

Scaffolding Children’s Sensemaking around Algorithmic Fairness

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Prior research has investigated children’s perceptions of algorithmic bias, but provides little guidance on engaging children in conversations on algorithmic bias that center their agency and well-being. To address this, we developed discussions and design activities based on three scenarios of algorithmic (un)fairness. We conducted these discussions and activities with 16 children (ages 8-12) in the US, and examined our data using qualitative thematic analysis. Grounded in lived experiences and situated knowledge, participants were capable of reasoning around both explicit and implicit effects of algorithmic bias. Participants also expressed distrust of technology, doubting technology’s abilities and preferring human approaches to resolve unfairness. This work contributes (1) a more nuanced understanding of children’s situated reasoning of technology, suggesting their potential for critical engagement and (2) a blueprint for engaging children in scaffolded yet open-ended sensemaking around algorithmic fairness, informing the design of tools, curricula, and other learning experiences for children.

CCS Concepts: • **Social and professional topics** → **Children**.

Additional Key Words and Phrases: algorithmic fairness, children, sensemaking, funds of knowledge

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1 INTRODUCTION

As computing becomes pervasive in children’s lives, it brings extensive benefits, but also puts children’s lives, families, communities, and futures at increased risk of harm. This has led to a flourishing body of work on youth’s perceptions of algorithmic bias, focusing mainly on interactions with AI agents or AI learning experiences. Several scholars have found that children tend to overly trust AI agents, precluding them from critiquing AI technologies [20, 31, 41, 56, 60, 61]. In contrast, others observed that children could identify unfair treatment from AI with some instruction, suggesting some capacity to reason about algorithmic bias [22].

While most prior studies targeted algorithmic bias within AI systems, other computing technologies also shape the lives of children. Researchers have only recently extended beyond AI, with Coenraad et al. finding that even without instruction, youth were aware of visible negative effects of technology, such as non-consensual data collection and use [14]. Although prior work has characterized children’s perceptions of algorithmic bias in AI, they do not provide much guidance on *how to engage* children in conversations around algorithmic biases that center their perspectives while safeguarding their well-being around a possibly difficult topic. This guidance is especially pertinent and timely with increasing calls to educate children on the social and ethical impacts of technology [35, 62].

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53 Based on the funds of knowledge position [28, 46] and sensemaking theory [17], in our prior work, we developed
54 discussions and design activities to scaffold children in making sense of algorithmic fairness¹, and explored them with
55 adolescents (ages 14-18) [4]. We found that adolescents introduced many factors that were not included in our prompts,
56 such as lived experiences and power dynamics, into their sensemaking practices. Through this observed process,
57 adolescents developed rich characterizations of algorithmic bias impacts by drawing from their funds of knowledge.
58

59 In this paper, we build upon prior work on youth perceptions of fairness in AI, as well as our own work [4] on
60 scaffolding adolescent sensemaking around algorithmic fairness more broadly, to examine youth sensemaking of
61 algorithmic fairness more generally. Prior work in moral development indicates that children first reason about morality
62 from a more egocentric stance and then learn to reason from others' perspectives as they grow older [10], suggesting
63 interesting potential differences between youth and adolescents. Therefore, we pursued the following research questions:
64

- 65 (1) What funds of knowledge might children use to make sense of algorithmic fairness?
 - 66 (2) How might the ages, identities, and backgrounds of children shape their sensemaking of algorithmic fairness?
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69 After analyzing sensemaking discussions and design activities with 16 children (ages 8-12) in the US, we make
70 two important contributions through this study. First, we contribute to a deeper understanding of children's situated
71 knowledge around algorithmic bias in computing more broadly, not only AI. This suggests potential entryways, such as
72 their own interpersonal relationships, for critical engagement with technology. Second, we contribute a blueprint for
73 engaging children in scaffolded yet open-ended reasoning around algorithmic fairness, informing the design of tools,
74 curricula, and other learning experiences in the growing movement to educate children on technology's social and
75 ethical impacts.
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78 2 BACKGROUND

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80 To examine how children approach and view algorithmic fairness and its intricacies, it is important to first consider
81 existing theories on children's moral development and its progression with children's age and experience. We then take
82 a closer look at the gradual process of understanding the concept of fairness and the theoretical foundations behind our
83 decision to consider children's context as a crucial factor in this study.
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86 2.1 Children's Moral Development and Perceptions of Fairness

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88 Chapman and Caperndale [12] proposed an interpretation of Kohlberg's general framework of moral development
89 stages that emphasizes the process of opinion and stance formation to be rooted in action. According to them, children
90 at different developmental stages construct moral values by internalizing their contextualized actions to develop moral
91 structures. Therefore, children may develop differently across contexts based on their life experiences.
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93 Furthermore, Piaget emphasizes the egocentric continuum in a child's moral development [10]. He posited that
94 children start by reasoning from a more egocentric viewpoint, then by getting to know themselves in relation to the
95 world around them, progress to a less egocentric view of values and morality. In Piaget's structural framework, this
96 view would explain the tendency of younger children (up to the age of 11) to characterize morality based on outcomes
97 rather than intentions, treating rules inflexibly and absolutely. Then, at an older age, children begin to see beyond
98 themselves and may view situations from others' perspectives, using that context to decide if a rule is right or wrong.
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102 ¹With our participants, we use the term "fairness" instead of "bias" because prior work [22] showed that "bias" might not be in youth's vocabulary. We
103 use "fairness" when specifically discussing with our participants but use the terms interchangeably elsewhere in the paper.
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105 Kohlberg [36] also worked to extend Dewey’s work of cognitive moral development by differentiating between
106 (1) the pre-conventional level of morality when a child’s recognition of a good or bad action is directly tied to its
107 consequences and their physical manifestations, such as punishments and rewards, and (2) the conventional level of
108 morality, where older children nuance their moral reasoning while incorporating the moral codes prevalent in the adult
109 society surrounding them. Therefore, it is important in our work to recognize our participants’ ongoing development of
110 moral standards, considering their stage based on their age and contextual backgrounds.

