Family as a Third Space for AI Literacies: How do children and parents learn about AI together?

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ABSTRACT

Many families engage daily with artificial intelligence (AI) applications, from conversations with a voice assistant to mobile navigation searches. While there are known ways for youth to learn about AI, we do not yet understand how to engage parents in this process. To explore parents' roles in helping their children develop AI literacies, we designed 11 learning activities organized into four topics: image classification, object recognition, interaction with voice assistants, and unplugged AI co-design. We conducted a 5-week online in-home study with 18 children (5 to 11 years old) and 16 parents. We identify parents' most common roles in supporting their children and consider the benefits of parent-child partnerships when learning AI literacies. Finally, we discuss how our different activities supported parents' roles and present design recommendations for future family-centered AI literacies resources.

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1 INTRODUCTION

In the current digital information era, families are rapidly engaging with technologies powered by artificial intelligence (AI). AI systems show great promise in helping families through improved online search quality, increased accessibility via digital voice assistants, and AI-supported learning [51, 100, 101]. Moreover, family use of AI and smart devices increasingly intertwines with existing media consumption, with voice assistants serving as a gateway for family media and connected devices [68]. This engagement with AI technologies is likely to increase due to significant growth in smart toys; further, more than 50% of North American households are expected to have a dedicated voice assistant by 2022 [109].

Several initiatives provide AI educational resources for youth [37, 75, 117]. However, few resources currently help parents mediate the use of AI technologies, despite growing parental concerns about their children's in-home use of AI. Pediatricians, policymakers, and parents associations struggle to provide family guidance for appropriate AI use, and their recommendations are influenced by the affordances and limitations of existing commercial AI products [1, 2, 105, 125]. Further, AI products such as voice assistants or smart mobile apps are not necessarily developed for youth despite increasing usage [1]. These products pose additional concerns in terms of (1) *inclusivity* for families of different ethnicities, familial structures, general technological literacies, and diverse socioeconomic backgrounds [9] and (2) *algorithmic fairness*, or subtle ways AI technologies can amplify bias, sexism, racism, and other forms of discrimination [10, 25].

Prior studies have described the benefits of families jointly learning about technology or engaging in technology co-design. For example, Barron et al. showed that parents could play various supporting roles, such as collaborator and learning broker [16]. More recent work by Michelson et al. emphasized the importance of balanced partnerships in family technology co-design activities [82], and Yu et al. showed that parents primarily act as spectators, scaffolders, and teachers when supporting children interact with coding kits [135]. Though these studies underline the importance of family engagement in children's technology learning, we remain primarily in the dark about best practices supporting family joint AI learning and co-design.

To understand joint AI learning, we explore how families can best develop multiple *AI literacies* in the home. Our work builds on the notion of multiple literacies [26], which emphasizes how negotiating multiple linguistic and cultural differences in our society is central to the lives of young people. By using the lens of multiliteracies, we aim to let families achieve twin goals for AI learning: (1) creating access to the evolving language of AI technologies and the power and community it can bring, and (2) fostering the critical engagement necessary to design social futures and meaningful use of AI in the home. For our purposes, *AI literacies include the ability to read, work with, analyze and author with AI* [37, 40, 41]. Our framing of multiple AI literacies also borrows from Freire's assertion that literacy is about not only the acquisition of technical skills but the emancipation achieved through the literacy process [48].

Parents are experienced learning designers, routinely improving learning experiences for their children. Suppose parents had a rudimentary understanding of how AI works and considered valuable applications of AI for their families. In that case, they could translate and explain AI terminology and concepts to their children and thereby guide meaningful adoption and use of this technology in the home, as was the case for video games [106], and

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digital media consumption [15, 86, 130]. To understand how families of different ethnicities, structures, technology exposure levels, and socioeconomic backgrounds interact with and learn about AI literacies, we pose the following research questions:

- RQ1: How do children and parents learn about AI together?
- RQ2: How can we design learning supports for family AI literacies?

To address these questions, we conducted a 5-week longitudinal study of 15 families with varying levels of prior knowledge about technology and AI, where they engaged with the AI literacies activities we created. We designed four learning sessions comprising of 11 learning activities based on the four dimensions for multiple literacies, a framework proposed by the New London Group (NLG) [26] that we adapted to the field of AI learning for families by building on prior work [40, 75]. In the 5th study session, we solicited feedback from families on the study learning activities.

We recorded and transcribed all study sessions to identify how family members supported each other to develop multiple AI literacies when engaging with our learning activities. We used the Joint-Media Engagement (JME) theory as formalized by Stevenson et al. when studying family learning with digital media [110] and the Parental Scaffolding Behavior theory formalized Ewin et al. when studying how parents support children during joint engagements with mobile devices [45]. We developed a set of inductive codes based on these theories, which we used to analyze our transcripts. Via thematic analysis of our codes, we identified eight parents' roles to support children's AI literacies practices. We then presented how our different activities supported parental roles in each session and proposed design recommendations for future family-centered AI literacies resources.

Our findings constitute a road map toward understanding family learning pathways to early AI literacies and contribute guidelines for supporting a constellation of family practices [98] and interests. Situating family AI literacies within the larger context of critical computational literacies [59, 64] and family as third space for socio-critical literacy [53, 107], this paper surfaces the benefits of partnerships between children and parents when reflecting on how to make use of AI for their family meaningfully. Finally, our study conceptualizes AI as a socio-material knowledge with social and societal histories and consequences.

2 BACKGROUND

In the following section, we discuss relevant prior studies on family learning and technology, family joint-engagement and parental scaffolding, and AI literacies for families.

2.1 Family Learning and Technology

Although a growing body of work suggests that technology-enabled tools could effectively scaffold parent-child activities, most to date have focused on supporting remote parent-child communication. For example, numerous projects have analyzed how technology-enabled systems can provide a virtual space where parents and children interact [58, 113, 133]. Other studies explored how to support remote parent-child activities, such as facilitating gameplay [47, 57] or reading together [96]. Recent work on parent-child interactions in co-located contexts has studied multi-touch tabletop applications [131], sensor-based exergames [103], and technology-enhanced storytelling activities [28, 115]. Although this work informs design, it does not speak to learning and AI literacies.

Barron et al. [16] interviewed the parents of eight middle school students engaged with an ongoing technology project, identifying seven distinct roles parents assume when supporting their children: teacher, collaborator, learning broker, resource provider, nontechnical consultant, employer, and learner. The students all came from a primarily upper-middle-class community, and at least one parent of each child worked as an engineer or designer in the computer industry. Our study expands upon this work by identifying parental roles that emerge from home-based parent and child interactions with AI across a diverse set of families.

Yu et al. similarly performed semi-structured interviews with eighteen parents, researching their roles and perceptions of the coding kits their young children use at home [135]. They found parents predominately acted as spectators, scaffolders, and teachers, although parents did not necessarily perceive themselves as playing these roles. Additionally, parents were concerned they would not be able to help their children due to their limited programming knowledge. Our study aims to identify parents' language and scaffolding strategies to explain AI concepts to their children when they both learn the concepts together; doing so offers an opportunity to identify potential future interventions that address this specific parental concern.

2.2 Family Joint-Engagement & Scaffolding

Stevens and Takeuchi completed a review of research on *Joint-Media Engagement* (JME), which they define as the "spontaneous and designed experiences of people using media together" [110]). Activities were designed, so children and parents work together and engage with various forms of media. Their analysis considered the six ideals of productive JME presented in the paper: (1) mutual engagement, (2) dialogic inquiry, (3) co-creation, (4) boundary-crossing, (5) intention to develop, and (6) focus on content, not control. [110] This joint media engagement framework guides both our study design and our analysis.

AI, as a unique form of media, elicits assumptions and interactions different from more traditional technological media forms, such as television. By engaging with it through the JME framework, we can see how it intersects with established JME parent-child dynamics and where it differs from or extends them. Furthermore, we build upon the third research case study presented by Stevens and Takeuchi by studying "ways that parents can be supported to engage in joint media engagement-creation (JME-C), even when they do not have expertise" and carrying out "micro-interactional studies to better theorize cognitive and relational ... [and] affective components of JME-C" [110]. The JME-C framework is of particular interest to our study as explorations of AI literacies applications in families are challenging since the mechanisms and opportunities of AI are unfamiliar to most people outside computer science.

