How smart are the smart toys? Children and parents' agent interaction and intelligence attribution

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ABSTRACT
Intelligent toys and smart devices are becoming ubiquitous in children's homes. As such, it is imperative to understand how these computational objects impact children's development. Children's attribution of intelligence relates to how they perceive the behavior of these agents [6]. However, their underlying reasoning is not well understood. To explore this, we invited 30 pairs of children (4-10 years old) and their parents to assess the intelligence of mice, robots, and themselves in a maze-solving activity. Participants watched videos of mice and robots solving a maze. Then, they solved the maze by remotely navigating a robot. Solving the maze enabled participants to gain insight into the agent's mind by referencing their own experience. Children and their parents gave similar answers for whether the mouse or the robot was more intelligent and used a wide variety of explanations. We also observed developmental differences in childrens' references to agents' social-emotional attributes, strategies and performance.

Author Keywords
Child-agent interaction; child-robot interaction; intelligence attribution; parental influence.

INTRODUCTION
Conversational agents and connected toys are becoming common in our homes. Prior studies show that children readily interact with and adopt these technologies [30, 32]. The increasing exposure to "intelligent" technology in the home raises important questions about the ways that children understand and interact with it, and how this in turn may impact their development, attitudes and behavior. In a previous study we discovered that children (6-10 years old) considered personal home assistants (Amazon's Alexa, Google Home) and smart toys (Anki's Cozmo robot, the My Friend Cayla doll) as more intelligent than they are even if these devices could not always answer their questions. This prompted us to further investigate how children perceive the intelligence of these devices in comparison with human or animal intelligence.

To investigate this question, we ran a pilot study where children watched videos of a small robot (Anki's Cozmo, see Figure 1) and a real mouse solve a maze. We invited children to compare how they would solve the maze by tele-operating the same robot through it. We asked children which agent was smarter in solving the maze and why. During these pilot sessions, we invited a few parents to participate in the experiment, too. Interestingly, we observed that in several cases, children and their parents expressed very similar choices and arguments even though they participated in the experiment separately.

Based on this observation, we conducted a full study, reported here, where we recruited pairs of children and their parents to participate. We pose the following research questions:

- Developmental differences. How similar are parents and children in their attributions of intelligence and their mental models?
- Intelligence attribution. How do parents and children attribute intelligence to different agents based on solving the same maze?
- Strategy vs outcomes. Are participants more focused on the strategy of the agent or the outcome?

Building on prior work, we explore through ontological, psychological and developmental lenses, how children and parents attribute intelligence to animals, people, and intelligent artifacts. We review prior research on children's mental models of intelligence and cybernetic intuitions of animacy, agency, and causality. We contextualize these prior psychological findings in families' relationship to technology. While several previous efforts have explored foundational questions around intelligence attribution and family learning culture, our study

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is the first one to explore how parental attitudes and understanding of intelligent devices influence children's behavior and development when interacting with these computational objects. We believe this investigation is particularly important to help motivate and inspire a culture of critical thinking about such technologies and a shift of power for families using these devices. We also propose a series of guidelines for designers and policy makers to support this.

RELATED WORK

In the following, we highlight previous work focusing on young children's conceptions of agents' intelligence and behavior, their ability to make sense of such behaviors through practice, and the import of parental influence in this process.

Mental models of intelligence

Intelligence is defined as the ability to acquire and manipulate or act upon information in an independent way [6], an adaptation of stability and change [38], or an expression of a learning process that involves perspective taking and object construction [1]. Intuitions about intelligence are at the core of many of the oldest lines of research in developmental psychology, including animism [37], theory of mind [47], psychology and biology [7]. Most of this work builds on distinctions between perception, emotions, beliefs, intentions, and knowledge [15].

