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The 4As: Ask, Adapt, Author, Analyze

AI Literacy Framework for Families

Stefania Druga, Jason Yip, Michael Preston, and Devin Dillon

Introduction

Children in the current digital information era are rapidly engaging with technologies powered by artificial intelligence (AI). AI refers to the intelligence possessed by machines, thus why it is also known as machine intelligence. Unlike humans, machines acquire intelligence through algorithmic techniques inspired from domains like statistics, mathematical optimization, and cognitive science, and they are fueled by computer processing power and a large amount of data (Legg & Hutter, 2007). AI systems show great promise in helping children and families improve online search quality, increase accessibility to internet search via advances in digital voice assistants, and promote AI-supported learning (Grossman et al., 2019; Ruan et al., 2020; Ruan et al., 2019). However, AI systems can also amplify bias, sexism, racism, and other forms of discrimination, particularly for those in marginalized communities (Angwin et al., 2016; Buolamwini & Gebru, 2018). Promoting critical understanding of AI—or AI literacy—for children and families is essential in this context.

Without AI literacy, families, mainly from historically marginalized groups, risk falling prey to misinformation and fear; they also risk missing potential opportunities for learning (Ferguson, 2012; Gebru, 2019; O'Neil, 2016). Families and children must work together to learn about AI systems and to think critically about how this technology impacts their lives (Druga et al., 2019). Prior research on family engagement with digital technologies stresses how important it is to consider variation among families and parenting styles (Coyne et al., 2017; Takeuchi & Stevens, 2011). Therefore, to support algorithmic justice in families, we need to consider how diverse families can access these skills (DiSalvo et al., 2016; Yardi & Bruckman, 2012).

AI literacy does not occur in a vacuum but is influenced by social, cultural, institutional, and techno-infrastructural contexts. We need to consider the ecological and situational issues surrounding families and how macrofactors and microfactors influence AI literacy in the modern family. Therefore, it is crucial to address the socio-ecological conditions that influence how families may adopt AI literacy and to create guidelines that integrate human-centered design into practice. An analysis of ecological systems (Bronfenbrenner, 1994) can explain how families could succeed with AI literacy; it can also unveil the broader implications of such an intervention. There is a parallel need to develop design practices and frameworks that support the development of systems encouraging equitable and informed understandings of the creation and use of AI (Gonzales, 2017).

Research on how families interact with home technologies is a growing area, providing implications for the design of new smart devices (Druga, 2018; McReynolds et al., 2017). Studies demonstrate that families can play a decisive role in guiding children on how to make meaningful use of technologies (Ito et al., 2009; Stevens & Penuel, 2010; Takeuchi & Stevens, 2011). However, the rapidly changing digital landscape is making it difficult for families to integrate advanced technology in meaningful and intentional ways.

Limited knowledge exists on how parents or guardians learn with their children using tools that promote AI literacy. We wish to advance this body of research by posing the following research questions:

How do children and parents from different countries and diverse socioeconomic statuses (SES) perceive and interact with AI?

How can we best support parents to scaffold their children's use of AI technologies in the home?

How can we design future technologies to best support families' AI literacy?

Our goal is to understand how to facilitate AI literacy in families better. We investigate this from two perspectives: an ecological evaluation of current AI systems and the design of new systems for AI literacy. Our research puts forth both a conceptual and empirical understanding of how families engage with AI literacy activities. Such an understanding can inform the design of culturally tailored tools and resources. We contribute new insights on family AI practices to address critical AI literacy needs in families. Finally, we develop a foundation that can encourage innovations to take advantage of family dynamics in a way that improves AI literacy learning. We analyze and compare different prior data sets to propose a novel, research-based, family-facing framework for thinking with and about AI.

We begin with a brief review of ecological systems that support AI literacy (Bronfenbrenner, 1994). Ecological systems theory refers to the nested systems—macrosystems, exosystems, mesosystems, and microsystems—that influence the development of learning for people in the following ways:

- Macrosystem factors: Social and cultural values
- Exosystem factors: Technology infrastructure and policies
- Mesosystem factors: Community centers, libraries, and schools
- Microsystem factors: Families, peers, siblings, extended family, and neighbors.

Through a review of the literature, we consider how current technological systems are supporting or not supporting the development of AI literacy. From our evaluation of ecological systems in AI literacy, we inductively develop a design framework that supports critical understanding and use of AI for families. Our framework considers four dimensions of AI literacy: *ask*, *adapt*, *author*, and *analyze*. We prototype and refine different learning activities such as detecting bias, testing a voice assistant, coding a smart game, and drawing what is inside the smart devices to explain how they work. These activities took place during four co-design sessions with an intergenerational group, consisting of adult design researchers, child participants ($n = 11$, ages 7–11 years old), and parents. The activities correspond to the different dimensions of our AI literacy framework.

Through a series of family co-design sessions, we found that children perceive bias in smart technologies differently from adults, and they care less about technological shortcomings and failures as long as they are having fun interacting with the devices. Family members supported each other in various collaborative sensemaking practices during the sessions by building on each other's questions, suggesting repairs for communication breakdowns with the voice assistants, coming up with new and creative ways to trick the AI devices, and explaining or demonstrating newly discovered features.

We demonstrate how our novel framework supports AI literacy development through play, balanced partnership, and joint family engagement with AI learning activities, concluding with a series of guidelines for families.

Finally, we engage in a broader discussion that connects the ecological systems theory with our AI literacy framework to draw implications for the broader perspective of AI practice, program design, public policy, and algorithmic justice.

The Ecology of Family AI Literacy

Based on our evaluation of ecological systems (Bronfenbrenner, 1994), we discuss the impact of multiple nested systems (i.e., macrosystems, exosystems, mesosystems, and microsystems) on family AI literacy.