In a systematic review of 27 papers, Ewin et al. identified various scaffolding techniques used by parents and children in JME scenarios [45]. They combined the scaffolding schemas of Yelland & Masters, Neumann, and Wood et al. into an extended version of Yelland and Masters' scheme, finding that most assistance can be categorized as (1) cognitive, (2) physical, (3) affective, (4) technical, (5) limited, and (6) negative [86, 130, 134]. We build on this schema when analyzing parental scaffolding in our activities.

A recent study on family mediation of preschool children's digital media practices at home also found that family members are often unaware of the extent to which they support children in developing competencies concerning media texts and devices [104]. By involving both parents and children in joint AI literacies activities, we aim to surface the roles family members play in supporting each other and make these roles explicit and visible to each other.

2.3 Family AI Literacies

With the advent of smart devices and connected toys in the home, there is an increasing need to better understand and support family-AI interactions [109]. This increased adoption also raises new concerns for parents and researchers as to how best to protect children's privacy and data [72, 73, 88]. Many AI devices have proven to be easy to compromise [8, 118, 129], and some companies designing these technologies engage in questionable practices [2]. However, current AI devices provide limited ways for parents to properly manage their children's data on such platforms [6]. Beneteau et al. also showed that parents play an instrumental role when helping their children better communicate with voice assistants [20] or identify assumptions these assistants make about children's questions [18]. Druga et al. showed that parental models of machine intelligence also influence how children attribute intelligence to machines [39] and that children and parents can successfully engage in joint AI learning activities [40]. More recently, Long et al. showed that parents and children can also co-design interactive AI museum exhibits [74]. While these studies provide important insights into how families perceive, interact with, and learn about AI, they do not address how children and parents could learn about different forms of AI together.

The unequal access to smart agents amplifies digital divides, with only some children learning to make sense of how smart toys and devices function [17, 33]. Prior work has demonstrated that parental attitudes, socioeconomic status, and cultural differences play a significant role in how children attribute agency, intelligence, and socio-emotional traits to the agents [37, 39]. Other studies have shown that children often misunderstand agents or tend to overestimate their abilities, either because children do not understand how these agents work or because artifacts like toys and phones can talk, express emotions, and engage with youth in ways other humans would: with persuasive and charismatic modes of engagement [46, 94, 132]. However, more recent studies have shown that children change their perception of AI abilities after engaging in AI programming and training activities [35].

In this context, we recognize the need for inclusive AI literacies to prepare a generation of children growing up with AI. We situate AI literacies as the ability to engage in the following practices: (1) multimodal and embodied situated practices, (2) AI conceptual learning, (3) critical framing of AI, and (4) design for future meaningful use. Our approach builds on the theory of "multiple literacies" [26]. This theory has been recently used to propose a transversal approach to computing education for youth [81], as a way to define critical literacies in a digital age [108], conceptualize digital games literacies for youth [12], and propose new computational literacies [121]. Other studies have also used the multi-literacies framework to frame family literacy as a third space [53] between home and school [89] and to observe family environments that foster kids curiosity [63].

In this context, we see the family and the home as a third space where children can develop AI literacies. Therefore, we aim to explore how to design family-centric learning activities that create zones of possibilities [85] by combining family social contexts for learning and their collective zone of proximal development [124].

3 METHODS

To understand how families jointly engage in AI literacies, we structured our study in the following order: observations of families engaging in four AI learning sessions, collecting family feedback on AI learning sessions, analysis of observations and family feedback to understand families' AI literacies practices and their use of AI learning resources.

3.1 Selection and Participation of Families

We recruited a total of 15 families for our study, consisting of 18 children and 16 parents participants. We posted an announcement on several family forums, social media groups, and Slack channels to recruit. Forty-four families applied to participate in the study. Our inclusion criteria for the study was to select families that were as diverse as possible along the following dimensions: family structure, ethnicity, geographical location, socio-economical background, children ages and gender. We selected 15 families. Of the 15 chosen, only 11 attended all the sessions. One family attended only one session, and three families attended only two sessions. The families unable to attend sessions cited extraordinary family circumstances as the reason or skipped sessions they deemed inappropriate for the young age of their child.

Children's ages ranged from 5 to 11 years old, with an average age of 8.5 years old. Ten children were female, and 8 were male. Of the total of 16 parents, 11 were female, and 5 were male. Of the 15 families, 5 were Asian American and Pacific Islander, 5 were White, 3 identified as multi-ethnic, and 2 were Hispanic or Latin. Families were located in 10 US states distributed evenly across the country. In terms of languages spoken, 10 families reported speaking languages other than English at home; these included 10 distinct languages and dialects such as Spanish, Chinese, Hindi, Tagalog, Gujarati, and Malayalam. Regarding technology literacy, 6 parents had professional experience with technology design, 3 had programming experience, and the remaining 7 had no programming experience. In addition, families reported in-home use of a wide range of smart technologies: 15 families used a computer and smartphone, 9 used a voice assistant, five used coding kits, and 4 had robots.

All parents and children older than age 7 signed digital consent forms reviewed by an institutional review board agreeing to participate in our study explained to them by the first author of this paper. A list of family demographics is presented in Table 1.

3.2 Study Design Rationale

We situate our AI literacies framing within the theory of "multiple literacies" proposed by NLG. This theory conceptualizes the

Family ID	Parent(s)	Language(s)	Child(ren) and Age(s)	Joint Time
F1	Mom (S.), Dad (J.)	English, Spanish	Son, 7 (G.)	2 hrs, 57 mins
F2	Mom (C.)	English	Son, 9 (Et.) & Son, 9 (E.)	2 hrs, 49 mins
F3	Mom (D.)	English, Gujarati	Son, 11 (R.)	2 hrs, 34 mins
F4	Dad (E.)	English	Daughter, 10 (Sb.) & Daughter, 6 (Sm.)	3 hrs, 21 mins
F5	Mom (K.)	English	Daughter, 9 (L.)	1 hr, 5 mins
F6	Mom (T.)	English, Spanish	Daughter, 10 (H.)	2 hrs, 44 mins
F7	Mom (G.)	English, Chinese	Son, 7 (R.)	1 hr, 9 mins
F8	Mom (L.)	English	Son, 9 (E.)	2 hrs, 14 mins
F9	Mom (J.)	English, Spanish	Daughter, 10 (C.)	2 hrs, 7 mins
F10	Mom (I.)	English	Son, 10 (S.) & Daughter, 8 (K.)	0 hrs, 29 mins
F11	Mom (R.)	English	Son, 11 (A.)	2 hrs, 25 mins
F12	Mom (N.)	English, French	Daughter, 9 (C.)	3 hrs, 19 mins
F13	Dad (N.)	English, Hindi, Marathi	Daughter, 7 (M.)	2 hrs, 56 mins
F14	Dad (N.)	English, Hindi, Malayalam, Gujarati	Daughter, 8 (M.)	3 hrs, 5 mins
F15	Dad (A.)	English, Tagalog	Daughter, 5 (L.)	1 hr, 49 mins

Table 1: List of families that participated in the study

pedagogy of multi-literacies along the following dimensions: (1) situated practices, (2) overt Instruction, (3) critical framing, and (4) transformed Practice [26]. We discuss below how we expand the definitions of the different dimensions proposed by the theory of multiple literacies in the context of AI learning for families. Thus we propose our own AI literacies dimensions, building on prior work in the field of AI education for families, and present how we used each of these dimensions to design our study learning activities presented in Table 2. Full descriptions of activities are included in the appendix.

3.2.1 ***Multimodal Situated Practice.***

The NLG group defines *Situated Practice* as "immersion in experience and the utilization of available discourses, including those from the students' lifeworlds, and simulations of the relationships to be found in workplaces and public spaces" [26, p. 88].

We define *Multimodal Situated Practice* as comprising of learning experiences where activities have images, sound, and text. These learning experiences connect to families' lived experiences and daily practices. Prior work on multimodal learning supports for families has proved that such designs can support various engagement styles and preferences and are beneficial for sustained engagement. Moreover, research on tangible learning for youth supports the case for a hybrid approach between providing digital and tangible supports when designing learning activities [56, 71, 78, 92, 93]. We use this AI literacies dimension to design the "Image Classification Game", "Image Anchor Game", and the "Draw What is Inside" learning activities presented in Table 2. These activities allowed students to engage with activities using either images, text, or tangible supports.