Intelligent agents such as robots, computers, and connected toys are part of children's everyday environments. These agents are capable of autonomous decision-making, programmability, communication, adaptive behavior, and knowledge accumulation. Children's increasing exposure to these "intelligent" devices raises questions about how children understand their intelligence [43, 44, 2] and how children's intuitive distinctions between living and nonliving objects are challenged [36]. Young children learn to distinguish agents as animate or inanimate, then use that distinction to guide their attribution of various characteristics, including intelligence [17, 18, 31]. Their ideas about the capabilities of living things together with their understanding of intelligence and the functions of the brain develop with age [35, 39, 24, 29].

Developmental psychology literature suggests that domain-specific knowledge is often a better predictor of knowledge representations and beliefs than developmental factors [9, 11, 21]. Children who have experience in a particular field express more complex knowledge representations than novices of any age [10]. Building on children and technology literature [26], we hypothesize that as children gain experience and exposure to technology, they will transition from the context of their naive biology theories [20, 48] to start thinking about computational objects as intelligent technologies.

We build on this work to further explore children's intelligence attribution patterns by asking children to compare different agents' intelligence as the agents perform the same task. This allows us to study to what kinds of entities children attribute social-emotional and cognitive abilities, how children might draw those conclusions, and compare them with those of their parents. We hypothesize that children who grow up with intelligent agents will develop new ways of thinking about them, and potentially at younger ages. As such, one goal of this study is to investigate how children's ideas about agents' intelligence change as they gain more insight into how the agents perceive the world and make decisions. One way of enabling this perspective is to have children teleoperate the agent to do the task from the agent's vantage point. Building on prior research on conceptual change in learning [12, 45, 4], we enable the children to experience this hands-on activity in order to investigate how their mental models about the robot could be refined to understand more in depth how the agent works, rather than just observing its superficial characteristics.

Children's cybernetic intuitions of animacy, agency, and causality

Not all computational objects can be readily classified as animate or inanimate due to their varying anthropomorphic characteristics; they can only be placed along an animate-inanimate continuum [28, 41]. Furthermore, children develop their understanding of technology along this continuum. Their sense-making process transitions from an initial observation of physical characteristics of a device to an understanding based on definitions. Understanding based on observed characteristics, e.g., a robot, as an object "with wheels and sensors", is typically subjective, where an understanding based on definitions, e.g., the description of a robot as a programmable object, has a more universally applicable character [22, 40].

Prior studies recognize programmability as a key concept in a domain-specific understanding of "intelligent" objects [14]. Before children are able to grasp this concept they make sense of computational objects' behavior by personifying them[5]. This personification should not be regarded as a naive strategy but as a foundational step in children's building of knowledge anchored in their primary distinction of self versus the world [2]. Work on children's cybernetic intuitions [43, 3] and children and machines [20] has shown that children do not distinguish between causation and agency in the ways most adults do. Instead, children older than 5 years old interpret mostly any transaction between animate and inanimate entities in terms of who controls whom, either through direct or mediated action. Introducing these computational objects as new ontological entities that are neither animate nor inanimate allows children to introduce new tools to their cognitive ecologies [26, 25, 27, 42].

Families and technology

Research on families' interactions with technology is a growing area with implications for the design of new agents [32]. As devices become more human-like in form or function, humans tend to attribute them more social and moral characteristics [26]. This raises the question of parental engagement and interventions in children's interaction with connected toys and intelligent agents [13]. Prior studies showed that parents scaffold children's behavior when interacting with robots or interactive devices together [8, 16].

Our work continues the theme of exploring parent and child reactions to technology by examining their attributions of connected toys' intelligence and by analyzing the influence parents might have over their children's mental models. In this work we seek to better understand parent's and children's attribution of intelligence for animate and inanimate agents, Participant Demographics

Group	*N*	*Age (Mean, S.D.)*	*Female Ratio*
Children (4-7 years)	20	5.35, 0.99	40.00%
Children (8-10 years)	10	9.00, 0.94	30.50%
Parents (30-54 years)	23	40.43, 6.41	66.67 %

Table 1. Demographics of participants in this study, separated into children and parents.

in order to provide parents and educators with relevant recommendations.