Macrosystem Factors: Sociocultural Values

Fostering an environment where different identities can flourish Macrosystems impact learning and technology practices within values, policies, and infrastructure (Bronfenbrenner, 1994). One macrosystem factor in AI literacy is the importance of promoting an inclusive AI education for multicultural and multilingual families from different socioeconomic backgrounds. This approach requires us to consider diverse families outside WEIRD populations (i.e., Western, educated, industrialized, rich, and democratic; see Henrich et al., 2010). To include multiculturalism as a macrosystem factor for AI education, we need to be reflexive and consider how researchers approach such issues (Schön, 1987). We also recognize that, as Medin and Bang (2014) describe, the answers to our research questions will be influenced by the sociocultural values of the person "who is asking." We build on prior work on technology literacy and joint media engagement among multicultural families (Banerjee et al., 2018; Pina et al., 2018). As we conceptualize AI literacy, we define the term *literacy* as practicing rather than developing one's skills (Cole et al., 1997; Kulick and Stroud, 1993; Scribner and Cole, 1981). We situate the AI literacy practice in the constellation of sociocultural practices that our families engage in (Rogoff et al., 2014). In our effort to discover, encourage, and promote best practices of families using AI technologies in meaningful ways, we acknowledge the need to recognize multiple literacies and the relationships of power they entail (Street, 2003). Therefore, we seek to foster an environment where heterogeneity, specifically different identities, goals, and forms of learning and growth, can flourish (Rosebery et al., 2010).

Exosystem Factors: Technology Infrastructure and Policies

The brave new world of connected homes Necessary technological infrastructure also determines access to AI literacy. For instance, a 2019 Pew study shows that in the US, broadband access is limited by data caps and speed (Anderson, 2019). As AI systems increasingly take advantage of large-scale technological infrastructures, more families may be left disengaged if they cannot connect to broadband (Riddlesden & Singleton, 2014). Moreover, it is essential for minority groups to not only "read" AI but also to "write" AI. Smart technologies do much of their computing in the cloud, and without access to high-speed broadband, marginalized families will have difficulty understanding and accessing AI systems (Barocas & Selbst, 2016). Families must be able to use AI systems in their homes so they can develop a deeper understanding of AI. When designing AI education tools and resources, designers need to consider how the lack of access to stable broadband might lead to an AI literacy divide (van Dijk, 2006).

Policies and privacy Risks to privacy are standard on the internet. Studies show that privacy concerns constitute one of the main worries among children in Europe (Livingstone, 2018; Livingstone et al., 2011; Livingstone et al., 2019), and adults widely support the introduction of data protection measures for youth, such as Article 8 from the EU's General Data Protection Regulations (GDPR) (Lievens, 2017; Regulation (EU) 2016/679 of the European Parliament and Council, 2016). According to a recent survey, 95 percent of European citizens believe that "under-age children should be specially protected from the collection and disclosure of personal data," and 96 percent think that "minors should be warned of the consequences of collecting and disclosing personal data" (European Commission, 2011).

Furthermore, many companies do not provide clear information about the data privacy of voice assistants. In this context, policymakers and technology designers must consider the unique needs and challenges of vulnerable populations. Normative and privileged lenses can impair conceptualizations of families' privacy needs while reinforcing or exacerbating power structures. In this context, it is crucial to provide updated policies that look at how the AI technologies embedded in homes not only respect children's and families' privacy but also account for future potential challenges.

For example, the Children's Online Privacy Protection Act (COPPA), which passed in the US in 1998, seeks to protect kids under the age of 13. Despite the proliferation of voice computing since then, the Federal Trade Commission did not update its COPPA guidance for businesses until June 2017 to account for internet-connected devices and toys. COPPA guidelines now state that online services include "voice-over-internet protocol services" and that businesses must get permission to store a child's voice (Federal Trade Commission, 2017). However, recent investigations have found that in the case of the most widely used voice assistant, Amazon's Alexa, only about 15 percent of "kid skills" provide a link to a privacy policy. Particularly concerning is the lack of parental understanding of AI-related policies and their relation to privacy (McReynolds et al., 2017). While companies like Amazon claim they do not knowingly collect personal information from children under 13 without the parent's or guardian's consent, recent investigations prove that is not always the case (Lau et al., 2018; Zeng et al., 2017).

Nonprofit organizations such as Mozilla, Consumers International, and the Internet Society have since decided to take a more proactive approach to these gaps by creating a series of guidelines that teach families how to better protect their privacy (Rogers, 2019). These efforts could be used to increase AI literacy by helping families understand what data their devices are collecting, how these data are being used or potentially commercialized, and how they can control their devices' privacy settings or require access to such controls when they do not exist.

Mesosystem Factors: Community

Mesosystem factors refer to interactions in one setting that can influence the interactions in another setting. For instance, what happens in a library, school, or community center for children and families can influence learning at home (and vice versa). Studies show parental involvement in learning at home significantly influences school performance (Barron, 2004; Berthelsen & Walker, 2008) and can be critical to children's future success. For instance, the AI Family Challenge (AIFC) was a 15-week program implemented with third- through eighth-grade students ($n = 7{,}500$) and their families in underresourced communities across 13 countries. During the program, families learned to develop AI-based prototypes that solved problems in their communities. The goal of AIFC was to determine whether AI was of interest to such communities and to determine the impact of such intervention on participants' AI literacy. To gain insight into these objectives, researchers conducted pre-program and post-program surveys as well as interviews with participants in the US, Bolivia, and Cameroon (Chklovski et al., 2019).

After AIFC, 92 percent of parents believed their children could better explain AI to others, and 89 percent believed their children were capable of creating an AI application. The study findings indicated the need to improve parent training materials, connect technical mentors to local sites, and improve the curriculum to be more hands-on, engaging, and better illustrative of machine learning concepts.

