing the need for a more novel prompt, the children proposed the idea of placing the Star Wars story on Earth. They all agreed on this new approach, thinking it would encourage *ChatGPT* to produce a more creative output. When they prompted *ChatGPT* with, "*Write me a story about Star Wars in a new galaxy,*" the model finally generated a creative output. In response, P7 said, "*This was a whole new story, but it seemed like it was in the same world, yet it felt like a completely different narrative.*"

Children also engaged in peer mediation while exploring AI classification during the word cloud activity (Fig.2). They collaborated to generate tangible inputs for the word cloud interface using materials like modeling clay, pipe cleaners, and construction paper. In one instance, to evaluate the AI's comprehension of emotions, P3 and P2 drew emotions on various objects, such as paper cups and paper straws. The children labeled the paper cups as a "*happy smoothie cup*" when a smiling face was drawn and a "*sad cup*" when a sad face was drawn. When they tested their "*happy cup*" and "*sad cup,*" the AI model classified the paper cups using words such as "paper," "milk," "beverage," and "office" to which P3 responded with, "*I think it just goes through a bunch of words in the dictionary or something.*" To this, P2 responded with his own hypothesis about how the emotion recognition would work, stating "*the camera takes in the facial features and matches it with the emojis....the emojis are stored online.*" In the group discussion, children further discussed how they conceptualised the word cloud classification. For example, reflecting on AI's outputs, P1 drew an analogy between the AI system and a child stating, "*It sometimes did the right thing, sometimes didn't do the right thing. It's still learning like a kid...first it gets it wrong, and then next it does it right...first it does it wrong, second it does it wrong, third it does it wrong, and fourth it does it wrong... and then infinitely does it wrong.*" Overall, these examples highlight how the children engaged in peer mediation to not only navigate and refine their interactions with AI but also to conceptualise the inner workings of AI models.

4.3.2 *Adult-Child Mediation.*

Adult-child mediation included adult co-designers often prompting reflection on the cultural implications of interactions with AI. This involved adults asking children to assess the quality of AI-generated text, check whether the results match the prompts in the way they desire, and reflect on the overall process of using GenAI. For example, when P11 prompted *ChatGPT* to generate "*a sad poem about rocks,*" after reading *ChatGPT*'s response, an adult asked P11 whether he thought "*the poem was sad enough*" for his expectations. This question allowed P11 to revisit the output and realize that he did not find the generated poem to elicit the desired level of sadness. In response, P11 issued a second prompt: *"make an even sadder poem about a rock that will make other rocks cry"* and a third prompt: "*make it even sadder and more creative.*" Despite repeated requests to generate a sadder and more creative response from the AI model, P11 noticed a pattern where the output remained largely unchanged despite varied prompts. His frustration was evident when he remarked, "*ChatGPT gives the same thing. It just makes it longer. At number 2, it found its limit and just repeated stuff.*" This observation highlighted his awareness that the model struggled to go beyond certain limitations, repeating phrases or ideas instead of successfully adapting to the requested changes in tone or emotion. During discussion time, where groups presented their final designs, the entire team reflected on the design experience with *ChatGPT*. When children were questioned, "*Do you feel that the first text you received was better than the last text you received?*" P3, P4, and P12 gave thumbs down, while P2 gave a thumbs up. P12 explained that, "*it gets harder because it's more difficult to explain things,*" implying that the initial stages of prompting were easier in comparison.

Adult co-designers also assisted children in navigating the specific functionalities and constraints of AI systems. For example, when children were creating storybooks using *DALL·E* and *ChatGPT*, P3 expressed the desire to provide two paragraphs of her story at a time to prompt *DALL·E*. In response, an adult explained to her about word limits when prompting the model. Additionally, when prompting *DALL·E*, P3 assumed that the model would know who her character "*Lisa*" is based on her previous interactions with the model. The adult then clarified that *DALL·E* does not remember previous user prompts and, therefore, would not recall who "*Lisa*" is without a full description. In response, they worked together to come up with the prompt, that provided a description of the girl detective and later discussed the potential challenge of maintaining consistent image styles. P3's challenge in achieving uniformity in image style with *DALL·E* was similarly shared by P10 and P11. P10 expressed dissatisfaction with the image generation process, stating she had to "*put in the same stuff over and over again, it was kinda tedious*" while P11 shared his frustration, mentioning that "*the pictures weren't turning out the way they wanted.*" When an adult asked for their feedback on missing *DALL·E* features, P11 suggested an "*English dictionary*", while P10 emphasized the need of a "*style picker to maintain consistency.*" Later in the group discussion, when children were asked about, "*how they would feel if the stories they liked were written by AI*", P2 expressed that he would lose the feeling of being connected to the author and that would "*dismantle some of the joy of reading.*" P1 agreed, stating he wouldn't like it if AI wrote the stories he read. However, P2 argued that AI could write books with more information, so he was not sure if he cared. P7, on the other hand, expressed that he would not like it because "*it feels too easy to just have the computer write something.*" These varied responses underscore the role of mediation [16] in enabling children to articulate their preferences and challenges with the AI system.