STUDY METHODS

The goal of our study is to advance research on children's conceptualization and interaction with smart toys [43, 2] given that these devices are much more advanced, widely commercially available, and children at younger ages have access to them.

Selection and Participation of Children and Parents

We recruited 53 participants (30 children and 23 parents) through announcements to local parent groups, mailing lists, and social media posts. In total, we had 30 pairs of children and their parents (some children were siblings). Children ranged from 4-10 years old (mean = 6.77, SD = 2.06). From the survey respondents, we scheduled interviews with thirty pairs of participants. Children and their parents participated in the study separately. Three of the children had previously used Cozmo, our robot, before this study. All participants were from the Greater Boston area, Massachusetts, U.S.A. Further information about the gender and age of participants are detailed in Table 1. Before beginning the study, parents and participants over the age of 7 signed assent forms.

Materials

Agents. The agents that we chose as stimuli for the study were a mouse and a robot (Cozmo), in Figure 1. Cozmo is a small robotic toy vehicle with with an expressive LED face, moving arm, moving head, and front camera. Operators can see through Cozmo's camera, control Cozmo's arm, move Cozmo's head, drive Cozmo, and trigger animations remotely. Videos of the agents were shown to participants as part of the questionnaire. The robot was also tele-operated by participants when solving the maze.

Maze. We used a maze-solving task to create a common reference for participants to compare the mouse, robot, and their own performance. We wanted a problem-solving task with a clear goal where agents can display different strategies. Figure 2 shows the physical maze made out of Lego where participants could tele-operate the robot to try to find the cheese. The maze we had in our study room had the same level of complexity like the mazes shown in the mouse and robot videos (equal number of corners and turns).

Tele-operation station. We set up a station with a laptop that allowed children and adults to see through the robot's camera and control the robot's movements to navigate the maze (Figure 3). Participants could also move the head up and down to adjust the viewing angle.

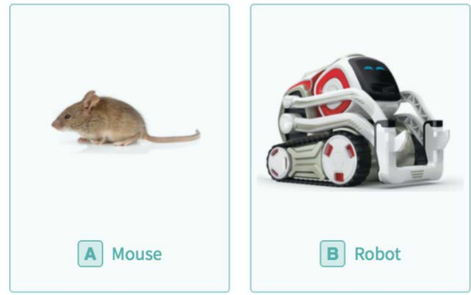

Figure 1. Agents used in the study: a mouse and the Cozmo robot from Anki. (https://www.anki.com/en-us/cozmo).

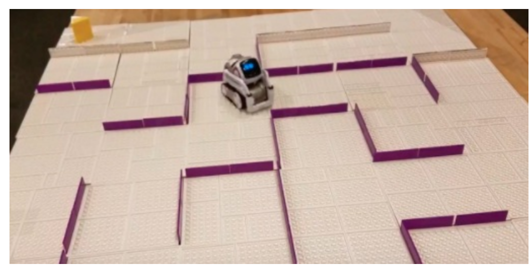

Figure 2. Lego maze used in the study

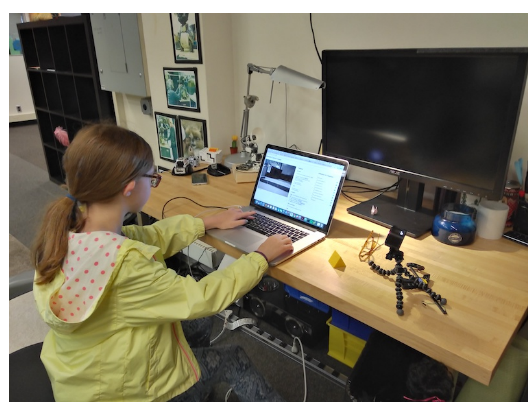

Figure 3. 10 years old participant tele-operating the robot

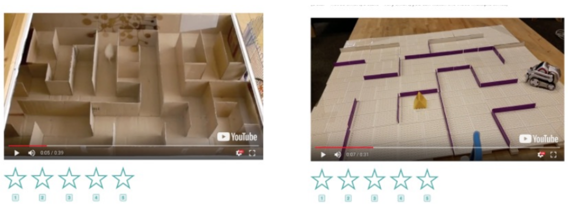

Figure 4. Examples mouse and robot videos

Figure 5. Study Setup: (a) Getting familiar with the maze; (b) Teleoperate the agent to solve the maze;(c) Take the intelligence attribution questionnaire and pre-test

Intelligence attribution questionnaire
The questionnaire consisted videos depicting the mouse or robot trying to find cheese in a maze. The questionnaire was presented on a tablet, examples are shown in Figure 4.