Microsystem Factors: Families, Peers, Siblings, Extended Family, and Neighbors

Microsystem factors refer to specific interactions within the local environment that influence family learning. For this review, we look closely at family interactions in the home around AI literacy.

An example of these sorts of family interactions, from Technovation, can be seen in figure 10.1.

A survey of 1,500 parents of elementary and middle school students, commissioned by Iridescent Technovation (2019), found that 80 percent of parents in the US believe AI will replace most jobs (not just low-skilled jobs), less than 20 percent understand where and how AI technologies are currently used, 60 percent of low-income parents have no interest in learning about AI, and less than 25 percent of children from low-income families have access to technology programs (Chklovski et al., 2019). Research on families' interactions with technology is a growing area, providing implications for the design of new agents (McReynolds et al., 2017). As devices become more humanlike in form or function, humans tend to attribute more social and moral characteristics to them (Druga, 2018; Druga et al., 2018; Kahn et al., 2011; Kahn, Jr., et al., 2012). These findings raise the question of how parents need to engage and intervene in children's interactions with connected toys and intelligent agents. Studies show that parents scaffold their

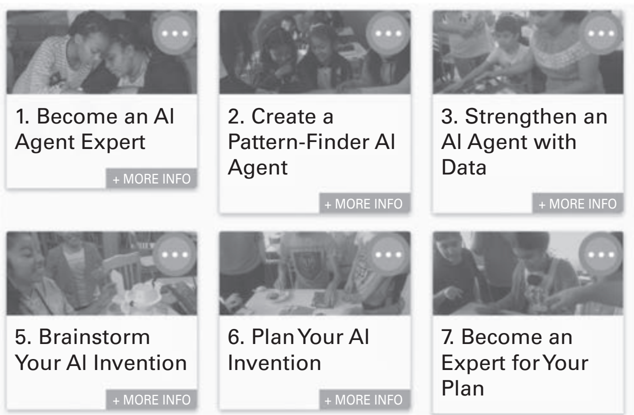

Figure 10.1
Example of curriculum modules created by Technovation for the international Curiosity Machine Competition for families.

children's behavior when the family interacts with robots or interactive devices together (Lee et al., 2006). We observed the same behavior when families interact with voice user interfaces (VUIs), particularly when parents help children repair various communication breakdowns with the conversational agents (Beneteau et al., 2019; Druga et al., 2017; Lovato & Piper, 2015). For instance, Beneteau and her colleagues (2019) noted that family interactions with Amazon Alexa devices facilitated joint media engagement conversations with parents. At the same time, however, the devices could not "code switch" between adult and child requests. This led to many frustrations and ultimately communication breakdown between the families and the voice assistant. In a longitudinal study analyzing families' uses of VUIs in the home, Porcheron et al. also showed that collaborative information retrieval is prevalent (2018). Both children and parents use classical conversation techniques, such as prosody changing or strategic use of silences, even if they dialogue with a more transactional agent like Alexa (Beneteau et al., 2019).

Methodology

Through our analysis of the ecological perspective on the state of AI understanding for families, and building on theories of parental mediation and joint media engagement (Takeuchi & Stevens, 2011), we propose a new framework for defining family AI literacy. To examine our framework in action, we adhere to the standards and practices of participatory design (PD), precisely the method of cooperative inquiry (Druin, 2000; Guha et al., 2004). Under Cooperative Inquiry in PD, adults and children work closely together as design partners, emphasizing relationship building, cofacilitation, design-by-doing together, and idea generation (Yip et al., 2017). Cooperative Inquiry works well for understanding AI systems and literacy because children already work closely with adults and are more likely to express their perceptions around childhood (Woodward et al., 2018). In design partnerships, there is a strong emphasis on relationship building, which allows children to be more receptive to experimentation and open dialogue.

Our co-design sessions focused on designing and eliciting responses from children and families around their perceptions of different aspects of AI systems. We conducted three 90-minute sessions from October to November 2019 with eight to 11 children. We also worked with families in co-design sessions in December 2019 to understand children's engagements with AI with their parents.

Participants

An intergenerational co-design group, consisting of adult design researchers (undergraduates, master's, and doctoral students) and children ($n = 11$, ages 7–11), participated in the four design sessions. The team was called KidsTeam UW (all names within the team are represented as initials). Children typically participated in the study for 1–4 years (2016–2019). In the fourth session, three KidsTeam UW children and their families (e.g., parents, siblings) came on a weekend co-design session to engage together and discuss their perceptions of AI technologies.

Design Sessions

Each KidsTeam UW design session (both child and families) consisted of snack time (15 minutes), where the children gathered to eat, share, and develop relationships through play. In circle time (15 minutes), we provided children a "question of the day" to prime them to think about the design session. We also provided the instructions (verbally and through activity printouts) for engagement. Most time was spent designing together (45 minutes), in which children participated in some design techniques (Walsh et al., 2010; Walsh et al., 2013; Walsh & Wronsky, 2019) with at least one adult partner. Children then

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broke up into smaller teams or remained together for a single design activity. Finally, the group came back together in discussion time (15 minutes) to reflect on the design experience.

We organized the sessions in the following way to investigate how the family AI literacy framework could be utilized as a series of design activities:

Design Session 1 (October 2019): We showed the children different video clips of “algorithmic bias.” Video clips included AI not being able to recognize darker skin tones, voice assistants stuck in an infinite loop, and a very young child unable to get an Alexa Echo device to start. We used big paper (Walsh et al., 2013), a technique that allows children to draw on large sheets of paper to consider what “bias” means.