4.3.3 *Summary Analysis.*

In both cases of human mediation, peer-to-peer and adult-child, the additional layer of human mediator acted as a scaffold to interpreting the symbols suggested in interactions with AI [44]. Peer interactions tended to focus on building understanding by providing new context that connected the provided cultural symbols. For example, during the creative writing session, children collaborated with each other to refine prompts for *ChatGPT*. On the other hand, adult interactions focused more on prompting reflection or providing new context via questioning of assumptions or provided cultural representations, as seen through discussions on children's design experience and their preferences for AI-generated content.

5 DISCUSSION

In our discussion, we first introduce the connection between AI as a cultural tool and new digital media, suggesting that this connection is an additional competency needed for AI literacy. Second, we introduce a set of three design principles and discuss their implications for designing educational tools and AI systems.

5.1 Understanding AI as a Cultural Tool

Our findings demonstrate that children perceive AI as a technology that mediates cultural signs through the reinterpretation of other personally culturally relevant media (4.1), initially informed by human selected data (4.2), and subsequently refined through human-to-human interactions (4.3). Moreover, the necessity for dialogues with peers and adult co-designers aligns with prior research suggesting that children may not inherently grasp the symbolic aspects of AI interactions without human mediation [30, 38]. Ultimately, these factors suggest that children may understand AI as a tool that mediates through *simulation* [69], as the children in our study were skeptical about AI's ability to accurately replicate the familiar media symbols they knew. The effectiveness of the simulation of culture in Human-AI interactions is in part dependent on the ability of both the user and the AI system to interpret cultural concepts. We see this as an affordance [70], which we deem an *affordance of cultural representation.* Additionally, this affordance may be further understood via the media theory of *remediation* as described by J. David Bolter and Richard A. Grusin [5]. Remediation as a theory posits a connection between new and old media, such that:

> New digital media are not external agents that come to disrupt an unsuspecting culture. They emerge from within cultural contexts, and they refashion other media, which are embedded in them or similar contexts. [5, p. 19]

More specifically, Bolter and Grusin suggest that the "repurposing" [5, p. 50] of media is dualistic. AI revitalizes old cultural symbols and is simultaneously constrained in the emergence of new ones. If understood through the lens of remediation, the act of comparison children exhibited in the interpretation of the cultural signs embedded in their own personal knowledge indicates children noted AI's *hypermediacy* [5]. That is, AI emphasizes the medium itself, exhibiting how AI allows for "*random access*" [5, p. 31] to information via multiple media elements (text, visual, sounds, etc.) in one interface bound by the data selected for training *as well as* the ability of the user to mediate their own cultural understanding. For example, the images generated by children in Figure 4, are not only images of *Back to The Future*, but they are representations mediated through the child, the computer, the data, and the larger media and political landscape that lead to their creation. In this way, the *affordance of cultural representation* is akin to Jenkins' concept of *participatory culture* [39] in that due to the possibility of simulating the creation of new cultural signs, both users *and* systems are encouraged to "*make connections among dispersed media content*" [39, p. 3], creating new meaning through layered remediation of not only the production/manipulation of media content but the user themselves. Hence, we can understand AI as a technical cultural tool that that magnifies remediated versions of cultural symbols, allowing us to reflect our own psychological tools [44] in a simulation of the larger media ecosystem [69].

Consequently, we argue that understanding AI as a cultural tool necessitates understanding its status as a new medium[60], and in turn, AI literacy may be scaffolded through other forms of media literacy. Positioning AI as a new medium allows for its comprehension through media literacy frameworks, which encompass not just practical skills but also a critical understanding of the broader social, economic, and cultural implications of these technologies [11]. Former exploration into AI mediated communication suggests that AI mediated communication can impact how trustworthy and potentially impact interpersonal communication [66]. Further approaches to AI literacy and exploration of bias in AI systems may benefit from not only defining these cultural representations (i.e., identifying that a system is biased toward one gender or another), but highlighting the other cultural media content that leads to that interpretation outside the system. Understanding AI's impact on human culture is a foundational competency to critically engage with the technology [57, 90]. However, it is important to give more focus to discussing the groups of people involved in creating these technologies, the social and economic structures that encourage them to do so (including digital environments such as the world wide web), and how this knowledge may impact a user's understanding of their own role in socio-political life. AI is not only a medium in itself, but is also a producer and interpreter of culture – through interactions with people and their cultural productions – that is integrated with other forms of media, a foundational concept of defining new media [54, 60]. As designers, researchers, and developers contend with these advances and changes in technology, the role that AI will take on in the cultural milieu is a crucial consideration.