Study Procedure
Children and parents were invited to participate separately from one another. Each participant watched videos of mice and robots solving a maze. The participants were also invited to solve the maze by navigating a robot from a first-person perspective. We interviewed participants after each encounter to understand their model of the agent's minds, which agent they believed was smarter, and how they compared the intelligence of the agents to themselves.

Pretest Upon arrival, participants were shown the study maze (Figure. 2) and asked if they ever solved a maze before. Half of the participants were assigned to solve the maze before watching videos and doing the intelligence attribution questions, and the other half did it after. Alternating the order of solving the maze before or after did not impact participants' answers.

During the intelligence attribution questions, each participant watched six videos depicting a mouse and or the Cozmo robot attempting to solve a maze (Figure. 4). The mouse or robot each appeared in three videos deploying a different strategy: *strategic*, *lucky*, or *random*. In the *strategic* case, agents demonstrated a systematic exploration of every option without ever returning to the same area twice. In the *lucky* case, the agent arrived at the goal on the very first try – without making any wrong turns or checking unnecessary sections of the maze. In the *random* case, the agent would arbitrarily make turns, often heading down the same path multiple times, before finally arriving at the goal. The three conditions were significantly different. The authors introduced the videos in a neutral manner to the participants by saying we will watch three different videos of a mouse or a robot trying to solve a maze and were shown in random order for each participant.

When the agents were introduced to study participants we did not mention if they are seeing the same mouse/robot or a different one. When we were asked if it is the same agent we returned the question to the participants ("What do you think? Why?").

After each video, the participant rated the intelligence of the agent on a scale of 1-5 (1 = not very smart, 5= very smart), as seen in Figure 4. After they watched all three videos of each agent, participants described how the agent solved the maze. Finally, participants chose which agent they believed was smarter.

Solving the maze via the agent Participants drove the robot from the tele-operation station shown in Figure 5b. A researcher demonstrated the driving controls and offered to drive for the very young participants (4-5 years old) if they had difficulties with the controls. When assisting with driving, the researcher asked for directions at every corner.

Post-test After solving the maze, participants answered six questions about their own experience in solving the maze. We asked whether the maze was hard or easy. We also asked them to explain their strategy. After solving the maze and watching all the videos, we asked if they thought the mouse or the robot was better at solving the maze than they were. Participants could request to watch any of the mouse or robot videos to answer these questions.

FINDINGS
In the questionnaires, we asked participants to explain how the agents solved the maze, how the participants themselves solved the maze, which agent they believed was smarter, and whether they believed any of the agents were smarter than themselves. We probed participants for their reasoning so that we could analyze the arguments that led to their decisions. The following sections detail our findings arranged by our guiding questions from the introduction.

Developmental differences
How similar are parents and children in their choices and mental models?
First, we measured how similarly each child-parent pair answered the intelligence attribution questions after watching three different strategies of the mouse and robot solving the maze. The difference between two participants' ratings were normalized and weighted equally across six questions. Overall, participants including children and parents answered quite similarly to each other (m=0.247, σ=0.11). We analyzed how

similarly each child-parent pair answered the questions compared to each other: *Do children attribute to intelligence more closely to their parents compared to with other children and adults?* Figure 6 presents agent intelligent rating distances between overall and younger and older child-parent pairs compared to distances between each participant and all other children and adults (non-child-parent pair). While we did not see significant difference between non-child-parent pairs, all-age child-parent pairs, and age 4-7 child-parent pairs, we saw significant similarity among older children (age 8-10) and their parents compared to the younger group (p=0.024) and non-child-parent group (p=0.028). This result suggests that by the age of eight, children form their perception of agent intelligence with heavy influence from their parents'.