Design Session 2 (October 2019): We provided children with different technology activities using three kinds of AI devices: Anki Cozmo (AI toy robot), Alexa Echo voice assistant, and Google Quick, Draw! (AI that recognizes sketches). Each intergenerational team went through the stations and documented what was “surprising” about the technology and whether they were able to “trick” the AI system into doing something unexpected.

Design Session 3 (November 2019): Using big paper, we asked children and adults to draw how they thought a voice assistant (Amazon Alexa) worked.

Design Session 4 (December 2019): Finally, five KidsTeam UW families came together on a weekend morning workshop to engage in multiple AI technologies stations. Stations included Amazon Alexa, Google Quick, Draw!, and the Teachable Machine. One station used Cognimates (Druga, 2018) and BlockStudio (Banerjee et al., 2018) to show models on how computers made decisions. Families spent, on average, 15 minutes per activity trying out the different technologies and then wrote their ideas and reflections on the technologies.

Data Analysis

We used an inductive process to analyze the themes captured from the audio of family AI interactions (Charmaz, 2006). We began with memoing and open coding during the initial transcriptions of the video files. Through memoing and open coding, we noticed emerging themes related to family AI literacy practices and family joint engagement. We then began coding literacy practices and joint engagement from transcripts of each of the five families, developing and revising codes as we found additional examples of AI joint engagement, reviewing a total of 17 hours of video capture. We continued this process until codes were stable (no new codes were identified) and applicable to multiple families. Once the codes were stable, we again reviewed transcripts from each of the five families for AI literacy practices and family joint engagement. We included AI literacy practices from each participant in our corpus of 350 AI family–AI interactions, systematically going through each family's transcript and pulling out for each code (when present). For our final analysis of each family's AI interaction, a total of 180 AI interactions falling under the broad themes of AI literacy practices were deeply analyzed by two researchers. We defined AI literacy practices as interactions between family members and the various AI technologies, as shown in table 10.1. We drew on the human-computer interaction conversational analysis approach to analyze family interactions in an informal learning environment, with a focus on the participants' experiences.

AI Literacy Dimensions: The 4 As

Based on our analysis of the ecological perspective (Bronfenbrenner, 1994) of the state of AI and building on our prior work (Beneteau et al., 2019; Druga, 2018; Druga et al., 2017; Druga et al., 2018;

Druga et al., 2019), we consider ways to connect design dimensions for family AI literacy. Building on parental mediation and joint media engagement frameworks (Takeuchi & Stevens, 2011), we aim to analyze and support the scaffolding parents might provide to enable their children's mental models of intelligent systems. In this section, we highlight our novel framework for family AI literacy (see table 10.1) based on a thorough examination of the literature and our inductive co-design study. Our framework is composed of four dimensions (4As)—ask, adapt, author, and analyze—and it describes family activities, literacy questions, and design dimensions for each of the dimensions. Although Touretzky et al. propose five big main ideas that children should learn about AI technologies (Touretzky et al., 2019) in their framework, our framework

Table 10.1
The 4 As: proposed framework for families' AI literacy dimensions

AI literacy layer	Family activity	AI literacy question	AI design guideline
Ask	Interact fluently with an existing AI application or technology	How do you make it do . . . ? Do you . . . ? Are you . . . ?	Transparency Explainability
Adapt	Modify or customize an AI application to serve their needs	How do I modify it?	Personalization Transparency
Author	Create a new AI application	How do I make a new one?	Progressive Disclosure
Analyze	Analyze the data and the architecture of their AI application and modify it to test different hypotheses	How does it work? What if . . . ?	Systemic Reframing

focuses on children as active learners and agents of change who can decide how AI should work, not just discover its current functionalities. Another contribution of our framework is that it also addresses parents and tries to engage and support them in making more informed and meaningful use of the smart devices they might integrate into their homes.

Kids and Parents Ask AI

In prior studies, we investigated the challenges and opportunities of children growing up with digital technologies and their impact on the digital divide. In this context, access to AI literacy for families could prevent an AI divide for the generations of children growing up with smart technologies. With intelligent agents in the home, children do not need to read and write to access the internet; they can ask an agent any question or request, and the device will return the first result with a humanlike voice and friendly prosody. What seems at first to be a playful interaction between a child and a voice assistant can easily trigger events of real consequences (stories of children buying dollhouses and candy with Alexa without parental approval has already made national news). Our prior work (Druga et al., 2017) shows that overall, children found the AI agents to be friendly and trustworthy but that age strongly affected how they attributed intelligence to these devices. Younger participants (4–6 years old) were more skeptical of the devices' intelligence, while most older children (7–10 years old) declared the devices were more intelligent than they were. In a preliminary study, we found that older children mirrored their parents' choices for the smarter agent and used very similar explanations and attributions, even if they participated in the study independently (Beneteau et al., 2020; Druga et al., 2018). These findings build on work in developmental and early cognitive psychology (Gopnik, 2020) to underline the importance of leveraging children's natural tendency to "think like a scientist" when interacting with smart technologies.

Families Adapt AI

To compare how children use VUIs in different countries, we studied 102 children (7–12 years old) from four different countries (US, Germany, Denmark, and Sweden). The way children collaborated and communicated while describing their AI perceptions and expectations were influenced by both their socioeconomic and sociocultural background. Children in low- and medium-SES schools and community centers were better at collaborating compared to children in high-SES schools. However, children in low- and medium-SES centers had a harder time advancing because they had less experience with coding and interacting with these technologies. Our findings show that children outside the US were overall more critical and skeptical of the agent's intelligence and truthfulness (Anders, 2019; Druga et al., 2019) and had less exposure to these technologies.

Author AI: From Coding to Teaching Machines

Today, children cannot easily design their own AI devices, program their connected toys, or teach them proper behavior. However, some initiatives have started to design tools and platforms that enable youth to author with AI (Code.org, n.d.-a; Druga, 2018; "A guide to AI extensions to Snap!," n.d.; "Machine Learning for Kids," n.d.).