112 As a subset of moral development, the concept of fairness has been shown to mature alongside other values children
113 acquire throughout their lives gradually. Children seem to have a deep aversion to inequality. They can identify unfair
114 behavior from a young age [57] while tending to prefer equity over equality the older they become [5, 33, 50, 55]. While
115 distinguishing between distributive fairness (favoring the results) and procedural fairness (recognizing the fairness
116 in the decision-making process) occurs at a young age, research has shown that younger subsets of children favor
117 fair processes over fair outcomes. In contrast, older children tend to favor distributive fairness, looking closely at the
118 outcomes of an action to determine its fairness, even if the process leading to it was not ‘fair’ [23, 29]. Regarding actions,
119 children older than eight were seen to be more likely to act upon perceived unfairness, while younger children are
120 more likely only to recognize, but not act upon it [8, 9, 44].

124 2.2 Children’s Perceptions of Algorithmic Fairness

126 With respect to children’s understanding of algorithmic fairness, a wealth of literature identified children’s perceptions
127 almost exclusively within the field of AI and agent interactions. In this work, we focus both on children’s direct
128 interactions with computing and an ‘ambient’ computation that may affect children more indirectly in our discussions
129 and activities. Reviews of the field [41] identified several studies that suggest that children often overestimate agent
130 intelligence [21] and consequently overly trust agents [20, 31, 60, 61]. Skinner [56] found that children equated kindness
131 with fairness in AI agents, using kind communication with people to justify fairness. Despite this, Druga et al. [22]
132 have shown that after showing them videos of algorithmic bias examples, children could connect those examples to
133 their daily lives, identifying situations of unfair treatment from AI based on race/ethnicity, age, and gender.

136 Research into children’s perceptions of algorithmic fairness that extends beyond AI to computing is nascent at best.
137 Coenraad [14], for example, discovered that without instruction, youth demonstrated an awareness of visible negative
138 impacts of technology more broadly, not only AI, and were able to provide examples of this bias within their lives. As
139 educators and researchers increase efforts to educate children in critical computing literacies [6, 13, 47], this study
140 offers a blueprint of how to leverage children’s knowledge and backgrounds towards developing a more robust moral
141 sensitivity to the complexities of algorithmic fairness.

144 2.3 Funds of Knowledge & Sensemaking Theory

146 We draw from funds of knowledge and sensemaking theories to support children in bringing their conceptions of fairness
147 into computing. The funds of knowledge approach posit that learners already have various skills, knowledge, and
148 competencies from their lives and their communities [28, 46]. This approach asserts that these assets are frequently
149 invisible because of asymmetrical power relationships in education, and educators should identify and incorporate these
150 skills when designing learning experiences. In K-12 STEM education, this approach has improved educational practices
151 and learning outcomes [3, 16]. Our prior study exploring attitudes towards algorithmic biases with adolescents [4] used
152 such experience grounded sense making techniques to understand scenarios questioning technology’s behavior and
153 showcased their ability to flesh out their explanations with details from their own lives.

157 Complementary to funds of knowledge is sensemaking theory, which postulates that knowledge is dynamic rather
158 than static [17]. It proposes that individuals actively process information from various sources to achieve understanding
159 rather than achieving an arbitrary pinnacle of knowledge. Through sensemaking, individuals can progressively develop
160 new understandings by participating in complex activities where they may not always have prior knowledge instead
161 of simply receiving information through direct instruction. In computing, sensemaking practices allow children to
162 play an active role in learning various concepts, such as AI [18, 19], and data literacy [52]. As our goal is to investigate
163 how children may engage in conversations around algorithmic fairness that center their perspectives, we ground our
164 methods in sensemaking theory to make space for different paths of achieving understanding.
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167 3 METHODS

168 3.1 Study Context & Timeline

169 From July to November 2022, the first and second authors conducted three sensemaking discussions lasting a maximum
170 of 45 minutes with 16 participants (ages 8-12) in the United States. As we had participants from three US states (North
171 Carolina, Virginia, and Washington), we allowed local participants to participate in the study in-person or virtually,
172 while non-local participants had to participate virtually. All participants chose to complete the study virtually. As the
173 three discussions were independent, we offered participants the flexibility of scheduling their sessions 1-4 weeks apart
174 to accommodate extracurricular activities, vacations, and other obligations.
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178 3.2 Participant Demographics

179 Parents/guardians of the 16 participants in our study filled out a form with free-response questions to disclose their
180 children's age, gender identity, ethnic identity, languages spoken at home, disabilities, and any other aspects of their
181 identity they would like the research team to know. Parents/guardians also provided their child(ren)'s chosen pseudonym
182 or 'superhero name.' If they did not choose a pseudonym, we use the last letters of their first and last names (Table 1).
183 All participants had internet-connected devices at home, but we did not ask for any more information about their prior
184 experiences with AI, data, or computing more broadly because (1) we did not require prior experience to participate
185 in our study and (2) prior work has associated perceptions of having less prior experience with a lower sense of
186 belonging and confidence in a computing context [43, 54], which may impact their participation in the study. Before
187 each discussion, we asked each participant for their assent to research participation and session recordings.
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190 3.3 Sensemaking Discussions

191 Table 2 shows the three sensemaking discussions participants engaged in, drawn from our prior study with adoles-
192 cents [4]. Each discussion centered on a specific *scenario* designed to highlight different aspects of algorithmic unfairness.
193 Each scenario started with seed text describing the *situation*. This was followed by the incremental reveal of different
194 layers of algorithmic decision-making — whether a *computer* was used in decision-making, what *algorithm* was, what
195 *data* was used, and what the composition of the *team* behind the algorithm was.
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198 To facilitate participants' sensemaking and provide artifacts for us to analyze, each sensemaking discussion involved
199 (1) a *warm-up question* before introducing the scenario, (2) *reflection questions* for each layer revealed, and (3) a semi-
200 structured big paper *design activity* where participants brainstorm ideas on big paper to support the unconstrained
201 generation of ideas [15, 25]. For virtual participation, we presented the warm-up and reflection questions on Google
202 Slides and the big paper design activity on Google Jamboard. As the scenarios were adapted from a prior study with an
203 older age group [4], we modified the discussion to be more suitable for this age group by (1) limiting the number of
204 participants per discussion to 2, as opposed to 6-7 with the older participants, (2) having participants respond verbally
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Pseudonym	Age	Gender	Ethnicity	Languages Spoken at Home	Disability
AN	12	Agender	Caucasian	English	No
Alex	11	Male	Asian	English, Chinese	No
Ashley*	9	Female	Middle Eastern	English, Arabic	n/a
Emily*	8	Female	Middle Eastern	English, Arabic	n/a
Blue Gamer†	8.5	Boy	Asian	English	No
Green Raven†	12	Boy	Asian	English	No
Ethan	9	Agender	Non-Hispanic, Ashke- nazi Jewish	English	No
Kalex	11	Female	Caucasian	English	No
Kitkat Krystal‡	9	Female	Caucasian	English	No
Magentafied	9	Female	Caucasian	English	No
Moonstone‡					
Leroy	11	Male	White	English	No
Minecraft Coder	9	Male	European	English, Dutch	ADHD
Po	12	Female	Pakistani	Urdu, Punjabi, Potwari, English	n/a
Spider§	8	Girl	White	English	No
Squidney§	10	Nonbinary	White	English	No
StoofCorg	10	Female	Asian	English, Chinese	No