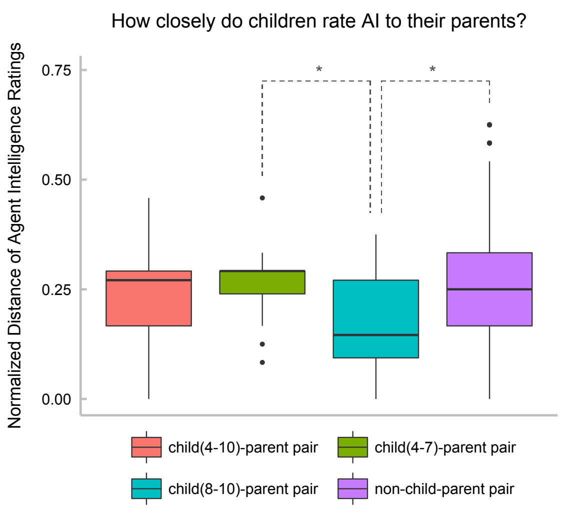

Figure 6. Normalized distance of agents intelligence ratings between child-parent pairs.

After transcribing the interviews, we analyzed children's and parents' answers to our structured questions. We coded these arguments using an approach proposed by Glasser et al. [19], where we iteratively developed a set of themes. Inter-rater disagreements were discussed until a consensus was reached. Participants referenced different aspects of the agents in their explanations, which we categorized into six types: sensory, agency, cognition, social-emotional, strategy, and performance. Both children and parents often used more than one kind of argument in their descriptions of the agent behavior.

- *Sensory*. Agent collects information using senses. E.g. "the mouse smelled the cheese"
- *Agency*. Kind of agent or kind of entity controlling the agent. E.g. "it is a robot and a robot just knows", "it was programmed where to go".
- *Cognition*. Mental abilities of the agent. E.g. "it remembered", "it had the knowledge".
- *Social-emotional*. Emotions or wants of the agent. E.g. "the mouse wants the cheese", "it was tired".

Attribute Category	*Children(4-7)*	*Children(8-10)*	*Parents*
Sensory	58%	45%	52%
Strategy	26%	91%	30%
Performance	32%	36%	9%
Cognition	37%	0%	35%
Agency	16%	27%	39%
Social-emotional	5%	0%	0%

Table 2. Participants' descriptions of the robot

Attribute Category	*Children(4-7)*	*Children(8-10)*	*Parents*
Sensory	53%	64%	39%
Strategy	32%	64%	70%
Performance	26%	18%	17%
Cognition	26%	9%	43%
Agency	0%	0%	0%
Social-emotional	16%	0%	0%

Table 3. Participants' descriptions of the mouse

- *Strategy*. Method the agent solved the maze. E.g. "it looked around and saw where the cheese was and went to it".
- *Performance*. Characteristics of the agent when solving the maze. E.g. "it went fast", "I bumped into the walls a lot".

Although children and parents completed the study independently from one another, we saw instances where pairs gave very similar answers. In 21 of our 30 pairs, children and their parents chose the same agent as being more intelligent. Ten parent-child pairs used very similar language when expressing their reasoning around how they perceived the agents' intelligence.

Tables 2 and 3 show how participants described the agents. Overall, we saw that children mostly focused on sensory abilities and strategy when describing the mouse and robot. Parents focused on different aspects depending on the nature of the agent. We see in Table 3 that, for the mouse, parents focused on strategy and cognition. Conversely, for the robot, most parents focused on sensory ability and agency, shown in Table 2. When children and parents compared their way of solving the maze to the mouse or the robot, they talked more about strategy than they did when just watching the videos of the mouse and the robot.