STEAM education has become a priority for schools and families around the world, and initiatives like Hour of Code and Scratch Days are currently reaching tens of millions of students in 180-plus countries (Code.org, n.d.-b). Learning how to program is also integrated into the curriculum in high schools across the UK and US. Meanwhile, parents are investing more resources to get their children involved in local technology and science clubs, camps, and coding events. Most of the educators, parents, and policy-makers are starting to recognize programming as a new literacy, which enables our youth to acquire and apply computational thinking skills. The technology used at home and in the classroom is changing fast. These advancements raise the opportunity not only to teach children how to code but also how to teach computers and embodied agents by training their own AI models or using existing cognitive services (Druga, 2018). An example of these kinds of AI coding platforms is shown in figure 10.2.

In a series of longitudinal studies, we found that programming and training smart devices changes the way children attribute intelligence and trust to smart devices. Participants from various SES backgrounds and different learning settings (public schools, private schools, community centers) became significantly more skeptical of AI's smarts once they understood how the AI worked (Druga, 2018; Druga et al., 2019). In traditional coding, children are used to sending a series of instructions to a machine and seeing how the code is compiled and executed. In AI learning, students have to understand the role of data and how it might influence the way machines execute algorithms (Cassell et al., 2000; Mioduser & Levy, 2010). Mioduser and Levy (2010) explored how children could understand robots' emergent behavior by gradually modifying the robots' environment. They discovered that young people are capable of developing a new schema when they can physically test and debug their

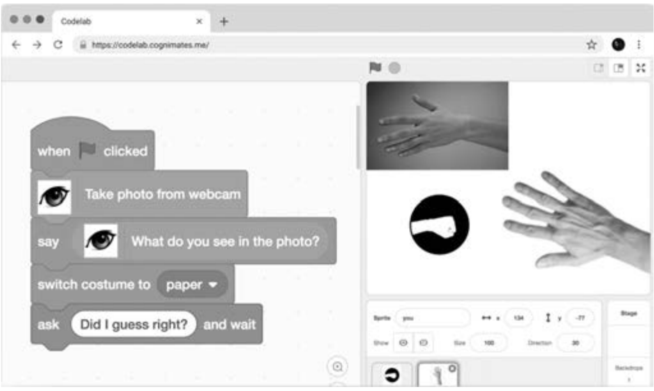

Figure 10.2
Examples of AI coding platforms (BlockStudio and Cognimates) piloted with families during our study.

assumptions. They also showed that the number of rules and new behaviors should be introduced gradually in the coding activity.

Programmability Helps to Analyze AI

Prior human-computer interaction (HCI) studies analyzing adults' mental models of AI technologies found that even a short tutorial with a researcher (i.e., 15 minutes) can significantly increase the soundness of participants' mental models. This phenomenon was consistent in Kulesza et al.'s study on intelligent music recommender systems and Bansal et al.'s study on the effect of different kinds of AI errors (Bansal et al., 2019; Kulesza et al., 2012). More so than users' explicit mental models, research on AI systems in HCI has focused on explainability and trust. Rutjes et al. (2019) argue for capturing a user's mental model and using it while generating explanations. At the same time, Miller (2019) invoked the concept of mental models through ideas of reconciling contradictions and our desire to create shared meaning in his comprehensive review of social science related to explainable AI.

When trying to understand how children and families analyze AI, we notice that programmability can play a significant role in influencing children's perception of smart agents' intelligence (Duuren, 1998; Scaife & Duuren, 1995; Scaife & Rogers, 1999). Additionally, parental mental models and attitudes can also influence how the children attribute intelligence to smart devices (Druga et al., 2018). Within this frame, we define sensemaking as a process by which people come across unfamiliar situations or contexts but need to process and understand to move forward (Klein et al., 2006). By creating activities and technologies that help families generate and test various hypotheses about how smart technologies work, we allow family members to not only test and understand how AI works; we also allow them to engage in systematic reframing and imagine how AI should work in order to support meaningful family activities (Dellermann et al., 2019).

The 4A Framework in Action

Ask dimension: Identify AI bias When we initially asked children to describe what bias means and give examples of bias as part of the co-design sessions (see figure 10.3), we found ourselves at a crossroads as we realized none of our participants understood what this term means. We quickly noticed, however, that children understood the notions of discrimination and preferential treatment and knew how to identify when technology was treating specific groups of people unfairly.

“Bias? It means bias,” said L, a 7-year-old boy. During the initial discussion in the first study session, we tried to identify examples of bias that children could relate to, such as cookies or pet preferences. When talking about cat people versus dog people, D, a 9-year-old girl, said, “Everything they own is a cat! Cat’s food, cat’s wall, and cat. . . .” We then asked kids to describe dog people. A, an 8-year-old boy, answered: “Everything is a dog! The house is shaped like a dog, bed shaped like a dog.” After children shared these two perspectives, we discussed again the concept of bias referring to the assumptions they made about cat and dog people. A summary of

Figure 10.3
Examples of families engaging with the smart toys activity during our co-design sessions.

the types of bias identified by children in sessions one and two is shown in figure 10.4.

Race and ethnicity bias: In the final discussion of the first session, children were able to connect their examples from daily life with the algorithmic justice videos they had just watched. “It is about a camera lens which cannot detect people in dark skin,” said A, while referring to other biased examples. We asked A why he thought the camera failed in this way, and he answered: “It could see this face, but it could not see that face . . . until she puts on the mask.” B, an 11-year-old girl, added, “It can only recognize White people.” These initial observations from the video discussions were later reflected in the children’s drawings. When drawing how the devices work, some children depicted how smart assistants separate people based on race. “Bias is making voice assistants horrible; they only see White people,” said A in a later session while interacting with smart devices.