3.2.2 ***Embodied Situated Practice.***

We also build on the *Situated Practice* definition proposed by NLG group [26] and the *Embodied Interaction* framework proposed by Dourish [34]. We define *Embodied Situated Practice* as comprising of learning experiences where families are engaged in the creation, manipulation, and sharing of meaning through interaction with artifacts connected to families' lived experiences and daily practices. Embodied interactions have been promoting learning in multiple domains of youth learning [4, 11, 43, 111, 112]. In addition, several studies explored how youth can learn more about AI via embodied interactions with pre-trained models [61, 75, 120, 137]. These findings encouraged us to explore and design new ways for children and parents to engage in situated embodied interactions with AI. We use the Embodied Situated Practice dimension to design the "Object Recognition", "Train AI" and the "Analyze AI" learning activities presented in Table 2. In the activities, family members got to manipulate, create and adapt interactive AI prediction applications.

3.2.3 ***AI Conceptual Learning.***

The theory of "multiple literacies" defines the *Overt Instruction* dimension as "Systematic, analytic, and conscious understanding." [26, p. 88]. In our study we build on this definition and we propose the *AI Conceptual Learning* AI literacies dimension. We define *AI Conceptual Learning as the act of engaging with different cognitive supports such as explanations, definitions, and examples to develop understanding of different AI concepts.*

Prior work on AI conceptual learning revealed many challenges, including the importance of children understanding the role of data in shaping machine behavior [84] and the persistent challenge of debugging and comprehension [114]. The ongoing work in the domain of explainable AI [127] highlights opportunities for AI conceptual learning by uncovering different features of black-box technologies [125] and by supporting learners to ask sense-making questions about AI technologies [35]. Building on designs and findings from this prior work, we used the AI Conceptual Learning dimension to design series of Playbook guides for families. The family playbook included scaffolds of AI concepts (i.e. "what is machine learning?"), reflection prompts (i.e., "how would a computer solve this puzzle?") and AI explanations. We sent a playbook guide to each family before each study session.

3.2.4 ***Critical Framing of AI.***

The theory of "multiple literacies" defines the *Critical Framing* dimension as "Interpreting the social and cultural context of particular Designs of meaning. This involves the students' standing back from what they are studying and viewing it critically in relation to its context." [26, p. 88]. We expand on this definition and consider how family members can interpret the social and cultural context of their AI use and understanding. We define *Critical Framing of AI* as the ability to analyze and critique different AI abilities and their applications.

Prior studies have shown that family members often misunderstand AI technologies and tend to overestimate their abilities [94] or even feel peer pressure from computer agents [132] or robots [29, 122]. In this context, we believe it is essential to situate family AI understanding and use within the larger context of critical computational literacies [60, 64, 79]. To do so, we used the Critical Framing of AI dimension to design the "Reflection", "Prediction Game", the "Compare with Voice Assistant", and the "Analyze AI" learning activities presented in Table 2. For each of these activities, we prompted family members to reflect on when to use or not to use AI, identify specific AI limitations and potential pitfalls of different AI technologies.

3.2.5 ***Design Future Meaningful Use.*** The NLG group defines *Transformed Practice* as "Transfer in meaning-making practice, which puts the transformed meaning to work in other contexts or cultural sites." [26, p. 88]. We adapt this framing to consider ways in which children and parents could engage in meaning-making practices that would allow them to use AI technologies at home better. Thus, we define *Design Future Meaningful Use* as the ability to imagine and design future AI features and applications that are meaningful and useful. Prior work showed youth can engage in *worlding* and imagine future meaningful uses of technology via speculative design [128] and suggested news ways for families to design future smart toys [36], engage in AI-based citizen science projects [27, 49, 116] or co-design AI-museum exhibits [74].

We used the Design Future Meaningful Use dimension to design the "Reflection", "Draw What is Inside", and the "Design AI" learning activities presented in Table 2. For each of these activities, we prompted family members to imagine and design future AI applications and think about how they could make smart technologies positively impact their families or society.

3.3 Study Procedure

Our study consisted of five sessions: (1) an image classification activity, (2) an object recognition activity, (3) a voice assistants activity, (4) unplugged AI learning and co-design activities, and (5) a reflection on study activities. The study took place online, and we used a free video conference application to connect with the families and guide them through the activities. In addition, detailed instruction playbooks, sent to each family one week before each study session, described the learning activity and provided links to tools, apps, or printed documents they needed to use during the activity (detailed descriptions of all study materials are included in the appendix).

Session 1: Image classification. In this initial activity, families learned how to classify images of various marine objects ("Classification Game"). They then learned how to pick a representative segment of each image (anchor) such that an algorithm could guess what the image was about solely by examining this smaller segment ("Anchor Game"). Both activities were conducted on a dedicated digital platform we designed and built. After these activities, families reflected on using them for good ("Reflection").

Session 2: Object recognition. In this activity, each family got to experiment with and learn about automatic object recognition. This session had 3 parts. The families (1) used a free smartphone app that recognized objects in their house and tried to tag them ("Object Recognition"), (2) trained their models for object recognition using a free public web app on their computers ("Train AI"), and (3) took a quiz that prompted them to guess what the computer model would predict for similar-looking objects ("Prediction Game").

Session 3: Voice assistants. For the third session, families engaged with voice assistants. This activity had 2 parts. (1) The families played a game with a voice assistant of their choice, comparing the assistant's answers with one of the family members' answers ("Compare with Voice Assistant"). If the families did not have a voice assistant, they were instructed to use Siri or download the Alexa mobile app. (2) The participants were asked to draw what is inside the voice assistant and how it works ("Draw What is Inside").

Session 4: Unplugged AI games and co-design. This last interactive session consisted of 3 parts. Family members (1) completed a set of prompts by getting their voice assistant to say or do specific things ("AI Bingo Game"), (2) compared humans, robots, and voice assistants on a printed scale that assessed dimensions of intelligence and socio-emotional attributes ("Analyze AI"), and (3) designed their smart assistant using different components from an AI toolkit we provided ("Design AI").

Session 5: Reflection on study and learning activities. In this final session, participants reflected on each activity. They were asked to describe the following: how much fun they had doing the activity, how easy it was to do the activity, and how much they learned. We also asked for suggestions about improving the activity and descriptions of what they liked the most. The first author then prompted the families to reflect on whether and how they would change their current uses of AI technologies and asked them to describe future AI learning activities they would like to use.

3.4 Data Collection and Analysis

Our study produced video recordings of all online sessions with individual families that participated in the study. A total of 35 hours of footage was collected from all sessions. The average duration for a family session was 33 minutes (see details of sessions duration for each family in Table 1).

For the qualitative analyses, the first author and a team of 3 undergraduate students transcribed the videos and noted comments on children's body language and non-verbal interactions. The final corpus included 1,704 pages of transcripts (368,159 words). Once all transcriptions were finished, the first two authors each reviewed half of the data independently, separately analyzing each transcript using a combination of etic codes, developed from our theoretical frameworks of joint-media engagement [110], and parental scaffolding [45], and emic codes that emerged from the interviews themselves [83, 91]. We listed all joint-media and parental technology scaffolding practices that we found in prior studies of families interacting with home technologies, mobile tablets or coding kits

	Activity Name	Activity Description	MSP	ESP	ACL	CFA	DFMU
Session 1	Classification Game	Sort a set of 12 images of marine life into groups and name each group.	X		X		
	Anchor Game	Select the most important part of each image for a set of 12 marine life images.	X		X		
	Reflection	Reflect on how to use the image games to make something useful for society.				X	X
Session 2	Object Recognition	Identify home objects with an object recognition phone app.		X			
	Train AI	Train an interactive game to recognize different images and produce animations.		X	X		
	Prediction Game	Predict how the Train AI game would recognize specific edge case image examples.			X	X	
Session 3	Compare with Voice Assistant	Compare answers to specific questions between a voice assistant and a family member.		X		X	
	Draw What is Inside	Draw what is inside a voice assistant and how it works.	X		X		X
Session 4	AI Bingo Game	Complete a set of prompts by getting voice assistant to say or do specific things.	X				
	Analyze AI	Analyze different characteristics of voice assistant along continuums (i.e. friendly to unfriendly).	X			X	
	Design AI	Design a custom AI device by selecting from a list of common AI toolkit features.	X				X

Table 2: Activities completed during the four sessions with corresponding AI literacies dimensions: Multimodal Situated Practice (MSP), Embodied Situated Practice (ESP), AI Conceptual Learning (ACL), Critical Framing of AI (CFA), Design Future Meaningful Use (DFMU).