5.2 Design Principles to Promote Understanding of AI as Cultural Tool

Based on our findings, supporting children's understanding of the way AI mediates cultural signs involves highlighting the *affordance of cultural representation* through: drawing attention to the way AI remediates cultural signs through repurposing cultural content (4.1), emphasizing the way data is chosen by humans (4.2), and provide opportunities for children to compare their interpretation of the signs identified in AI-child interactions with other human agents (4.3). Based on these insights, we suggest three design principles we think would be helpful in supporting understanding of how AI may act as a cultural tool that mediates cultural concepts, providing scaffolding that can assist young people in understanding the complex reciprocal relationships of AI and culture.

5.2.1 Principle 1: Highlight the Concept of Remediation in AI Systems. We first suggest that AI literacy education should highlight the role that remediation plays in AI systems. This includes developing scaffolds that help people understand the ways that AI systems are dependent upon changing between other forms of cultural tools, such as language into mathematics, as well as as how these systems interpret the cultural signs they are familiar with such as the signs that arise from media content (4.1). AI presents a hypermedia environment, wherein remediation should be highlighted [5], but our findings suggest a focus on understanding how AI *repurposes* cultural signs differently than human cognition is essential for critical engagement with AI as a cultural tool. Remediation inherently includes transformation. This means that to develop transparent AI systems, we must explain the cultural background in which these systems were made. This includes not only why certain data was chosen but also the reasons behind creating the systems and how we, as users, fit into the broader socio-cultural environment. Additionally, understanding the role that AI plays as a cultural tool includes recognizing that AI is embedded in networked culture, encouraging connections and changes between new and old media [89]. Furthermore, this remediation in our current digital culture is reliant on participatory culture, such that individuals are not only consumers, but actively involved in the creation, modification, and sharing of culture in networked environments with digital tools [39].

5.2.2 Principle 2: Structure Experiences with AI to Align with Personal Cultural Understanding. Building on prior work showing that creating learning experiences that bridge AI concepts with familiar cultural contexts allows children to develop a more critically informed perspective on AI [32, 68, 92], our work highlights that children who critically engage with AI content draw upon their prior knowledge and cultural experiences to evaluate AI representations [67]. While engaging with AI technologies for creating artifacts can enhance student engagement and learning outcomes [32, 68, 92], it is crucial to acknowledge that many AI systems are not designed with children as the intended audience, user, creator, or consumer, thus making such tools difficult to use and interpret. By extension, many novice adults (either by youth or by level of technological literacy) do not have the education to help them identify how certain AI tools may support their experiences with AI [48]. Additionally, due to the lack of cultural understanding of AI systems there is concern that potentially harmful cultural representations found online and elsewhere may be further amplified via the use of AI integration into other technologies by novice users (or malicious actors) [51]. In order for these tools to act as cultural mediators, they must meet users where they are and users must understand where they are, which also leads to the third design principle.

5.2.3 Principle 3: Recognize that AI Can Serve as a Cultural "Object to Think With". In our design sessions, we observed numerous instances of tinkering [78, 79], as children refined their ideas about AI's capabilities and limitations. As part of this trial and error process, children actively engaged in dialogue with their peers and adult co-designers, who helped mediate their cultural understanding [82]. The ability to iteratively tinker and mediate through discussion with others becomes a powerful opportunity for collaborative exploration. In this way, AI served as what is referred to by Seymour Papert, a key figure in constructionist learning theory, as "objects to think with" [72]. Interactions with AI systems and concepts served as as a mediator to allow children to not only reflect on and refine their ideas about AI but also to adjust their ideas about how AI integrates with their understanding of culture. Projects like these that involve the revision and development of ideas also provide a pathway for learners to "uncover the 'why' behind concepts, delve into underlying logic, assumptions, and principles rather than accepting them at face value" [p.15] [85]. This not only equips youth to pose more refined questions but also empowers them to identify and challenge AI's outputs and reflect critically on AI's limitations [18]. Furthermore, dialectical engagement with their peers enable children to recognize diverse approaches to problem-solving in the AI context [36]. In contrast, neglecting these opportunities for mediated discussions – such as shutting down discussions of AI in the classroom – can hinder the development of critical perspectives by limiting the diversity of ideas and preventing meaningful engagement with the complexities of AI.

5.3 Applications for Children and Beyond

Overall, we suggest that to understand AI as a cultural tool, and its potential impact, we must be aware of the ways that AI continually remediates elements from previous media such as literature, photography, or cinema [5], and more broadly consider how AI may simulate cultural symbols in a dualistic nature. In Vygotsky's language, children in our study understood AI to function as both a *technical tool*, manipulating forms of media, but also as a *psychological tool*, helping them understand their own cognitive models [44]. AI is not only "amplifying bias," it is *mediating* the ways that we understand what bias is in our own cultural experiences. This implies that AI literacy education focusing solely on AI-as-technology may not prepare children – or their surrounding adult ecosystems of parents, teachers, and beyond – to understand the cultural impact of this new technology.