Age bias: When children watched the video of a little girl having trouble communicating with a voice assistant because she could not pronounce the *wake* word correctly, they were quick to notice the

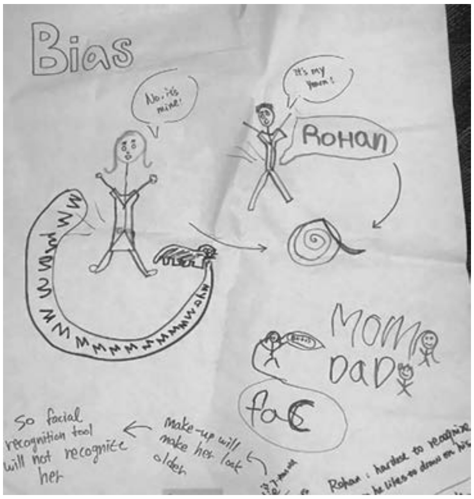

Figure 10.4
Examples of bias identified by children in sessions one and two.

age bias. "Alexa cannot understand baby's command because she said *Lexa*," said M, a 7-year-old girl. "When I was young, I did not know how to pronounce *Google*," she added, empathizing with the little girl in the video. Another boy, A, jumped in, saying: "Maybe it could only hear different kinds of voices," and shared that he does not know Alexa well because "it only talks to my dad." Other kids agreed that adults use voice assistants more.

Gender bias: After watching the video of the gender-neutral assistant and interacting with the voice assistants we had in the space, M asked: "Why do AI all sound like girls?" She then concluded that "mini Alexa has a girl inside, and home Alexa has a boy inside," and said of the mini Alexa: "I think she is just a copy of me!" While many of the girls were not happy that all voice assistants have female voices, they recognized that "the voice of a *neutral-gender* voice assistant does not sound right" (B, 11 years old). These findings are consistent with the UNESCO report on implications of gendering the voice assistants, which shows that having female voices for voice assistants by default is a way to reflect, reinforce, and spread gender bias (UNESCO, EQUALS Skills Coalition, 2019).

Adapt dimension: Trick the AI In the second design session, we invited participants to engage directly with the smart technologies and see if they could trick them. We wanted to provide the children with concrete ways in which they could test the device's limitations and bias, and we learned from our prior studies that children enjoy finding glitches and ways to make a program or a device fail (Druga, 2018). Such prompts not only give them a sense of agency but also provide valuable opportunities for debugging and for them to test their hypotheses about how the technology works. During our workshop, children imagined and tested various scenarios for tricking the different smart devices and algorithmic prediction systems. When playing with Anki's social robot, Cozmo, they decided to disguise themselves with makeup, masks, glasses, or other props so the robot could not recognize them anymore. They also decided to disguise other robots as humans to see whether doing so would trick the robots' computer vision algorithm. Children also used this strategy in our prior AI literacy workshops for families in Germany, and it is a fun activity that could easily be replicated at home.

When playing with the Quick, Draw! app, children were at first amazed at how quick and efficient the program was in guessing their drawings, so they decided to deploy many strategies to confuse the program. They first tried to draw nonsensical drawings to see if they would still get object predictions. They then decided that multiple children should try to draw on the same device at the same time so that the program would have a hard time keeping up with their drawing speed. When interacting with Alexa, the children probed it in various ways to find out whether it was biased. For example, they tried to speak Spanish to see if the device would recognize a new language; they used different names for calling the device *Lexa* to see if it could interact with more informal language; they asked "silly" questions to see if the device could engage in child play (e.g., "Call me 'princess'"); and they also tried to see if it could sing songs from different locations, such as the North Pole or the Indian Ocean. Very often, children built on each other's questions during the interaction and helped each other reformulate a question when needed. This finding is consistent with prior work in this field that demonstrates how much peers or family members can help repair communication breakdowns when interacting with voice assistants (Beneteau et al., 2019; Druga et al., 2017). While trying to probe and trick the voice assistant, children voiced several privacy concerns. "Amazon can hear everything users have said to their Alexas," said A, who then added, "Alexa buys data, takes data, and gives it to people who build Alexa." D was worried that "the tiny dots on Alexa are tiny eyes where people can see users," so she decided to cover the device with Post-it notes. From these examples, we see how children's privacy concerns can vary widely based on their naive theories (Inagaki, 1993), experiences with these technologies, and conversations they had had with or heard from their parents.

Author dimension: Design, code, teach the AI The democratization of current AI technologies allows children to communicate with machines not only via code but also via natural language and computer vision technologies. These new interfaces make it easier for children to control and even "program" an agent via voice, but they make it harder for children to debug the machine when it does not behave the way they expect. During our design sessions, children had the opportunity to discover a series of AI programming applications individually before using them with their parents. Sometimes families would start by playing with example games (figures 10.5a and 10.5b) that would recognize their gestures or objects. We would then ask them to make the games more or less intelligent. Other times families would come up with their project ideas and would start a program from scratch. We would ask the children to explain specific concepts from their project. For example, one of the researchers asked a child, M, "What does the loop mean?" M answered by drawing a circle in the air. We also asked both children and parents to reflect on how they could make the technology suitable and meaningful for their families. D's older sister said they could program the Sphero ball robot for "maybe dog chasing."

In all the authoring activities, families were trying to test their programs in various ways, moving their bodies together, standing up and sitting down. Meanwhile, one of the family members was going back and forth to modify the code blocks or the parameters of the smart games to see what would happen. Children and parents engaged in a balanced partnership, especially when using the applications where it was straightforward for multiple people to take turns interacting with the program (i.e., Quick, Draw!, Cognimates motion games, Teachable Machine vision training). Similar to prior studies, parents helped scaffold their children's behavior when interacting with robots or interactive devices together (Chang & Breazeal, 2011; Freed, 2012).