[16, 86, 136] and identified connections with a series of themes that emerged from our study.

After a final coding frame was developed, all transcripts were independently coded by the first two authors. To ensure the validity of the analysis, the two authors regularly met to discuss and reach agreement on any newly emerging codes, any discrepancies in the analyses, and any refinement to the codes [62, 70]. The coding frame was changed, and the transcripts were reread according to the new structure. This process was used to develop categories, which were then conceptualized into broad themes after further discussion. Towards the end of the study, no new themes emerged, which suggested that all major themes had been identified [22]. Table 3 shows the final list of themes that describe different parental roles, their definitions, and their connection to prior work theory.

Once the parental roles were identified, both authors looked at the transcripts for each activity with each family and marked roles as present or not present. We discussed discrepancies until we reached agreement. Each time a role was present for the pairing of a family and activity, we counted it as an *instance* of that role. We used the counted instances to address RQ2.

4 RESULTS

In this section, we summarize our perceptions of children's experiences and then discuss our results concerning RQ1 (how do children and parents learn together about AI) and RQ2 (how to design activities to support family AI literacies).

4.1 RQ1: How do children and parents learn about AI together?

We now turn to a more granular analysis of families' joint-learning of AI literacies. Our qualitative analysis revealed a clear set of roles that parents play when supporting their children's development of AI literacies described in Table 3. What varied was the way parents took on these roles for the different study activities. To illustrate this variation, we present examples of prominent parental roles for each study session.

4.1.1 ***What were parents' attitudes towards AI?***. Our participant families reported varied use of technologies at home. All 15 of our families reported using computers and smartphones daily. Of these 15 families, 13 reported using mobile tablets, 11 reported using gaming devices, 9 used voice assistants, and 5 used coding kits.

Convenience. Some families enjoyed using smart devices in their homes, sometimes reporting having multiple voice assistants in different rooms (F4), or using voice assistants to control other connected appliances in their homes, such as smart lights (F11). However, some families were concerned about *privacy issues* with voice assistants or other AI technologies. For example, the father in F14 said he does not feel comfortable using Google Home, although they own the device. Parents echoed these privacy concerns in F3, F8, F9, and F11, with some parents recognizing that sometimes they do not know what information access they consented to when setting up their smart devices.

Control. Parents from families F1, F2, and F11 expressed the desire for more personalized answers but said they would like to control what information the voice assistants and other AI applications get access to:

> *"I would like an app where you can add personal information. It'd be nice if they [AI devices] don't know unless you give them that information. Otherwise, it seems creepy"* — R., mom F11.

These findings are consistent with recent studies showing that often parents are not aware of the privacy settings of their smart devices [9, 66] or smart toys[80]. Prior work has also found that parents would like to have more control of smart devices and decide what information they choose to disclose or not [6].

Quality. Many families recognized the utility of voice assistants in providing answers to factual questions (F1, F4, F9, F11, F12), and some described the voice assistants as knowledgeable (F1, F11, F4) and confident (F6).

Accuracy. While recognizing a voice assistant's abilities to answer factual questions, some of the parents (F13, F14) encouraged their children to recognize what assumptions the device is making before answering the questions, similar to parental roles observed by Beneteau et al. [19]:

> *"You assume [talking to his daughter] that the egg that we are talking about is from a chicken. Alexa had no such assumptions."* — N., dad F13.

Human element. In other cases, it was the children that would point out the device's limitations when it comes to answering questions that require human reasoning and opinions (F3):

> *"Nowadays, AI is supposed to have intelligence, but it doesn't have thinking, like a brain that can have opinions(..). Computers don't have opinions; they just look at the facts."* — R., son F4.

Families sometimes perceived the voice assistants as "chatty"(mom F2) and not good at engaging in conversation (i.e. "I think we are more personal than Alexa" said mom F1). The fact that parents recognized the voice assistants as not always fit for engaging in conversations led to them actively trying to scaffold the device's conversations with children, either by helping children reformulate their questions or by helping them make sense of the device's answers. This parental role is consistent with other studies that explored how parents mediate child interaction with voice assistants [19, 20, 38].

Transparency and Intelligence attribution. The level to which both parents and children saw the voice assistants as knowledgeable and trustworthy was influenced by how smart they thought the devices were. We noticed that both children and parents would influence each other in terms of intelligence attribution to the voice assistants.

Inclusive design. Several of the multilingual families complained that voice assistants had trouble recognizing their voice or accents:

> *"Siri has a lot trouble recognizing my voice, which annoys me."* — J., mom F9, who speaks Spanish as a first language.

Cultural relevance. As our study population comprises diverse families in terms of ethnicity and spoken languages, several family members raised issues concerning the cultural relevance of some of the interactions with the smart devices. For example, C. (mom F2) complained that "some of her favorite songs are not there."

We identified nine concerns that parents considered necessary when evaluating the use of AI technologies at home: convenience, quality, accuracy, the human element, privacy, control of settings, transparency, intelligence attribution, inclusive design, and cultural relevance. In addition, we noticed that parents' and children's initial concerns would determine if, when, and how they chose to engage with AI technologies at home.

These findings are consistent with a large scale pediatric study on parental attitudes towards AI medical support for their children's treatment which found that parental openness was positively associated with quality, convenience, and cost, as well as faith in technology and trust in health information systems [105]. Families with different perceptions and concerns towards AI could still find important, value-affirming discussion material in our study sessions. For example, F15's dad was against voice assistants and would use the interactions with AI to show his daughter what their limitations are. Meanwhile, F11's mom, who embraced smart devices in her home, would use the study sessions to geek out with her son about how excellent the assistants are.

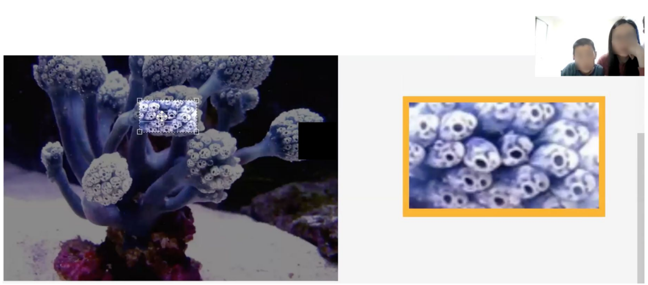

Figure 1: Example of family engaging in the Anchor Game from the first session.

4.1.2 *How did families learn image classification together?*

Fourteen families participated in this initial study session where they got to play two games classifying and summarizing various ocean images and then reflect on their process. Children primarily drove the activities during the image classification and image summarizing and created their own rules for categorizing the corals. Their categories ranged from grouping corals by color, size, or texture (i.e. "bumpy" vs. "sticky") to creating stories about the corals (i.e. "with fish" or "no fish"). Parents acted primarily as collaborators (31 instances), mentors (22 instances), mediators (17 instances) and teachers (17 instances) in this session (see Fig. 6a). There were also three instances of families with older children where parents also learned from their children's logic and image classification reasoning.

When acting as *collaborators*, parents would primarily support their children with scaffolding questions meant to help them identify image unique features. Parents would also try to support children's flexibility in changing their classification groups or image sections. The collaborative aspect of the family interaction in this activity was particularly useful in identifying and discussing various image classification and summarizing strategies.

The more difficult pictures had several different corals in them or showed a zoomed-in version of a coral. The images often caused children to pause and look to their parents for help. This happened in 12 of the 14 families that participated in this activity. Complex images also sometimes led families to consider renaming their image groupings or grouping images differently, however renaming of groups only happened in 6 of the 14 families, as children were more reluctant to change their initial decisions. Sometimes the role of *collaborator* would shift into a role of *mentor* for parents, as they would prompt children to reflect on how a computer would make sense or be able to distinguish their examples.