Table 1. Participant Demographics. “n/a” denotes parent/guardian declined to disclose. Matching symbols (*, †, ‡, §) denote siblings.

to the reflection questions immediately, instead of having them write down their reflections first and then debating verbally, and (3) assisting the participants with typing for the big paper design activity as some of them had difficulty balancing between voicing their ideas and expressing those ideas on the big paper.

Scenario	Seed Text	Situation	Computer	Algorithm	Data	Team
Search Engine (‘Search’)	<i>Ahmad is making a presentation for what he wants to major in college: nursing. When he searches online for images of nurses, he can barely find images of man nurses. Almost all the images are of women.</i>	✓		✓		✓
Smart Speaker (‘Speaker’)	<i>Alex and her friends are playing with her family’s new smart speaker, Blurty. She notices Blurty responds to all her friends except Maximo, who just moved to the US from Mexico.</i>	✓		✓	✓	✓
School	<i>There are two schools, School A and School B, in the same city. There are the same number of kids who go to both schools. Here are some of the kids who go to School A (show a group of white children) and here are some of the kids who go to School B (show a group of Black children). In School A, every classroom has six boxes of school supplies, such as books, calculators, art supplies, and notebooks, to use when kids are learning. In School B, every classroom has one box of school supplies.</i>	✓	✓	✓	✓	✓

Table 2. Seed Text & Layers Discussed in Each Scenario.

We made intentional choices to prioritize the safety and agency of participants, accounting for our participants’ ages, backgrounds, and the power imbalance between the researchers and participants. As such, we did not directly ask participants about their harmful experiences with technology. Instead, we selected scenarios that might resonate with them based on prior literature. If they brought up their own experiences, we encouraged them to do so on their terms. If participants were siblings, they participated in discussions together because, in pilots of this method, we observed siblings being able to co-regulate and debate with each other. We wanted co-regulation because we were discussing topics that could be emotionally difficult, and siblings could perhaps support each other. We also wanted to encourage debate since all our scenarios do not have obvious conceptions of fairness. Lastly, we made deliberate terminology

261 choices to minimize reliance on prior computing knowledge. As with ‘fairness’ (see the footnote in Section 1), we used
262 the term ‘rules’ to describe the algorithm. We contextualized the data used in each scenario (e.g., voice recordings in
263 the Speaker scenario) rather than simply using the term ‘data’.

264
265 Regardless of the scenario, we adhered to the following protocol to encourage elaboration: (1) if the participant(s)
266 mention another group of people not mentioned in the scenario, ask them how the rules would affect those people, and
267 (2) if the participant(s) mention an interesting point, repeat their point back to them and ask them why.
268

269 *3.3.1 Scenario Design.* We created three scenarios of algorithmic decision-making that surfaced potential fairness
270 issues to seed sensemaking discussions. These scenarios were selected because they do not have straightforward
271 conceptions of fairness and, thus, may elicit interesting insights from participants.
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- 273 (1) The Search Engine (‘Search’) scenario was based on biases in representation from search results [48, 59].
- 274 (2) The Smart Speaker (‘Speaker’) scenario was based on the failure of many voice recognition systems to recognize
275 other languages or accents [38].
- 276 (3) The School scenario was adapted from the scenario used in [24] to understand youth’s perceptions of social
277 resource inequality to reflect algorithmic redlining [53].
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280 We presented scenarios in this order to highlight an increasing scope of harm. In the Search Scenario, only a single
281 individual is harmed. In the Speaker scenario, while only a single individual is harmed, the harm results in group
282 exclusion. In the School scenario, a community is harmed. We also designed the scenarios to have varying technical
283 focuses, with the Search scenario involving only software components, the Speaker scenario including hardware and
284 software components, and the School scenario involving a covert, non-obvious technical component.
285

286 Table 3 gives a detailed overview of the School scenario. The Search and Speaker scenarios followed a similar
287 structure, with some key differences. First, both scenarios had an apparent technical component that did not require
288 uncovering. Second, they had different high-level abstractions of the algorithm. The Search Engine followed a naive
289 search algorithm accounting for keyword presence in images’ metadata and the Smart Speaker being activated by a
290 specific phrase. Third, the Search scenario had no training data as it was not a machine learning-based algorithm, while
291 the Speaker scenario had training data of voices from English-speaking countries. Lastly, the various teams in the
292 Search scenario differed based on gender, while the Speaker scenario differed based on country of origin.
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295 *3.3.2 Warm-up Questions.* Participants discussed a warm-up question at the beginning of each sensemaking discussion.
296 These questions asked participants to share their experiences and were intended to help them get comfortable reflecting
297 and voicing their perspectives. Table 3 shows the question used in the School scenario.
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300 *3.3.3 Reflection Questions.* After warm-ups, we revealed different layers of the algorithmic decision-making one at a
301 time to scaffold the sensemaking process, inspired by sensemaking practices in math and data science education [37]
302 (see Table 2). For each layer (e.g., algorithm, data) that was revealed, we prompted participants with reflection questions
303 that were focused on either: (1) understanding or (2) evaluating the decisions in each scenario to encourage divergent
304 or convergent thinking, respectively (Table 3).
305
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307 *3.3.4 Design Activities.* After the reflection questions, participants brainstormed ideas to address the bias in the scenario.
308 Consistent with the big paper method [25], they wrote their ideas either on the jamboard or on sticky notes (Figure 1).
309