We compared how many children and parents used a kind of argument to describe the agents using a series of Fisher exact tests. Children were significantly more likely to talk about the robot's performance, whether it completed the maze and how quickly, than parents were ($p = 0.048$). Other interesting differences we saw were that children referenced the cognitive abilities of the mouse and robot less often than the parents.

The only references made to agency were for the robot. All of the parents who made this argument believed that the robot was programmed. Children, on the other hand, either suggested that it was programmed, that someone was controlling it, or that robots are just naturally good at solving mazes.

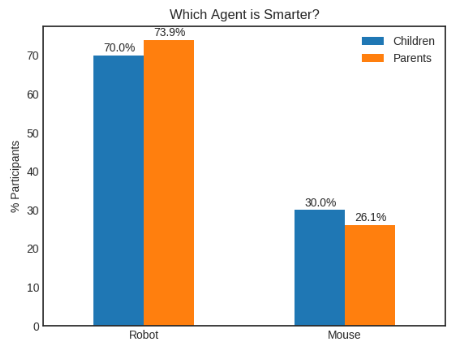

Figure 7. Children and parent responses to "Which agent is smarter?"

No parents talked about social-emotional characteristics of the agents, but some children did. This confirms the findings from Weisman's prior study [46] where children were asked to evaluate a variety of mental capacities of beetles versus robots. Relative to adults, children in this study attributed greater socio-emotional capacities to beetles and robots, suggesting that intuitive ontologies of mental life could be critical for making sense of children's developing understanding of the social world [23].

Finally, when discussing performance, parents would refer to the mouse as being able to solve the maze quickly. Children said the opposite, claiming that the robot was faster and the mouse backtracked a lot. This suggests that children were more likely to overestimate the capacity of the robot.

Our findings show differences in socio-emotional and strategy arguments between children of different ages. We divided children into two groups: younger children, 4-7 years old and older children, 8-10 years old. This separation was chosen based on previous literature that found developmental differences between children around the age of 5. We compared younger and older children using a series of Mann-Whitney U-tests. We saw a significant difference between the number of younger and older children who referenced the social-emotional abilities of the mouse ($p = 0.041$). Although it was not statistically significant, we also saw that older children referred more to the strategy of the mouse ($p = 0.057$).

Intelligence attribution

How do parents and children attribute intelligence to different agents?

The majority of children and parents said that the robot was more intelligent than the mouse (determined with Binomial tests $p = 0.013$ and $p = 0.0173$, respectively). When comparing the agents to themselves, Figure 8 shows that there were no large differences between children and parents. About half of the participants said that both agents were smarter than them, and no one said that just the mouse was smarter.

Many participants referred to their answers about whether the mouse or robot was smarter when comparing the agents to themselves. For example, parents who felt that the mouse was

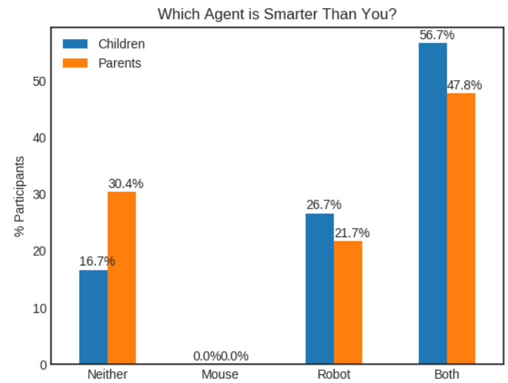

Figure 8. Children and parent responses to "Is the mouse smarter than you? Is the robot smarter than you?"