Parents also played the critical role of *mediator.* This manifested when parents would help children understand the instructions or the goal of the activity or help children recall the decisions they made in previous activities. In addition, if the family had multiple children participating in the study, the parents would help mediate the collaboration between the siblings.

Parents played the role of *teacher* in multiple ways throughout the 3 parts of his first session activity. During the image classification and anchoring games, parents taught children by providing cognitive or affective scaffolding [45]. For younger children, parents also provided support with domain knowledge (i.e. "what is a coral?") during the two games. During the reflection activity, parents acted as *teachers* by helping children link the current activity with other prior relevant experiences. Sometimes parents had to come up with elaborate stories and examples in order for children to understand how we could use applications of computer vision technologies in order to make something good for the planet:

> *"Maybe the computer can group it by where in the world it was taken. Kind of like if we go to SeaWorld. Then we take pictures, then people are going to be like, oh, where did you take this in SeaWorld?"* — J., dad F1.

Other parents (F4, F13) also prompted their children to think about algorithmic bias and consider what happens if the people who give examples of images to the computer make mistakes.

Role	Description	Example	Connection	MSP	ESP	ACL	CFA	DFMU
Cheerleader	Emotionally support the child during an activity or display excitement.	*"It's okay. You don't have to use that. You can make your own."*	Spectator [135]					
Mediator	Mediate between siblings and help them work together. Direct a child's attention or explain task instructions.	*"You guys need to be talking about this."*	Enforcer [135]	X	X			
Mentor	Guide the child to a more nuanced understanding. Encourages child to explain and clarify their reasoning.	*"So how would you describe that one?"*	Scaffolder [135]				X	X
Student	Learn a new concept or a new practice from the child. Change perspective towards AI functionalities.	*Child demonstrates how to use Siri.*	Learner [16]			X		X
Teacher	Explain a new concept or a new practice to the child. Provide guidance to use AI functionalities.	*"Pi is a mathematical term. You use it to define the area of the circle or the circumference of the circle."*	Teacher [16, 135]			X		X
Observer	Let the child do the activity alone. Step in when help is needed or asked for.	*Child to parent after working alone: "Ok, you do this one".*	Spectator [135]	X	X			
Joint Engagement Roles								
Tinkerer	Encourage the child to break, fix, and test the AI. Model this tinkering behavior.	*"What if you yell it? What happens if you say it loudly?"*	Scaffolder [135]		X		X	X
Collaborator	Work with the child as a friend, and be actively engaged in the activity.	*"I don't think there's a lot of corals that would be categorized as smooth. That's all I'm thinking."*	Collaborator [16]	X	X			

Table 3: Summary of final codes and definitions for parents roles with their AI literacies dimensions: Multimodal Situated Practice (MSP), Embodied Situated Practice (ESP), AI Conceptual Learning (ACL), Critical Framing of AI (CFA), Design Future Meaningful Use (DFMU).

Parents also played the role of *student* in this activity. This either happened when children were older and had prior programming experience (this was present in 4 families participating in this first session) or when children would come up with scenarios for future AI applications that parents had not considered, such as involving scientists and experts in the process of crowd-sourcing image classification games.

> *"A computer would make mistakes because everything makes mistakes. Because computers, they are just people programming something new."* — L., daughter F8.

When thinking about future potential applications for image classification and image anchor detection games, both children and parents proposed various ideas. However, children were more likely to propose fun things, such as recognizing different types of dogs (F11) or recognize children's drawings (F13). Some of the older children went much further in their reflections for future computer vision applications, imagining either how people could collaborate in the future with machines by playing games or imagining how computers could learn rules from the current image classification and image anchor detection games to program themselves:

> *"So when you make a program you create some rules. So for the anchors you could think of a rule that a computer could follow to know where to put the anchor [...] most likely where the most colors changes."* — R., son F3.

4.1.3 *How did families learn object recognition together?*

Fourteen families participated in the second study session, which focused on object recognition. First, families looked for objects that would confuse a mobile recognition app ("Objects Recognition" activity). Then, they trained and tested *Teachable Machine* application with three objects ("Train AI" activity). Finally, they predicted what the computer would choose when trained on two objects and tested with a different type of object ("Prediction Game" activity). Across all three activities in this session, parents acted primarily as collaborators (37 instances), mentors (30 instances), cheerleaders (25 instances), teachers (20 instances), and tinkerer (19 instances) (see Fig. 6b).

When acting as *collaborators*, parents would display their enthusiasm and actively make suggestions, and help children with the tasks. One source of enthusiasm from both children and parents was the act of "tricking the AI," first introduced in the object recognition app testing, but carried into the *Train AI* activity by some families. Children and parents collaborated at two main points

Voice Assistant (VA)	Google Voice		Alexa	
Questions	**Child F11 answers**	**VA answers**	**Parent F2 answers**	**VA answers**
Do I have any pets?	No, I don't	Sorry I don't understand	Yes, you have a lizard named Lazer	Here's what I found on Wikipedia...
How's the weather today?	Cloudy and rainy	Today there is thunderstrom (detailed information)	The weather is perfect is 75 and sunny	Currently in city xx there is 76.5 degrees. You can expect clear sky
Can you recite the first ten digits of pi?	N/A	On website xx they said the first 15 digits are ...	3.141	The approximate number of pi: 3.1415926... I gotten you this far
Which came first: the chicken or the egg?	The egg came first; the chicken was an accident invention	On website xx they said two birds made an egg by accident..	Ooo, the chicken because they lay eggs.	I can't seem to crack that one

Table 4: Examples of families' answers to the activity "Compare with Voice Assistant" from session three: child F11 answers interacting with Google Voice Assistant and parent F2 interacting with Alexa Voice Assistant.

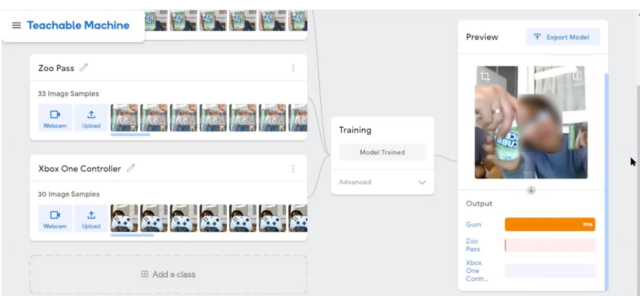

Figure 2: Example of a father using hand-on-hand scaffolding to help his son position the object correctly during the "Train AI" activity.

during the prediction activity: (1) when determining what the computer would predict, (2) when learning their initial prediction was incorrect. When the machine defied their expectations, family members jointly tried to determine why their prediction did not work. In addition, parents and children sometimes collaborated to work through technical challenges:

> *"We should probably aim it at the ceiling, cause we have a bunch of pillows [in the background]."* — A., son F11, suggesting how to fix the background being noisy when training the AI.

In the "Train AI" activity, parents engaged as *mentors* when younger children would sometimes choose unusual objects to train their AI with (e.g., their pet), to which parents sometimes had to set ethical and safety boundaries (e.g., telling them they were not going to train it on their dog).

When acting as *teachers*, parents provided explanations for (1) what the object recognition application was doing, (2) what companies and other technologies supported object recognition, and (3) how the computer's behavior was similar to or different from the child's. When parents took on the *tinkerer* role, their interventions varied between the three activities. In the first activity, they would suggest different objects for the child to test with the object recognition app. Then, they would point to objects, pass the child objects, or suggest that a child looks for a certain kind of confusing object. In the "Train AI" activity, families got to "fix" some recognition issues because they trained the AI themselves. Parents would suggest different edge cases for the child to test their AI with by picking different objects with similar shapes (F14), picking objects of the same color (F15) or rotating initial objects (F1) (see Fig. 2).

Though the number of instances of parents taking on the *student* role was low (only 5 instances), some children taught their parents how to use the *Teachable Machine* platform (daughter F12), while others taught them specific terms or gave them new insights into their previous experiences with object recognition applications (son F11).