310 For the design activities, we prompted participants to imagine that they were the boss and in charge of designing
311 the algorithm and, if applicable, the data used in each scenario. We chose this framing because, in early trials of this
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Stage	Phase	School: Questions & Revealed Layers
Warm-Up	–	<i>Ask:</i> Where do you go to school? When you walk into your school, what do you see? When you walk into your classroom, what do you see?
Worksheet		
Situation		<i>Reveal seed text (Table 2)</i>
Computer	Understanding	<i>Ask:</i> Why do you think School A has more supplies than School B?
	Evaluation	<i>Reveal:</i> A computer decided how much supplies each school should get.
Algorithm	Understanding	<i>Ask:</i> a. What do you think of a computer making that decision? b. Why do you think a computer decided to give School A more supplies than School B?
	Evaluation	<i>Reveal:</i> School A is in neighborhood A and School B is in neighborhood B. The computer made its decision using this rule: “For every \$100 the neighborhood gives to the school, every classroom gets an extra box of school supplies.”
	Understanding	<i>Ask:</i> a. What do you think of the rules the computer used? [If participants don't mention fairness] How fair do you think the rules are? Why?
	Evaluation	b. How do the rules impact different people? c. What are the pros and cons of using a computer to make that decision?
Data	Evaluation	<i>Reveal:</i> The computer used data about how much neighborhoods gave in the past to decide that each neighborhood should give \$100 for each box of school supplies.
	Evaluation	<i>Ask:</i> a. What do you think of the data that the computer used? b. How fair is it that the computer used past data? Why?
Team	Evaluation	<i>Reveal:</i> The team who designed the rules and data the computer used was made up of all white people. <i>Ask:</i> a. What do you think of this team? [If participants do not mention fairness for questions a, b, and c] How fair do you think this team is? Why?
	Evaluation	b. What if the team was made up of all black people? What do you think of this team?
	Evaluation	c. What if the team was made up of people from different races? What do you think of this team?
	Evaluation	d. Which team is the most fair? Why? [If participants bring up other factors] If you don't think any of the teams are the most fair, what would be the most fair team? Why?
Design	Brainstorming	<i>Ask:</i> - Imagine you're the boss & you're in charge of the rules. What rules would you use to decide how much supplies each school should get?
Activity	Brainstorming	- Who will be applying the rules? Will it be a computer? A person? A team? Both?
	Brainstorming	- How do you make sure the rules are fair? [Follow-up questions if needed:]
	Brainstorming	- What kind of team would be the most fair in designing these rules?
	Brainstorming	- How would you and your team design the rules fairly?
	Brainstorming	- How would you and your team test the rules fairly?

Table 3. School Sensemaking Discussion Questions in full. *Italics* denote actions performed by facilitators.

method, pilot participants struggled with the agency they had in each scenario, getting preoccupied with whom they would answer to instead of the task at hand. Throughout the activity, we prompted them to consider the fairness of the different layers of decision-making they designed (see Table 3 for specific prompts).

3.4 Data Collection & Analysis

We discussed the Search scenario with all 16 participants, the Speaker scenario with 14 participants (AN and Squidney dropped out), and the School scenario discussion with 12 participants (AN, Spider, Squidney, and Magentaified Moonstone dropped out). As siblings participated together, this resulted in 33 transcripts (32-45 minutes long) and big paper designs.

To understand how participants engaged with the discussions and design activities, we used a deductive thematic analysis approach to analyze the transcripts and big paper designs using participants' responses as our data source, with at least two authors coding each transcript and resolving disagreements by consensus. We adopted the practice of taking

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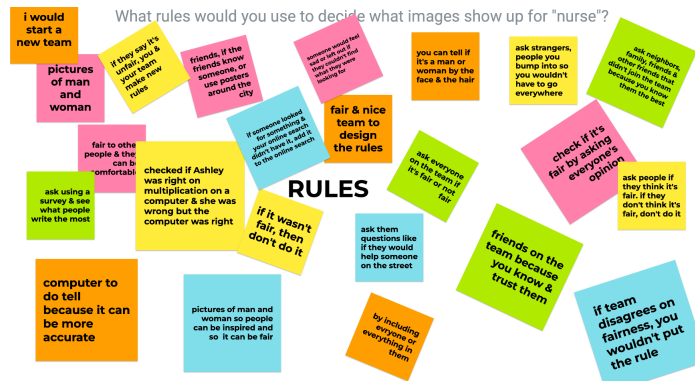


Fig. 1. Example from a Big Paper Design Activity

participant quotes and big paper responses ‘literally’ to minimize inference. We did not capture agreement metrics such as inter-rater reliability throughout this process. Instead, we chose to resolve uncertainties through discussion and consensus-building, consistent with the position of Hammer and Berland [30] on qualitative coding that uses codes as an organizational aid for thematic claims about the data.

Our codebook was drawn from our prior study [4], using the metaphor of a camera as an analysis guide. Since the adolescent participants made sense of algorithmic fairness using many factors beyond those in the scenarios, in the post-hoc round of that study’s thematic analysis, we organized those factors into a camera metaphor to describe how participants used different factors in their sensemaking and how these factors related to each other.

In this metaphor, we specifically used the lenses and filters of a camera. Photographers utilize lenses to modify the scale and resolution of a shot and affix different filters to a lens to photograph the same subject differently, resulting in varying final images. In this metaphor, the participants are photographers, viewing algorithmic fairness in different scales/resolutions and lights to make sense of them. Each participant has their camera with their own set of lenses and filters. In [4], we found that participants used two different *lenses* to make sense of algorithmic bias at different levels: (1) a human lens, which spanned individual to societal factors, and (2) a technical lens, which included technology creators and other technical factors. Along with adapting the scale and resolution with their lenses, we observed that participants employed different characteristics, such as gender and race, as *filters* to alter what was most relevant to their sensemaking in each scenario. This categorization scheme is reflected in our codebook (Table 4).

Categories in the codebook were not mutually exclusive and often overlapped. For example, if a participant used a programmer’s gender bias to make sense of the Search scenario, their quote would be coded in both ‘biases’ under technical factors and ‘gender’ under characteristics. Factors that did not fit in any of the categories were coded as ‘Other’ under human factors, technical factors, or characteristics. While the first three authors reached a collective understanding of most codes, some were more often disagreed upon and required more discussion to build consensus: (1) *individual: principles* because for some participants, it was hard to determine if they espoused these principles themselves, or if they were simply naming a societal ideal, (2) *individual: stereotype* and *society: societal stereotypes* because for some participants, it was difficult to identify if they held the stereotype themselves or if they were naming a societal stereotype, (3) *community: membership* because it was sometimes difficult to identify the community that participants were referring to without inference. Upholding Hammer and Berland’s stance on qualitative work [30], we report on these disagreements for transparency on which themes were more subject to different interpretations.