When M and her dad were playing together with the Teachable Machine platform (see figure 10.5), the dad would frequently probe his daughter with helping questions. For example: "So I put in 150 pictures, and you put in 25, so that model knows me better because I put more pictures in it. The more pictures I put in, the more the model will learn. How would you fix it?" he asked. M replied, "Add

Figure 10.5
Examples of children coding a game with BlockStudio and a family training a custom model with Teachable Machine.

more," and proceeded to add more pictures of herself. When she realized she could not add more pictures after a model was trained, she would say, "No, we have to redo it. Daddy goes first this time." After training their model for a second time, M and her dad tried to trick it, and both faced the camera at the same time to see which one would be recognized. M noted that they looked very similar to the machine but that because she had a pink bow, she thought the machine could recognize her. She thought of another way to trick the machine by giving her pink bow to her dad.

We observed the same behavior when families interacted with voice assistants. All family members helped each other repair various communication breakdowns, as in prior studies (Beneteau et al., 2019). For example, R's dad was trying to get the voice assistant to act like a cat by saying "meow" when talking to the device. "Oh, you have to say something," replied R, his 11-year-old son, who then added, "If you wanna wake her up, you should say something like *Alexa*." At his command, the device turned blue, and R said, "Meow." After, the voice assistant started to meow.

From these examples, we see how children build on experiences and skills developed in prior study sessions for probing the technology as they are designing it, either by asking it questions, trying to trick its games, debugging collaboratively with their families, or teaching and supporting each other. In this way, our ask, adapt, and author framework dimensions become intertwined in practice, helping families better understand and control AI technologies.

Analyze dimension: How does it work? How do we make it better? The last step in our design sessions with families was critically analyzing the technologies discussed, used, or created in all the other study sessions. This critical analysis was done in a group discussion at the end of the study, in which children, parents, and researchers participated in a circle. The analysis was also done throughout the other sessions every time we asked participants to draw and explain how the devices worked and what they had inside. With these prompts, we aimed to discover the families' mental models of AI technologies and observed how these explanations drew on or influenced their direct interaction with smart devices. The analyze discussion also elicited systematic reframing so that families could reflect on how they might use AI systems better in the future and to think about when and if they should use such technologies.

What is inside? To help uncover how children conceptualize smart devices, we asked them to draw what was inside the device and explain how it worked. Children resorted to various representations and explanations: a computer, a series of apps, a robot, a phone, or a search engine was inside the device. "There is a search engine inside the Alexa, but I do not know what it looks like," said L, a 10-year-old boy.

Y and S, two 9-year-old girls, said that there was an army of people who sit at their computers inside the "Company of Alexa" and reply to all the questions after they research the answers online. "There is a bunch of cords and a speaker inside the Alexa. It would connect to a computer and link it to Amazon people. If the question is 'What is the weather?' it [the person] would search the weather and type it up and let Alexa say it," said Y, a 9-year-old girl.

The most common analogy children made was of the mobile apps they are so familiar with. Children imagined how the voice assistant would use different mobile apps depending on the question the user asks. D, another 9-year-old girl, also imagined how the different devices were linked to each other: "If Alexa does not know an answer, it asks other Alexa[s] first before asking Amazon. Once one Alexa gets the answers . . . every single Alexa in the world will get that answers." The younger children (6–7 years old) provided more vitalistic explanations, consistent with prior studies (Inagaki, 1993). "There is a brain inside Alexa, and there is a part that connects to a computer with a speaker. The speaker will shout out the answer," said M, a 7-year-old girl. The older children (8–11 years old) had a very different explanation, primarily related to other technologies or applications they were using: "Alexa looks at every place it can search for an answer: Amazon, YouTube, internet, weather, map, anyplace," said A, an 8-year-old boy. "The database is a box with stuffs in it. The stuffs are statements you tell Alexa," added R, an 11-year-old boy.

It is as simple as 2+2: During the design sessions, children tried to validate their mental models by probing the different devices with questions. Children also tried to find out the age of the devices to determine how much they could trust them. Children were disappointed by the answer Alexa gave them when they asked how old it was: "It is as simple as 2+2." They described this answer as "questionable," as they found it hard to believe a voice assistant could possess so much information at the age of 4. B said the assistant must be at least 20 years old.

When children would find bugs or limitations in the device's answers, they thought the errors happened because the device "relies too much on the internet." Children requested to know who programmed the voice assistant so they could understand why the device was lying about its age. From this example, we see how our participants were able to draw on prior workshop experiences, not only understanding how the device behavior was linked to the way it was programmed but also figuring out what questions to ask in order to test the device.

Discussion

Our modern world is governed by the decisions made through AI and algorithms. While these tools show incredible promise in health care, education, and other fields, they also need to support ways in which people (mainly from vulnerable and marginalized populations) can carefully critique how AI could amplify racism, sexism, and other forms of discrimination. For people to start considering algorithmic justice early in life, we must find ways they can develop forms of literacy around AI. We argue that AI justice and AI literacy begins in early interactions, inquiries, and investigations in the family.

AI literacy, however, is not a form of knowledge that can be simply taught in a didactic and lecture-based form (Druga, 2018). Instead, designers need to consider how to promote sensemaking, collaboration, questioning, and critical thinking. How can they design future AI systems for families that tap into the idea of "children as scientists" and leverage children's curiosity and both the explore and exploit paradigms? Prior work shows that children are developmentally primed for this type of exploration (Gopnik, 2020), and we believe it is a missed opportunity to not provide AI literacy opportunities by designing future smart technologies and via parenting.