4.1.4 ***How did families mediate learning with voice assistants?*** Twelve families participated in the third study session, where they engaged in two activities related to voice assistants. During the "Compare with Voice Assistant", either children or parents answered the game questions. Different families chose different assistants to compare themselves to (see Table 4). If the families did not have a home voice assistant, they used Siri or the Alexa app. In the first activity parents acted primarily as *collaborators* (11 instances) and as *mentors* (11 instances). In the second part of this third session, for the "Draw what is inside the assistant" activity, parents acted primarily as *mediators* (6 instances), *teachers* (5 instances) and *mentors*(4 instances) with only two parents (F4, F11) making a drawing. The cumulative count of parent roles showed that they acted primarily as mentors and as collaborators (15 instances for each), teachers (12 instances), mediators (11 instances), cheerleader (7 instances), student (7 instances), observer (6 instances) (see Fig. 6-session 2).

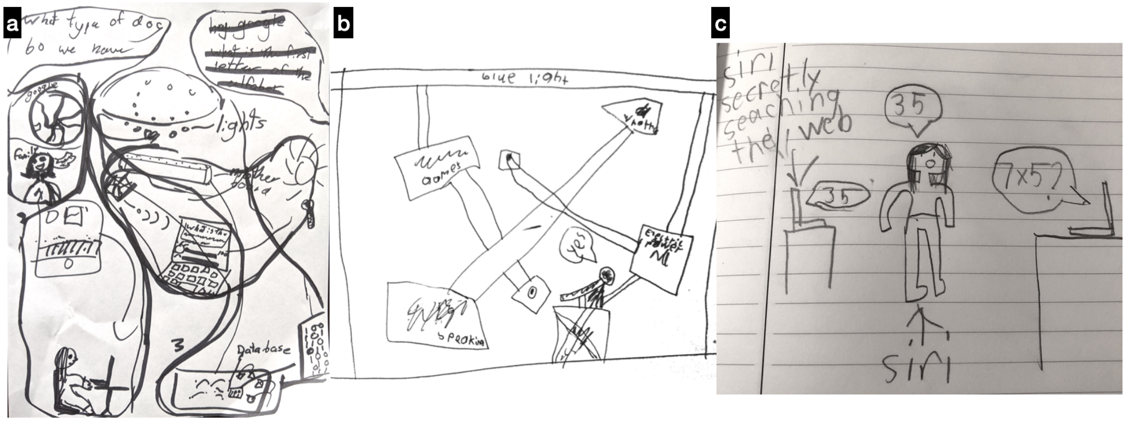

Figure 3: Examples of children's drawings from the "Draw What is Inside" activity: a.) child F4 drew Alexa as a girl typing and connecting to databases, lights, Google, b.) child F8 drew Alexa as parts of the phone's circuitry, c.) child F14 drew Siri as a girl searching the web and telling the answer to a computer.

In the first part of session three, parents and children collaborated in coming up with new questions to ask the voice assistant. For example, when family members wanted to give an advantage to each other in the game against the voice assistant, they would ask personal questions such as "what is my favorite color ?" (F8), "who is your favorite ballerina?"(F12) or "what is the most fun activity you do?"(F13). Other times family members would inquire for facts related to their interest (i.e. "who is the best NBA player of all times?"(F2), "why does the T-rex have tiny hands?"(F14)) or ask about trivia facts (i.e. "what is the black hole in the middle of the Milky Way?"(F3), "when was memory foam invented?"(F1).

Parents primarily acted as *mentors* in the first part of this session when they were guiding their children to reflect on what makes a human answer better or not as compared to the voice assistant's answers. During the drawing activity, parents also acted as mentors by prompting their children to think of specific examples or situations to help them plan their drawings. When mentoring, parents also encouraged children to explain their AI understanding in more detail by asking clarifying questions:

> *M:"Mmm, maybe the programmer could translate human into robots."* — M., daughter F14.
> *N:"I see. So it needs to have something that converts voice into words?[daughter nods] (..)* — N., dad F14, responding.

The above dialogue with her dad leads M.(F14) to draw her assistant Siri as a girl who "secretly" searches the web to answer the questions. It then says it back to the "other computer" that presents the person asking with an answer via voice (see Fig. 3c). M.'s drawing of Siri was very similar to S.'s drawing (F4), who drew Alexa as a girl typing and connecting to databases, lights, google (e.g., Fig. 3a). Other children and parents used various metaphors to describe their vision for what is inside the voice assistant, such as drawing different parts of the phone's circuitry (e.g., Fig. 3b).

When acting as *teachers*, parents either explained specific domain knowledge concepts (i.e. "what is pi?") or directly explained to their children how certain functionalities of the voice assistants work. Parents also played the role of *student* and learned from their children knowledge and ways of reasoning about how the voice assistants work, how their children would compare different voice assistants:

> *"If Alexa was smart enough, she could have seen (..) we don't order any of the pet products, which probably means that we don't have pets."* — R., son F3 talking to his mom.

Examples of discussions on sensitive topics, such as race and religion, between children and voice assistants, lead parents (F2, F4, F6, F12, F13, F14, F15) to recognize that these devices are not always neutral [10, 31, 50, 76] and that it is critical for families to have conversations about when to trust the voice assistant's answers. Some families (F1, F2, F4, F12) emphasized the importance of differentiating what questions are best suited to ask family members and which ones are best to address to a voice assistant:

> *"'Do we have a dog' would be a question for the family, the pi question would be for assistants [dad asks how do you differentiate] for family-related questions we would ask the family."* — Sa.,daughter F4.

When trying to find future meaningful applications for voice assistants and AI families proposed a series of ideas: support with family learning either by "having better support for homework " (son F2) or by enabling more convenient image search (dad F14).

4.1.5 ***How did families co-design future AIs?***

Twelve families participated in the fourth session. Across the activities for session four, the "AI Bingo Game" was most engaging, and the "Design AI" activity was most collaborative. Engagement and enjoyment for the bingo game varied and seemed to depend heavily on the quality of the voice assistant's responses, which sometimes were funny and appropriate, but other times were unrelated or not engaging. Engagement dropped off when families were subject to a succession of interactions where the voice assistant could not provide answers or misunderstood participants.

The third "Design AI" activity prompted active discussions around privacy and AI ethics. Family members shared their previous experiences and collaborated to understand how features and hardware/software components connected and how they could build

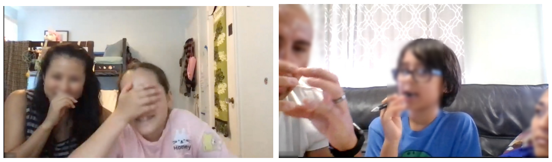

Figure 4: (left) A family laughs when they accidentally call Siri "Alexa" during the "AI Bingo Game". (right) A father suggests adding sign language support to their "Design AI" project.

safeguards into their designs. Parents were not always more privacy-minded than children but often could explain to children which settings on their AI assistant led to certain behaviors, like the assistant knowing their home address.

The most common roles observed in the fourth session's activities were collaborator (33 instances), mentor (32 instances), teacher (26 instances), cheerleader (25 instances), and tinkerer (18 instances).

As *collaborators*, parents engaged in back-and-forth conversation with their children and gave suggestions relevant to the activity at hand. In the first activity, the bingo game, the families' collaboration involved taking turns asking the voice assistant different questions and suggesting different ways they might accomplish a task. Active collaboration sometimes meant family members would build off each other's voice assistant interactions, as a group trying to narrow in on a specific query that would get the desired response, such as "make AI tell a lie" (dad F4).

In the second "Analyze AI" activity, collaboration often took the form of parents and children sharing their views of the AI and agreeing on how to rate the AI's different characteristics. In addition, they often drew on their previous experiences with AI when giving justifications.

The third "Design AI" activity, where parents and children co-designed their ideal assistant, had the most engaged and personal collaboration of the three activities. When deciding which features and behaviors to include in their AI, parents would offer suggestions, sometimes rebuffed by children who thought their suggestions would create an AI that was "too creepy". Often, collaborations involved discussions of privacy concerns around AI and potential safeguards. Parents scaffolded ethical conversations by offering help on how to design against a specific concern:

> *"What if it was like a face that looked more like a robot face? Would that still be creepy? [C. nods]"* — N., mom F12, suggesting potential modifications to their AI design.