Factor	Explanation
Human Lens	
<i>Individual</i> : Stereotype	Participants drew from a stereotype they espoused themselves.
<i>Individual</i> : Lived Experience	Participants drew from their own lived experiences.
<i>Individual</i> : Principles	Participants drew from their views of right and wrong.
<i>Community</i> : Geographic Location	Participants drew from the location of a community.
<i>Community</i> : Membership	Participants drew from <i>who</i> is in a community.
<i>Society</i> : History	Participants drew from past events and phenomena.
<i>Society</i> : Societal Stereotype	Participants identified a problematic idea as a 'stereotype'.
<i>Society</i> : Power Distribution	Participants identified issues of power/agency or lack thereof.
<i>Society</i> : Systemic Marginalization	Participants problematized marginalization as a result of larger systems.
Technical Lens	
<i>Creators</i> : Qualifications	Participants expressed both technical and interpersonal qualities that made tech creators (un)qualified for the job.
<i>Creators</i> : Biases	Participants cited biases held by the tech creators.
<i>Creators</i> : Power Dynamics	Participants accounted for power dynamics within teams of tech creators.
Characteristics as Filters	
	Characteristics participants used to describe the factors above: gender, country of origin, language, accent, (dis)ability, age, academic performance, economic status/class, race/ethnicity

Table 4. Codebook using the metaphor of a camera from [4] as an analysis guide. We coded for the presence/absence of these factors in participant transcripts and big paper designs.

After all the transcripts were coded, the first and second authors collaboratively grouped the 'Other' factors into common categories using affinity diagramming [42]. The first author then coded the 'Other' factors into those common categories, with the second author verifying their codes and resolving uncertainties through consensus. Lastly, the first and second authors conducted a post-hoc analysis of all the codes to synthesize higher-level themes.

3.5 Author Positionality

Positionality statements make explicit the relationship between the authors' identities and the research topic and the identities of the participants [32, 39, 51]. Each author wrote statements to describe experiences and perspectives that influenced their engagement with the research.

The first author identifies as a woman of color. Some participants used her visible identity facets in the sensemaking discussions. For instance, when making sense of why most nurses were women in the Search scenario, Blue Gamer hypothesized that it was because women "get less pay for some weird reason" and then asked the first author if she got enough pay. Her experiences with systemic marginalization in computing and society led to her interest in critical computing literacies for youth and adolescents. She led this project to understand the youth's perspectives and engagement with ideas around algorithmic bias.

The second author grew up and currently resides in a liberal and technology-centric city. Through their work in various communities throughout their career, they have come to recognize that their background may lead them to view technology as an integral and irresistible part of society - a reality that is not reflected by all participants in this study or otherwise. They are therefore motivated by their hope to challenge the culture of mystery, silence, and unchallenged acceptance of technological advancements. They seek to grant children the opportunity to see beyond the black box of technology and clearly understand its motives and inner workings.

The third author positions herself primarily as an activist for better and more inclusive technology education. Before deciding to embark on a Ph.D. journey, she worked for more than eight years on hands-on STEAM education in different communities worldwide as part of the organization she created called *Anonymized*. In the past three years, she has led

multiple co-design sessions with families focused on AI literacy and created *Anonymized*, one of the first platforms for AI education, which is free and open-source.

The fourth author identifies as a mixed-race, queer, gender non-conforming parent and a computing researcher. She has had a lifelong interest in youth development and approached this project with a curiosity about youth capacity for moral reasoning about computation. Her role in the work was mentor, advisor, and facilitator.

4 RESULTS

Using the camera metaphor from our prior study with adolescents as an analysis guide (see Section 3.4), we characterize the two lenses, the *human* lens and *technical* lens, and the filters, or the *characteristics*, participants in this study used to make sense of algorithmic bias. Since participants often used the lenses and multiple filters in conjunction, featuring a quote for one particular lens or filter does not mean it did not contain others.

4.1 Human Lens: Different Scales of Human Factors

The human lens encompassed factors relevant to groups of people of different sizes: individual, community, and society.

4.1.1 Individual. The individual level included factors connected to an individual. One factor that participants accounted for in reasoning about the unfairness in a scenario was stereotypes (Search: 9/16; Speaker: 2/14; School: 1/12). When brainstorming how people designing a Search Engine would identify images of different gendered nurses, Emily suggested, “*You could tell by the face and hair?*”, reflecting physical gender stereotypes.

Participants also attributed the unfairness to an individual’s pitfalls (Search: 6/16) or an individual’s interaction with technology (Speaker: 5/12; School: 4/12). In reasoning about why the Smart Speaker did not respond to Maximo, Green Raven hypothesized, “*he might have said it wrong*”, faulting the individual in the scenario.

Across all scenarios, two factors were especially salient to participants. The first was their lived experiences (Search: 11/16, Speaker: 9/14, School: 8/12). Po drew from her school district when making sense of the unfairness in the School scenario, “*In the less wealthy side of <Po’s hometown>, the district divides it purposely so the wealthier people go to one school, and then the less wealthy people go to another*”, using observations of wealth distribution in her neighborhood.

The other particularly salient factor was their principles or beliefs of right and wrong (Search: 16/16, Speaker: 14/14, School: 12/12). In critiquing the rules in the Search scenario, AN said, “*It’d be nice to have a search that would include some sort of diversity, but I don’t know what kind of rule that would be.*” Although they did not how to accomplish it, AN believed that diversity was important in designing the rules for a search engine.

4.1.2 Community. The community level covered factors linked to a collective group of people. At this level, membership, or *who* was in a community, was especially relevant to participants in their sensemaking process (Search: 11/16; Speaker: 7/14; School: 8/12). When brainstorming who should design the rules in the School scenario, Alex wanted “*a team of parents who have children who go to all the schools in the city*”, conceptualizing potential stakeholders in that scenario.

Most participants also examined aspects of interpersonal relationships, such as bullying, empathy, and collaboration, when making sense of the unfairness in scenarios (Search: 10/16, Speaker: 12/14, School: 8/12). When making sense of Ahmad’s feelings from seeing mostly women as nurses, Kalex compared it to an instance of bullying: “*I have a friend who is vegetarian [...] there was a kid in my class who would bully her for it.*” Similarly, Minecraft Coder empathized with Maximo’s struggle in the Speaker scenario: “*it would make you think you should speak another language, and you would ask every time Alexa can you repeat that again?*”. Participants also accounted for collaboration while brainstorming the design team. When asked if the team designing the Speaker should be from different countries, Magentafied Moonstone

questioned, “*Can the team all speak one language? Because then it’s not really a team if they can’t collaborate*”, suggesting that good teamwork was a priority, perhaps even above diversity in countries or languages.