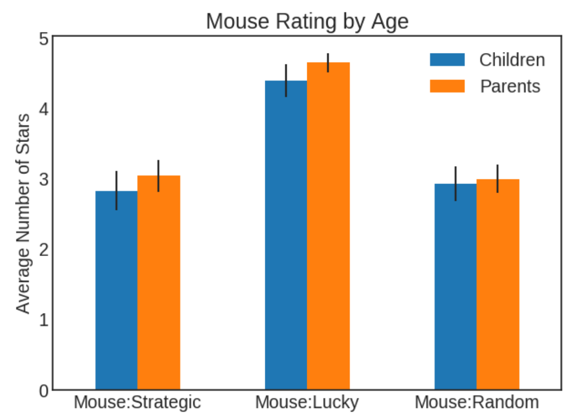

Figure 9. Average number of rating given to mouse by strategy (scale of 1-5 where 1 is not very smart, 5 is very smart).

smarter than the robot felt that they were definitely smarter than a mouse. Children who said that neither agent was smarter also said that the robot was smarter than the mouse and reasoned that a robot lacks human ingenuity, therefore neither agent could be smarter.

Strategy vs outcomes

Are participants more focused on the strategy of the agent or the outcome?

To analyze whether participants focused on strategy or outcomes, we looked at the different intelligence ratings given to each mouse and robot with different strategies. In the mouse videos, the lucky mouse was rated as more intelligent than the other mice. This mouse completed the mazes very quickly, showing that participants focused on results over strategy when deciding if the mouse was intelligent. Interestingly, Figure 9 shows that the random mouse received ratings that were similar to the strategic mouse. Participants penalized the strategic one for taking longer to solve the maze although the strategic mouse clearly did not backtrack as often.

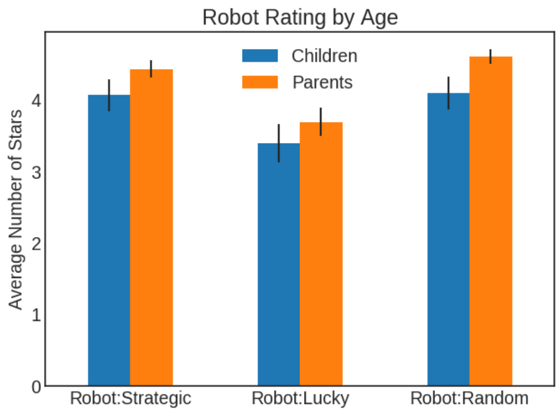

Figure 10. Average number of stars given to robot by strategy (scale of 1-5 where 1 is not very smart, 5 is very smart).

Participants interpreted the robotâĂŹs maze solving differently. Figure 10 shows that the strategic and the random robots received similar ratings, while the lucky one received lower ratings. The fact that the lucky robot made no mistakes led participants to believe that it was given the answers ahead of time. Therefore, contradictory to the way the mouse was evaluated, this robot was penalized for its quicker performance.

DISCUSSION

We found that some of our results are explained by previous work. For one, many more participants believed that the robot was smarter than the mouse, although we designed the experiment to make the mouse and robot equal. The difference between the number of participants who chose the mouse and the robot is likely the result of previously held beliefs about the intellectual superiority of devices or animals, as detailed in Bernstein et al. [6]. During the study, several children and parents expressed their underlying expectations for both agents which brought to light contrasting points of view:

- "I mean, robots are already smart"- Participant 1, 7 years old.
- "I am not sure I would call the robot smart, it's not doing anything smart, it is just going around and when it sees [the cheese], it sees it"- Participant 1's mom.

However, their perspectives changed after trying to solve the maze by tele-operating the robot. Solving the maze allowed participants to experience how the mouse or the robot might see the maze. Many of the children requested to go and see the maze from above when they were getting lost. Some parents expressed difficulty in trying to remember the path or orient themselves.

- "The maze was a lot harder for me as I couldn't see everything"- Participant 2, 10 years old.
- "This was difficult. You are used to go where you can see with your eyes. You move your body."- Participant 2's mom.

We saw that children relied on observable characteristics like performance, strategy, and sensory abilities instead of unobservable characteristics like cognition. This is in tune with prior work from Kiel et al. where children built their arguments first on observed characteristics [28]. Younger children (4-5 years old) were very creative with their arguments when their expectations contradicted their observations. For example, Liam (4 years old) said the mouse was very smart because he was very fast and he was very fast because he was very hungry. Then, after he watched the robot videos, he changed his mind and said the robot was even smarter and faster. When asked to clarify, he projected his understanding of the mouse onto the robot, "[The robot] was very fast because he was very hungry".