Sometimes, children wanted more safeguards than parents, like in family F6, where the daughter wanted no biometrics information recorded, but the mother was ok with using those sensors. However, in these collaborations, children would more often make fun of the AI and had lower expectations of the technology. In one case, the son of family F1 even made fun of Alexa's accent for pronouncing "La Cucaracha" without a Spanish accent.

During all three of session four's activities, parents often took on the role of *mentor*. For example, during the "AI Bingo Game", parents primarily helped repair communication breakdowns with the assistant (asking children to repeat their query, slow down, or enunciate), operate the assistant, and phrase or rephrase queries that the child wanted to pose. For the "Design AI" activity, parents scaffolded conversations around ethics and helped children connect certain behaviors they wanted their AIs to have to the required sensors for these behaviors. In some instances, they would nudge their children to consider designing the AI for others or encourage them to think beyond the affordances of the AIs they already know.

When parents acted as *teachers*, they taught their children a wide variety of topics, ranging from simple definitions of words to detailed explanations regarding the people and programming that make voice assistants possible. Similarly, they gave detailed explanations about the distinctions between (1) the people vs. a company that builds an AI, (2) lying vs. not knowing something, and (3) common vs. uncommon AI queries and the expected behaviors for common queries. In the "Analyze AI" activity, parents continued these explanations and tied them to characteristics of the AI, like friendliness, truthfulness, and agency.

In the "Design AI" activity, discussions around privacy and ethics led parents to teach children about current concerns around AI and specific design patterns that could mitigate against them:

> *"You can make a password for her. You can say "flower" and then maybe she'll obey."* — M., daughter F13, adding a password to her AI.
>
> *"But then it's the same thing as 'Alexa', right? When you want to ask about flowers, what do you do?"* — N., dad F13, highlighting potential shortcomings.

Parents supported their children as *cheerleaders* during the three activities by expressing excitement for the activities, consoling children when the voice assistant did not understand them, and supporting children's creativity.

4.2 RQ2: How can we design learning supports for family AI literacies?

In this section, we consider how our AI literacies resources supported various parental roles for each activity and present families' final evaluations of each study session.

4.2.1 ***Support for parental roles.*** We counted instances of each parental role identified in RQ1 by marking whether or not a role was present for each pairing of a family and an activity. Thus, there were a total of 142 possible instances for each existing pairing (three activities and 14 families in session one, three activities and 14 families in session two, two activities and 11 families in session three, and three activities and 12 families in session four, see Fig. 6).

For the first session, the cumulative count of parent roles showed that parents acted primarily as collaborators (31 instances), followed by mentor (22 counts), then mediator and teacher (both 17 counts) (see Fig. 6-session 1). The second session had the same top two roles. Parents again acted primarily as collaborators (37 instances), followed by mentor (30 instances), and then cheerleader (25 instances), and teacher (20 instances) (see Fig. 6-session 2).In the third session, mentor and collaborator tied for the most common role (15 instances), followed by teacher (12 instances) and mediator (11 instances) (see Fig. 6-session 3). During the fourth session, parents acted primarily as collaborators (33 instances), mentors (32 instances), teachers (26 instances), and cheerleaders (25 instances)

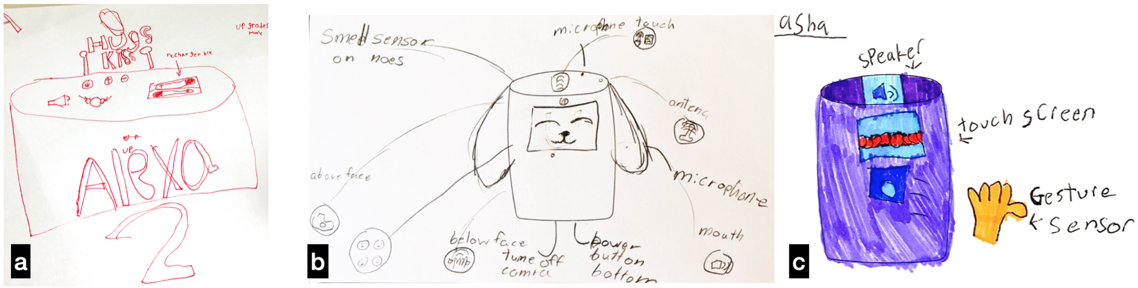

Figure 5: Examples of kids' and parents' drawings from the "Design AI" activity: a.) child F13 designed a new portable/rechargeable Alexa with a hug and kiss kit, b) older child F4 designed an animal-like assistant with buttons to control all privacy features and a sensor for the smell, c) child F12 designed "Asha" to detect gestures and touch input, allowing for non-verbal commands.

(see Fig. 6-session 4). Roles that were not in these top roles all appeared most in the fourth session: tinkerer (18 instances), student, and observer (both 14 instances) (see Fig. 6-session 4). The two activities that had the most joint engagement, found by summing the instances of *collaborator* and *tinkerer* were "Train AI" (23 instances of joint engagement roles) and the "AI Bingo Game" (22 instances of joint engagement roles).

4.2.2 ***Sessions feedback***. The 11 families that provided feedback for the study sessions described session one on image classification as relatively easy but expressed varied opinions on fun and learning activity levels. Overall, families described session two as more fun than session one (except for F15, who had a very young child). Overall, families reported learning less but having more fun in session two compared to session one. Finally, families scored session three interaction with voice assistants with relatively high scores across the three dimensions of learning, having fun, and ease of use. They scored it slightly less fun than session two, but they said they learned more. Because the final session consisted of many unplugged activities, most families described this session's activities as relatively easy to play. However, the scores assigned for fun and opportunities for learning varied more from family to family.

What did families like the most? For the image classification session, all families expressed that they appreciated the interactive nature of the activity and the ability to pick the games' pictures. Several families reported they enjoyed testing, breaking, and tricking the object recognition applications and the voice assistants. Some families (F2, F6, F13) mentioned they liked the "Compare with Voice Assistant" competition aspect. From session four, families said their favorite activity was the "Design AI".

What improvements did families suggest? Families suggested expanding the games collection of images to include images from Minecraft (F1), animal pictures (F8), cities and ponds (F2), and "other crazy parts of the ocean"(F11). Families also suggested that the game should be online and collaborative (F3) and that the game should suggest more questions or explanations about the pictures (F13). Finally, when referring to the "Compare with Voice Assistant" activity, some families (F6, F2, F11) suggested creating more activities where family members could interact with multiple voice assistants and compare their answers to different questions. For the "Design AI" activity, family F3 suggested coming up with ways to bring the design to life virtually, and family F14 suggested that it would be fun to design their own AI toolkit parts.

5 DISCUSSION

Our work contributes several new insights about AI literacies for families by addressing our initial research questions:

RQ1: How do children and parents learn about AI together? Our qualitative results show that parents mediate children's learning by playing different roles ranging from *Mentor* to *Student.* However, we observed balanced learning partnerships between family members, primarily when parents play the *Collaborator* and the *Tinkerer* roles. Furthermore, while children and parents collaborate in all our different AI literacies sessions, they primarily tinkered together in the sessions that support hands-on interactive games (session two) and unplugged learning activities (session four) (see Fig.6). While some of the roles we identify are similar to parent roles present in other family technology learning activities [16, 135], the *Tinkerer* and Student roles we found are unique to AI learning activities. As sometimes parents and children in our study differed in their experiences, opinions, interpretations, and imagined futures of AI behavior, the home became a transformative third space [52] for AI literacies where the potential for an expanded form of learning [42] and the development of new knowledge was heightened.

RQ2: How can we design learning supports for family AI literacies? We found that our designs of supports for AI literacies let families with different perceptions, attitudes, and knowledge about AI engage in the following learning processes successfully: exploring multi-modal and embodied situated practices with AI, developing AI conceptual learning, engaging in critical framing of AI, and reflecting on future meaningful uses of AI at home. Activities in sessions two and four best-supported families to engage in all these learning processes (in particular the "Train AI" and the "AI Bingo Game"). Activities in session one best-supported AI conceptual learning and critical framing (in particular in the *Reflection* activity). Activities in session three primarily supported AI conceptual learning (in the "Draw AI" activity) and reflections on future meaningful use of voices assistants for families (in the "Compare with Voice Assistant" activity). By designing activities that allowed families to move in and across a repertoire of practices [55, 98] we

Figure 6: Radar charts presenting the distribution of parents' roles for the different study sessions and AI literacies activities.

supported multiple forms of participation [54, 85] and created the potential for authentic interactions and expansive learning [42].