4.1.3 *Society*. The society level encompassed factors attributed to larger structural issues. Participants accounted for history (Search: 10/16, Speaker: 1/14, School: 11/12), issues of power distribution (Search: 12/16, Speaker: 3/14, School: 11/12), systemic marginalization (Search: 9/16, Speaker: 2/14, School: 9/12), and societal stereotypes (Search: 11/16, Speaker: 7/14, School: 8/12). Interestingly, while participants considered systemic issues in their sensemaking, they tended to attribute these issues to individuals. This tendency was exemplified in the following exchange between Ethan and a researcher while discussing the Speaker scenario:

Researcher: Why do you think the speaker would respond differently to someone from a different place?

Ethan: Because America is mostly a bad place, and so we build bad things.

Researcher: Alright, why do you say it’s a bad place?

Ethan: It’s getting better, but [...] it doesn’t accept a lot of stuff.

Researcher: What do you mean when you say it doesn’t really accept that much?

Ethan: Not the president now, but who used to be president like, a few years ago, Trump.

In this exchange, Ethan voiced a larger structural issue, a country’s unwelcoming environment, but blamed it on a specific person. Similarly, when making sense of why schools received different amounts of school supplies, Green Raven hypothesized, “*The white person’s like white supremacy cuz it’s what white people think*”. While Green Raven identified the systemic issue of white supremacy, he attributed it to individual white people. Both these instances reveal an awareness of systemic issues but only a vague, individualistic understanding of them.

Participants also considered societal ideals. These are distinct from the principles at the individual level because it was not clear if the children espoused these ideals themselves (Search: 16/16, Speaker: 12/14, School: 9/12). In his evaluation of an all-men team in the Search scenario, Minecraft Coder critiqued, “*the team would think the same*”. While he accounted for the societal ideal of diversity in his sensemaking, it was not definitive if he believed in this ideal.

4.2 Technical Lens: Different Resolutions of Technology Factors

Participants used the technical lens to account for technology-related factors to varying degrees of specificity. This lens was not as well-formed as the human lens, which was expected because we did not require prior computing experience.

4.2.1 *Technology Creators*. We grouped engineers, programmers, designers, and others involved in developing technology under the umbrella of ‘creators’, as participants did not meaningfully distinguish between them. When sensemaking, participants accounted for the creators’ qualifications (Search: 16/16, Speaker: 14/14, School: 12/12) and biases (Search: 15/16, Speaker: 7/14, School: 8/12), as well as power dynamics within teams of tech creators (Search: 11/16, Speaker: 5/14, School: 6/12). For instance, Alex contemplated the skill of navigating team disagreements in deciding who would be qualified to design rules for the School scenario: “*Some people might disagree on how much you should price it [...] but as long as they could always find some way to agree they’ll be a very good team.*”

4.2.2 *Users*. Participants also considered technology users (Search: 7/16; Speaker: 10/14; School: 7/12). This largely came in the form of testing the technology with users conceptualized by the participants, both real and hypothetical. In brainstorming how she would test the Speaker, Ashley said, “*they could have many people who speak different languages*”. She also included people in her life in testing, “*Your family? Maybe your neighbor? Maybe other people you see?*”

In conceptualizing hypothetical users, some participants made assumptions about them, such as Squidney in making sense of the rules in the Search scenario: “*They probably would know that having a label would increase the chance of*

573 *having it in the list or photos that come up when you search nurse.*” Squidney indicated an assumption of some technical
 574 knowledge from a user, which may not necessarily be the case.
 575

576 4.2.3 *Attitudes towards Technology.* Lastly, participants reflected on their attitudes toward technology in their sense-
 577 making. Most participants voiced doubts over a computer’s abilities (Search: 11/16; Speaker: 11/14; School: 12/12). These
 578 doubts were often cited as reasons to absolve the computer, such as StoofCorg in the Search scenario: *“the computer*
 579 *is just following whatever the people say”*. These doubts might have also shaped the computers’ role in the solutions
 580 participants designed. For instance, an idea from Ethan’s design board was *“Use the computer for the emails and*
 581 *the phone”*, relegating technology to a communication role.
 582

583 Participants also demonstrated a preference for humans over computers in addressing the unfairness in the scenarios
 584 (Search: 6/16; Speaker: 1/14; School: 7/12). In making sense of the computer’s decision-making role in the School
 585 scenario, Po critiqued, *“Instead of making a computer do it and being extremely specific, [...] then I think it’s just be a*
 586 *better idea for a human to do it. Because there’s less room for error if a human just did it.”*
 587

588 4.3 Filters: Characteristics Salient in Sensemaking

589 After participants determined the scale/resolution of their sensemaking within the human or technical lens, they
 590 decided which filter to attach to the lens to make different *characteristics* more relevant. Participants tended to use
 591 characteristics from both the prompts and their conceptions to reason about the algorithmic unfairness in the scenarios.
 592 Participants sometimes used multiple characteristics simultaneously, so using a quote for a specific characteristic does
 593 not mean it did not contain other characteristics. We begin with the characteristics used only in the scenario where
 594 they were prompted, followed by characteristics that participants introduced into only one scenario, and end with
 595 characteristics used by participants in all scenarios regardless of mention in the prompts.
 596
 597

598 4.3.1 *Characteristics Used only in the Prompted Scenario.* All participants (14/14) used both language and a closely
 599 related though not explicitly stated factor, accent, to make sense of the fairness in the Speaker scenario. When evaluating
 600 a multilingual design team for the Speaker, Blue Gamer prioritized language inclusivity, *“Yeah, it would include everyone.*
 601 *Even if they made bad decisions, it’s still better than everyone knowing only one language.”* As for accents, when making
 602 sense of the rule used to trigger the Speaker, Kitkat Krystal hypothesized: *“If you think about people with accents, like*
 603 *Maximo might have, maybe when they say ‘Hey, Blurty’, it may sound a little different that Blurty may not understand.”*
 604
 605