Based on our prior research and this study's findings, we propose a novel AI literacy framework for designers and educators to consider in order to support families' critical understanding and use of AI systems. We believe it is important to consider this design framework in the context of our current analysis of nested ecological systems (Bronfenbrenner, 1994).

In asking sessions, children and families can inquire and interact with AI agents through various means, such as calling out with voice interactions, drawing, and playing. However, embedded in these interactions with asking are privacy policies that need to be transparent for families (exosystem). Families have several questions about the impact and interplay of privacy, technology, policy, and their children (Zeng et al., 2017). Therefore, how do we support families to ask and interact with AI agents in a way that deems their information safe and confidential? Designers also need to consider how at-home interactions happen between children and families (microsystems). In this context, are families able to collaborate and ask AI agents together? How do prior relationships with technology in families mediate how comfortable family members are engaging with AI at home?

With adaptation sessions, families are shifting and mitigating their perceptions and engagements around AI to fit their contexts. However, as families adapt to AI, questions of negotiation and power remain (Barocas & Selbst, 2016). AI systems are unable to code switch and recognize children and adults (Beneteau et al., 2019), raising the risk that age-inappropriate content may be accessed by children. How does AI think about more substantial cultural capital and social contexts (macrosystems) of families? For instance, bilingual families can switch and merge languages (e.g., Spanglish) in their routine conversations with one another. For AI voice assistants, this means having to adopt a single language. Similarly, AI systems have difficulty recognizing different languages and accents (macrosystems). In this case, families who may have grown together in specific social and cultural norms now face systems that are unable to adapt to these larger macrosystems.

For the author dimension, families need a chance to build and create in order to develop AI literacy. We ask, though, who has an opportunity to build? Even if designers create authoring systems for AI engagement, those systems can depend solely on technology infrastructure at home (exosystems) (Riddlesden & Singleton, 2014). Authoring may also mean learning how to build, which may privilege individual families in communities, libraries, schools, and networks that can teach and build knowledge capacity.

Finally, under analyze, AI learning tools can be designed with collaboration and sensemaking in mind (Ash, 2004; Paul & Reddy, 2010). This approach assumes that different family units work together (microsystem). Therefore, how is a careful reflection on AI designed to deal with real family constraints, like working families, families with limited time, and families who always move (i.e., children living between households)? How might designers create activities and technologies that support diverse families, allowing those families to generate and test various hypotheses about how smart technologies work and systematically reframe how AI should work to support meaningful and inclusive family activities (Dellermann et al., 2019)?

Overall, while complex ecological systems need to be considered within design frameworks, there are still takeaways for families who have adopted AI literacy and justice. Our study shows that with the ask, adapt, author, and analyze dimensions, parental roles and relationships still matter when families are learning about AI together. Aarsand (2007) describes "asymmetrical relations" between parents and children as both a challenge and an opportunity for families to jointly engage with assumptions about media like computers and video games. The "digital divide"—through which children are considered experts with digital media while adults are positioned as novices—becomes a "resource for both children and adults to enter and sustain participation in activities" (Aarsand, 2007). Children can teach parents about AI technologies, but it is also the parents' responsibility to teach children about the values in their community that matter and how AI tools and systems align with these values (Friedman et al., 2008).

Design Features That Encourage AI Literacy for Families

Using our findings, we can examine the conditions and processes that our family AI literacy framework could support. We use our findings to show how the ask, adapt, author, and analyze dimensions can lead families to adopt a critical understanding of AI (Druga, 2018; Druga et al., 2019), specifically through a balanced engagement with these new technologies (Sobel et al., 2004; Takeuchi & Stevens, 2011; Yip et al., 2017). This balanced engagement involves:

- **Mutual engagement** (i.e., multiple family members should be equally motivated to participate): Families in this study were able to participate in different ways, whether they were asking several questions to voice assistants, playing and authoring together with new AI systems, or trying to analyze how bias is introduced into smart technologies.

- **Dialogic inquiry** (i.e., inquiry by families inspires collaboration and meaning-making): Families can try to analyze the AI systems and try to figure out how they work. They can also determine how the AI systems need to adapt to their families' culture, rules, and background.
- **Co-creation** (i.e., people create shared understanding through co-usage): Parents and children can come together to **ask**, **adapt**, **author**, and **analyze** AI systems in order to find out what they know and what they would like to know more about.
- **Boundary crossing** (i.e., AI spans time and space): Families can consider how AI systems are pervasive in multiple technologies, whether in internet searches, YouTube recommendation systems, or voice assistants of multiple forms. If families can recognize how pervasive AI is becoming on many platforms, they can shape how AI itself is crossing boundaries.
- **Intention to develop** (i.e., families gain experience and development): Families can consider how they are adapting to AI systems. For instance, are the questions they are asking voice assistants changing? Are families noticing when AI systems may be present? Interestingly, families can develop as they understand how AI systems themselves are adapting to different people and contexts.
- **A focus on content, not control** (i.e., interface does not distract from interaction): With some AI systems, families can engage in multiple straightforward ways. Through asking voice assistants questions, seeing if AI systems can recognize drawings and sketches, and engaging with computer vision models, families can now question and critique AI systems using many simple mechanics.

Conclusion

Our aim in designing technologies is to ensure we are supporting families in raising a generation of children who are not merely passive consumers of AI technologies but rather active creators and shapers of its future. With our AI literacy framework, we aim to encourage and enable families to learn how to develop a critical understanding of AI. We propose this framework from an ecological systems theory perspective and present examples of implications for supporting family AI literacy across various nested layers of our society. As designers of technologies, we aim to support a diverse population of children and adults and provide significant inspiration and guidance for future designs of more inclusive human-machine interactions. We hope that by democratizing access to AI literacy through tinkering and play, we will enable families to step in and decide when and how they wish to invite AI into their homes and lives.

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