Our results suggest that engaging families in joint AI literacy practices can lead families to envision new ways for them to learn about these technologies. Moreover, introducing families to the novelty of AI concepts and applications together with the hidden potential risks of using these technologies enabled parents and children to envisions sites of possibility [85] and contradiction with their individual and joint dispositions and repertoire of practices. Notably, newly acquired practices and skills led some families to consider making meaningful use of AI devices they already have in their homes and re-design their interactions with them. These findings suggest that family has the potential to act as a third space for learning, where both children and parents can develop AI literacies by combining family social contexts for learning and their collective zone of proximal development [124].

Limitations. One important limitation of our study is that half of the parents had some professional technology experience (six parents had user-experience design backgrounds, and three had programming experience). Some limitations in the study complicate the interpretation of our findings. It was impossible to systematically observe every family interaction in every activity, especially with the study's limitations online. For the interactions we could observe, observing a family interact during a study does not necessarily indicate ground truth for their typical interactions outside of the study setting; for example, it may be the case that parents were playing a less active role in some sessions because they considered their children's opinions to be more relevant to the study. Some families also did not participate in all four sessions, nor did our sites cover the many possible ways that culture, community, and collaboration might have shaped participation. Finally, because our observations were collected during study sessions and with a subset of each family, they may only hold a subset of the interactions that the family regularly uses when engaging with AI. For example, our data do not include interactions that involve grandparents or younger siblings or instances when the family engages with their voice assistant during a mealtime conversation. Therefore, while our results suggest that the families in our sessions demonstrated diverse roles and perceptions, other populations could reveal new roles and different shifts in perceptions.

Parents' and children's roles. By using niche cultural references, speaking in different languages, or finding examples of confusing images, families used all the resources at their disposal to solve a given AI activity. Children and parents would build on responses they elicited from the agents to identify increasingly narrow edge cases. We interpreted this to be similar to practices observed in studies on AI understanding with the use of counterfactual examples [7, 125]. As families learned new tricks, they used them in different activities (i.e., the practice of "tricking the AI" continued from session to session). Similar to other examples of playful debugging [67], both parents and children took great pride in finding a case that would confuse or mislead the AI device or application and would share their discovery with their family members. The *Tinkerer* and *Collaborator* roles facilitated joint engagement between parents and children. Parents took on *Mentor*, *Mediator*, and *Cheerleader* roles to keep their children engaged with the activities. Parents as *Mentors* provided scaffolding for children to understand the activities and connect the activities to their understanding of AI. *Teacher* and *Student* roles allowed parents and children to learn from one another, while the *Observer* role allowed parents to discover their child's habits more passively. The parental collaboration, mentoring, mediation and emotional support has been found in prior studies on family use of technology [16, 24, 32] and studies on families engaging with coding kits [135] or videogames [87], however the *Tinkerer* and *Student* roles we identified in this study appear to be unique to family interactions with AI.

As parents and children learn together to negotiate and reclaim agency from the smart devices by breaking, fixing, and testing them when they tinker [5, 13], we see opportunities to design family AI devices and applications that are more explicit about their functionality and abilities [3, 44, 97]. Prior work shows that youth can influence their parents' digital media use [30] and suggests the importance of parent and peer contexts for children's moral reasoning development [126]. In our study, we also found that as parents are still unfamiliar with some aspects of AI literacies, children step in and share their knowledge and perspectives [38, 69, 119, 120]. However, parental guidance and scaffolding are still necessary when reasoning about ethics of AI [92, 93] and algorithmic bias [10, 40].

Embodiment and technologies maturity impact level of engagement. We found that the learning activities that supported embodiment provided rich environments for children and parents to build up egocentric speculations, extrapolating from their ideas about performing a task or solving a problem to the AI's behavior. This is consistent with Papert's findings on body synchronicity, where children project robot geometrical puzzles on their own body to solve mathematics problems in Logo [90] and with Vartiainen et al. who found that children reason about the relationship between their bodily expressions and the output of an interactive image prediction tool [120].

Additionally, we found that training an AI model allowed families to test hypotheses and even break the AI because they could fix it. When families had the opportunity to train the AI, they could build a more accurate picture of the AI's behavior and capabilities. This finding is consistent with prior work, which shows that learning how to train smart games to support children to understand better machine intelligence [35].

Importantly, we found that when breaking and fixing the AI, families must be provided with conceptual and technical support to help them determine the cause of the AI's erratic behavior (e.g., hardware limitations, noisy data, limited bandwidth), so they have the opportunity to fix it and refine their understanding. Furthermore, when families encounter technical difficulties, it is challenging to debug and engage in interactive learning activities. This finding suggests the need for more mature AI applications and technologies that are well-tested with families [21, 95].

Perceived utility impacts family use and mediation. How parents choose to regulate their use of specific technologies is colored by perceived utility, which in turn results from how well they understand the technology and can support what their kids do with it [23]. Joint engagement with AI allows parents to do both at the same time. They gain insight into their children's habits with these smart agents, learn more about the capabilities and limitations of the agents, and have the chance to engage in active mediation [114]. Our observations of family AI perceptions expressed in our study were similar to Brito et al., who found that families assign meaning and intelligence to smart technologies before using them and that this process influences the decision to adopt them [24]. Especially in session four, families who had already adopted voice assistants had more accurate or fun responses from the assistants and were, therefore, more engaged in the activity.

Joint-Media Engagement for AI literacies. Our results also have implications for prior work on children developing AI literacies. Prior work has revealed many challenges, including the importance of family members understanding the role of data in shaping machine behavior [84]. Other studies with adults have explored methods of bridging these comprehension gaps by helping people develop more robust mental models about AI (e.g., [14, 65, 102]). Our findings suggest that similar approaches may work for families, at least when families are engaged in interactive learning activities that use AI applications. Our qualitative findings of families' AI literacies joint engagement also suggest new interpretations of prior research on child AI education. Whereas prior work has largely focused on children's experiential and cognitive accounts of AI understanding (e.g., how children make sense of machine intelligence or learn how machine learning works [35, 77]), our investigation of AI literacies from a joint-media engagement lens [110] suggests that children and parents support each other in significant ways to understand AI behavior. These supports include social strategies for enacting scientific activities such as observation with family members, discussing hypotheses with family members, and explaining and teaching other specific domain or task-specific concepts for inferring models of AI behavior.

Guidelines for designers and educators. Our findings have implications for both designers of learning technologies and AI literacy resources for families. The embodied interactive activities in session two and the unplugged activities in session four were the ones that supported the most diverse set of parental roles and therefore resulted in families learning about all the different AI literacies. This trend is consistent with recent studies analyzing families co-designing interactive AI museum exhibits [75], and research on families engaging in creative coding activities [99]. Designers and educators might therefore consider methods for supporting more embodied and tangible supports for future AI learning [71, 93]. Another clear trend was that families used their experiences in generating training data to make inferences about AI abilities. Designers and teachers might explore methods for engaging families in reflecting on the relationship between the training data, the AI's use of that data, and its resulting behavior. As our study population included a multilingual and multi-ethnic group of participants, we found it was important to design reflection activities that allowed families to approach AI literacies through the lens of culture and power [123] and provided families with opportunities to envision and imagine meaningful future AI designs. Designers and teachers might explore ways for critical reflections and AI speculative designs that leverage a families' culture, lived experiences and dreams, and diverse constellations of practices [54, 98].

6 CONCLUSION

After a 5-week observational study in the home, we found that families with different perceptions, attitudes, and knowledge about AI successfully can develop AI literacies in a variety of joint-engagement roles. By increasing childrens' and parents' AI literacies, we would allow them to use smart technologies and imagine, design meaningfully, and create future AI applications relevant to their lived experiences and community needs. This vision *must* be attained if our children and their families are to live in a just and equitable society.

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