606 4.3.2 *Characteristics Introduced by Participants.* Some participants (4/16) used economic status to make sense of the
 607 unfairness in the Search scenario, although it was not mentioned at all. Participants often reasoned about economic
 608 status through gender, a characteristic included in the prompt. When assessing the fairness of an all-male design team,
 609 Spider hypothesized, *“this team probably gets paid a lot of money [...], and so the woman is out lots of money.”*
 610
 611

612 Another characteristic that participants introduced was (dis)ability into the Speaker scenario (3/12). In critiquing the
 613 rule used to trigger the Speaker, Alex described his own pronunciation difficulties: *“If people speak with accents or speech*
 614 *impediments, like lisps, then perhaps it will be harder to understand. For example, I have to wear these retainers every night.*
 615 *When I wear them, it’s hard for me to pronounce my Ls and Rs. If I tried to say, ‘Hey, Blurty’, it might sound a little weird.”*
 616 Participants also considered different traits of speech (10/14). For example, Ethan brainstormed testing with voices of
 617 different pitches, *“If it’s high pitch, accent, or low, or deep, we can find out if it can still recognize it as Hey, Blurty.”*
 618
 619

620 In the School scenario, participants introduced the school or neighborhood population (5/15) to make sense of the
 621 unfairness. When it was revealed that a computer decided the distribution of school supplies, Kitkat Krystal rationalized
 622 its decision based on class size, *“It can also just be based on how many kids are in your class. In school A, say there were 32*
 623
 624

625 *students in a class. But then for school B, there were 22. So it's okay, they can get a smaller amount of boxes.*" On a related
626 note, participants also introduced the distribution of resources (4/15). In brainstorming solutions, Ashley ideated: *"I*
627 *think they should split the money to both schools. They can get the supplies they need"*.
628

629
630 **4.3.3 Characteristics Salient across all Scenarios.** Four characteristics were used by participants to make sense of
631 algorithmic fairness in all the scenarios: gender, country of origin, race/ethnicity, and age.

632 Gender was only mentioned in the Search scenario, but was relevant in all scenarios (Search: 16/16; Speaker: 7/14;
633 School: 3/12). For instance, when deciding who he would want in his design team for the School scenario, Leroy
634 suggested, *"a mix of races and genders"*, layering gender in addition to race (which was included in the scenario).
635

636 Similarly, country of origin was only brought up in the Speaker scenario but was added by participants in all scenarios
637 (Search: 3/16; Speaker: 14/14; School: 1/12). As an example, in designing a solution to the Search scenario, Green Raven
638 said, *"I guess every country has a say. So it's a worldwide thing."*
639

640 Race/ethnicity was also only included in the School scenario, but became pertinent to participants across all scenarios
641 (Search: 9/16; Speaker: 4/14; School: 12/12). For example, when choosing which accents and dialects to include in the
642 training data for the Speaker, StoofCorg brainstormed, *"definitely Mexican because you get a lot of Mexican immigrants,*
643 *Chinese because there's a lot of Chinese immigrants, African Americans, maybe British."*
644

645 Interestingly, age was not prompted in any of the scenarios and yet was utilized by all participants in their sensemaking
646 (Search: 9/16; Speaker: 4/14; School: 1/12). Age was often used as a gateway for participants to introduce their own
647 conceptions of fairness into their sensemaking process, such Magentafied Moonstone (age 12) who was participating
648 with her sibling Kitkat Krystal (age 9): *"When you have someone that's 9 versus someone that's 12, clothes might cost*
649 *more. So you might have to give us a different amount of money, but it's still fair."*
650

651 5 DISCUSSION

652 5.1 RQ1: What funds of knowledge might children use to make sense of algorithmic fairness?

653 Through the scaffolded sensemaking in these scenario discussions and design activities, all participants reasoned around
654 algorithmic fairness using factors both explicitly and not explicitly mentioned in the scenarios. Participants used two
655 lenses to adjust the scale and resolution of their sensemaking: (1) the human lens and (2) the technical lens.
656

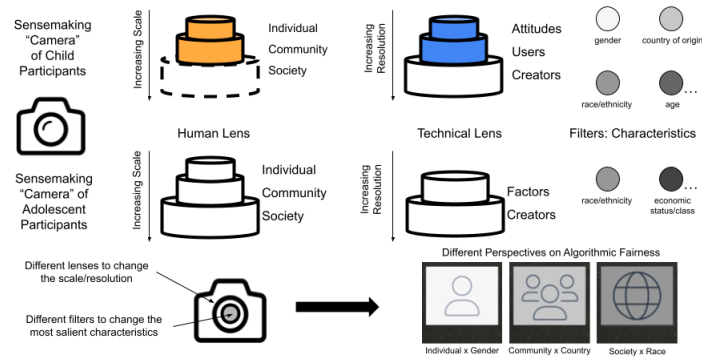
657 In the human lens, participants used factors at increasing group sizes ranging from individual to society, which
658 reflects ecological system theory that views an individual relative to their communities and larger society [11]. At the
659 individual level, participants often grounded their sensemaking in their lived experiences and principles. Similarly, at the
660 community level, participants tended to base their reasoning in both real and hypothetical interpersonal relationships,
661 which often arose when hypothesizing the impacts of algorithmic bias. However, while participants also reasoned at
662 the societal level, this sensemaking was more vague — participants tended to attribute structural issues to individual
663 bad actors, not fully comprehending the large, systemic scale. Participants also expressed societal ideals when making
664 sense of the unfairness, but it was not always clear if they believed in themselves. This vagueness may be because these
665 issues are more abstract, coming from surrounding adult society, and less grounded in their own lived experiences [36].
666

667 As for the technical lens, participants often developed specific conceptualizations of users, drawing from both
668 real people in their lives and hypothetical users. This mirrors the relevance of lived experiences and interpersonal
669 relationships observed through the human lens. In contrast with prior work [20, 31, 41, 60, 61], participants also exhibited
670 a distrust towards technology, doubting computers' abilities and displayed an inclination towards a human approach to
671 address unfairness. This may be due to various reasons, including but not limited to (1) the lack of personification of
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677 the technology in the scenarios [26], (2) the child characters in the scenarios were easier to empathize with, (3) lived
 678 experiences with or exposure to adult tech use [49], and (4) a broader attitude change towards technology in society.
 679

680 5.2 RQ2: How might the ages, identities, and backgrounds of children shape their sensemaking of 681 algorithmic fairness? 682