Our work positions understanding remediation as an important concept for children and other learners with regard to the computational aspect of AI literacy, as AI also remediates other forms of cultural tools such as language. Moreover, our principles suggest that AI literacy activities should be based in personal cultural understanding and provide opportunities to iterate with AI tools or concepts [67, 72]. The use of peer discussion emerges as a particularly apt way to guide children through reflection of their own *psychological tools*, highlighting their own cognitive processes in understanding cultural concepts [82]. Subsequently, adults and peer facilitators can prompt moments of reflection [44], enabling children to compare their cognitive process with those of AI.

While we have explored these concepts of mediation with children, we see these principles as useful in supporting AI literacies in adults as well. Research has suggested that adults remain wary of AI mediated communication [35, 55], which may in part be due to the lack of attention paid to adult AI literacy education [95]. This is especially true for marginalized communities, whose socio-cultural differences are critical to understanding their trust and use of AI [49]. In their literature review on AI Literacy in adult education, Wolter et al. [95] suggest a need for relevant professional and sector-based competencies for adults. This suggests that AI Literacy that is culturally relevant – meaning that it is built upon personal cultural context such as a work environment – is a potentially fruitful avenue to also help adults contend with the changing technologies that are increasingly integrated into their cultural lives. For example, there is already increasing research exploring the perceptions and needs of adults using AI in the health field [71, 88]. Additionally, there is discussion around options for public AI literacy that may happen in informal learning and inter-generational spaces [56, 59]. Arts-based representational techniques and media has increasingly been used as a strategy to facilitate AI literacy [4, 33, 93], suggesting that cultural mediation is one way to promote interest across all ages in AI and its societal impacts. Likewise, providing scaffolded opportunities for understanding AI's role, applications, and implications in the context of broader digital culture can help to enhance AI literacy by encouraging people of all levels and expertise to explore how AI interfaces with other technologies, cultural artifacts, and their own socio-cultural expectations. [40]

6 LIMITATIONS & FUTURE WORK

While our research was well-grounded in precedent and methodology, we acknowledge several limitations inherent in our study. The study's reliance on a relatively small sample of 13 children was consistent with prior PD sessions with children (e.g., [24, 28, 100]) and allowed for an in-depth exploration [27]. However, this may have limited the extrapolation of results to a larger and more diverse group of children. Additionally, due to the structure of our co-design group, not all children were present for each session, potentially further limiting the generalizability of our results. Furthermore, the children in this study were from a single geographic location, somewhat privileged backgrounds, and had existing familiarity with technology and co-design methods. While this prior experience resulted in children comfortable with freely sharing their opinions with researchers [63], the results may not fully capture the diverse perspectives and capabilities of children across a broader socio-economic spectrum. Future work could aim to address these limitations by expanding the participant pool to include a more diverse demographic, especially when conducting remote PD sessions. Additionally, the extended duration of our study–over eight months–presented challenges in maintaining consistent participation, potentially affecting data consistency and the evolution of the children's responses over time. Future studies might benefit from more frequent sessions or shorter study periods to reduce these impacts. Considering the rapid evolution of AI technologies, future work could also investigate how children adapt their mental models to keep pace with technological developments and how this, in turn, influences their interactions and decision-making processes with the technology. Lastly, the principles and methods presented here have strong potential for being adapted to additional populations beyond children. Such PD interactions could include understanding the specific cultural needs of teachers, parents, older adults, individuals with accessibility concerns, novices, or others who are underserved by current AI literacy practices.

7 CONCLUSION

In this work, we demonstrate how children in co-design workshops came to understand AI as a cultural tool. Our findings revealed that children were able to recognize and articulate the influence of AI on culture. The effectiveness of AI in mediating cultural concepts depended on its alignment with the child's personal cultural experiences, the availability of opportunities for iteration, and discussions with peers and adults. Based on our findings, we argue that framing AI as a cultural tool situates it within the domain of new media. This perspective suggests an affordance of cultural representation, highlighting the double role that AI plays as a psychological and technical tool. As a result, we propose that foundational competencies in AI literacy for children should include the ability to connect AI interactions to personal cultural experiences and a comprehensive understanding of how data intersects with culture, centering on how these elements arise via remediation. Additionally, we introduce three design principles to facilitate a nuanced comprehension of AI as a cultural tool. First, we advocate for highlighting the concept of remediation [5] within AI systems. Second, we propose that AI experiences should align culturally with users' personal backgrounds. Third, we contend that AI can function as a cultural "object to think with" [72]. We hope that these contributions will be useful to scholars and practitioners who aim to help learners become informed and critical users of AI technologies.

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