683 Compared with the adolescent participants in our prior study [4], participants in this study tended to draw more
 684 heavily from their own experiences, perhaps indicative of a more egocentric viewpoint of morality characteristic
 685 in children [10]. Interpersonal relationships were very salient to participants in this study but not as salient for
 686 adolescents. This observation may potentially be because, at this age group, most children are learning to navigate
 687 interpersonal relationships and refining those skills [45]. In the human lens, the differences between the child and
 688 adolescent participants seemed to be reflected through the larger relevance of the individual and community levels
 689 and the relative vagueness of the societal level (Figure 2). In the technical lens, this study’s participants often expressed
 690 detailed characterization of users in their testing, as opposed to the previous study’s adolescent participants often
 691 designing for the ‘average user’, possibly indicating the salience of interpersonal relationships. This study’s participants
 692 also drew from their own skeptical attitudes around technology, potentially reflecting a more egocentric viewpoint.
 693
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 696



710 Fig. 2. Comparison of the Sensemaking ‘Cameras’ of this study’s participants & adolescents from [4]. The individual and community
 711 levels of the human lens were more salient (orange), while the societal level was more vague (dashed line). The technical lens had
 712 new aspects of ‘users’ and ‘attitudes’ (blue).

713 In addition to reasoning fairness at different scales and levels of specificity, participants often introduced character-
 714 istics beyond the prompt in their sensemaking. Participants introduced economic status into the Search scenario,
 715 (dis)ability into the Speaker scenario, and population and resource distribution into the School scenario, none of which
 716 were prompted. Participants may have added economic status into the Search scenario because it involved genders
 717 and occupations; some may have been sensitive to occupational stereotypes [27] or have existing knowledge of the
 718 gender pay gap [58]. Participants may include (dis)ability in the form of speech impediments because of their own
 719 experiences [7]. Similarly, participants may have accounted for school or neighborhood population, as well as resource
 720 distribution because schools, classrooms, and neighborhoods are contexts they are familiar with.
 721
 722

723 Participants seemed to be especially attuned to gender, race/ethnicity, country of origin, and age, as they used them to
 724 make sense of the unfairness in all scenarios regardless of whether they were prompted. In contrast, race/ethnicity and
 725 economic status/class were particularly salient for the adolescent participants in [4]. Children develop identities around
 726 gender and race from a young age as part of learning social competence [34], which may explain the salience of gender
 727
 728

729 and race. While we did not specifically ask in our demographics form, some participants brought up their immigrant
730 backgrounds, which may account for the relevance of country of origin across the scenarios. Age may be particularly
731 salient to participants because many developmental milestones in childhood are tied to age [1]. The seemingly lower
732 relevance of economic status/class for participants in this study compared with the adolescent participants in [4] may
733 be grounded in lived experience. We did not recruit based on economic background for this study, but we recruited the
734 adolescent participants from a program targeting students from low-income backgrounds in [4]. By understanding how
735 learners' funds of knowledge may change based on ages, identities, and backgrounds and by considering their stage of
736 development, learning experiences, such as these discussions and activities, can scaffold learners in leveraging their
737 funds of knowledge to make sense of algorithmic fairness, enabling them to reason more deeply.
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742 5.3 Limitations, Contributions, & Future Work 743

744 Although our study provides valuable insights, its design has some limitations. While we prioritized participants'
745 well-being and safety throughout the study, elements of the inherent power dynamic between an adult researcher
746 and child participants still persist. For example, by following up on a participant's idea to encourage their thinking, a
747 researcher signals importance to the participant, which can influence them to emphasize ideas differently. Participants
748 may also have perceived us as authority figures, possibly affecting their behavior in sessions. They may have acted
749 differently to impress us or may have been more engaged because perceived authority figures were listening to them.
750 Also, while our participants were from different US states, they were all from locales that had a technology industry
751 presence, which may have shaped their attitudes toward technology. Lastly, our participants only represent their own
752 unique views and experiences, which do not generalize (neither was generalizability an objective of this study).
753
754

755 In spite of its limitations, this work reveals crucial insights into children's reasoning around algorithmic fairness.
756 When provided opportunities to use their situated knowledge, such as in these discussions and design activities, children
757 were not only aware of algorithmic bias but also capable of sensemaking around both its explicit and implicit negative
758 impacts. This characterization of participants' funds of knowledge can help designers uphold design principles for
759 children, by gathering and respecting children's unique perspectives [40] and by supporting proactive measures to
760 protect them from algorithmic bias [2], such as education. Understanding potential funds of knowledge also inform the
761 design of learning experiences on algorithmic fairness by understanding potential paths for children to engage in a way
762 that centers their agency and well-being. Since learners' funds of knowledge evolve with age, experiences, and social
763 circumstances [28, 46], it is important that such experiences designed for children consider both their lived experiences
764 as well as their moral and interpersonal development so that their existing experiences and knowledge may serve as a
765 bridge into a new domain.
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768

769 While this study offers one blueprint for incorporating children's funds of knowledge through open-ended sense-
770 making, future work could explore other tools and techniques to do so. As our participants only represent their own
771 knowledge and experiences, it is also crucial that future studies replicate this study with participants of different
772 identities and backgrounds. Future studies may also investigate how different stakeholders in different contexts, such as
773 families, teachers, designers, and policymakers, may be responsive to children's funds of knowledge when engaging
774 them in learning experiences on algorithmic bias. Learning experiences, tools, and other interactions with technology
775 that meaningfully integrate children's situated knowledge can better enable them to take advantage of their unique
776 perspectives in navigating this increasingly technological world.
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6 SELECTION AND PARTICIPATION OF CHILDREN

We recruited children through our networks, social media, and local parent groups. We selected children based on their ages (7-12) and attempted to get a mix of genders, ethnicities, languages spoken at home, and disability status. Before any discussions with children, both the children and their parents read and signed a consent form, describing the study purpose, procedures, potential risks, stress, or discomfort, confidentiality, and the de-identified public dissemination of research results. At the start of each discussion, the researcher first told the children that it would take up to 45 minutes, and that we would start by discussing a scenario with computers, followed by an activity where they would get to be the boss and design some rules. We then asked the children if they assented to the discussion being recorded and that they can stop the recording at any time. Lastly, we reinforced to the children that they should only share what they are comfortable sharing and that if they no longer want to participate, they can tell us without getting in trouble with us or their parents. Throughout the discussion, we also looked out for signs of discomfort from the children, so that we could skip questions or shorten/end discussions if they were uncomfortable.

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