Prior work showed that if children think of robots as analogous to an animal, they are more likely to apply a definition of intelligence that includes both cognitive and social/psychological characteristics ([6]). Our analysis showed that children who saw the robot as more similar to the mouse tended to anthropomorphize it more, and did not necessarily see it as more intelligent. For example, Participant 10, who is 8 years old wasn't sure how the robot knew where to go. He asked, "does the cheese smell like anything for the robot?" When the researchers replied they don't know if the robot can smell the cheese, he added that the "mouse was smarter because he has a nose to smell cheese". Sometimes children would attribute certain "vitalistic" attributes to the robot and later change their mind. Participant 6 (5 years old) had the following exchange with one of the researchers:

- "It's a robot and sometimes robots can get to places fast." [How do you think it gets to places?]
- "Like...With it's feet."[How does it know where to go?]
- "Because of its brain?" [Do robots have brains?]
- "Hmm...No..?"[Do you think Cozmo has a brain?]
- "Hmm..He is too little to have one..."[So how do you think he figures it out if it does not have a brain?]
- "With...So, with his eyes...?"

He concluded that the robot "is a rat because he follows the cheese" and that only the mouse has a brain "but very little". When participants perceived the robot more as a technological device, they either referred to its observable characteristics (sensors, camera, motors), or to its inferred capabilities, assuming either that someone was controlling it or that it was programmed to behave in a certain way. Participant 5 said she didn't know the robot's strategy, "because he wasn't driving the computer was driving him. [What do you think the program told him to do?] Not to bump into the wall and to go around". Charlotte said the robot used "sensors and trial and error just like the mouse", she then added that the robot "never tried to go back where they went because they remembered" and that the robot seemed to be smarter "because it could see things in a way that the mouse couldn't".

Children and their parents would view the fact that the robot has been programmed either as proof of its superior intellect or an explanation of why it couldn't be smart.

- "I would choose the mouse as smarter because the mouse is an animal, the robot is programmed by humans"- Participant 3, 9 years old.

- "Either the robot is being driven by a person with a remote control, or by software, and either way it's not smart because it's not alive."- Participant's 3 mom.

- "The mouse was similar to the way the robot solved the maze. The robot was more fluent. It's similar to the mouse, but since the robot was programmed by humans it could go through the maze more easily."- Participant 4, 8 years old.

- "The robot is controlled by a human, and the human may be smarter than the mouse" - Participant's 4 mom (said the robot as smarter than the mouse).

Programmability was recognized as an important concept to help children make sense of how the mind of computational objects might work [14]. In our study we saw that children and parents were both confused when asked if the fact that the robot was programmed means it is intelligent. We hypothesize that if participants could probe more the extent to which the robot's program would allow it to autonomously learn and react in new scenarios (different mazes) they would be less confused.

The need for this kind of probing scenario, where children could gradually build an understanding of emergent behavior by modifying the environment, was also explored by Mioduser et al. and Chi et al. [34, 10]. They showed that children are capable of developing an emergent schema when they can physically test and debug their assumptions by modifying the environment where robots perform a task. In our study, many of the children's arguments about the agent's strategy became more complex after they got to solve the maze by controlling the robot. This lead us to wonder to what extent we can use tangible abstractions for reasoning (e.g. solving a maze) to help children gradually develop a higher level of understanding of computational objects. We believe that exploring children's mental models of new technologies in playful and interactive ways, such as solving a maze together, will help to further understanding in their cognitive and conceptual development.

Lastly, another important discussion is around the question of how parents play a role in children's understanding. The results we've presented regarding how closely children attribute agent intelligence to their parents align with prior studies showing parents' tendency to scaffold children's behavior while playing with robots or using other technologies such as interactive books [16, 8]. As our result suggests, by the age of eight, children already build their thoughts and perception of agent intelligence heavily influenced by their parents. We invite parents to be mindful of how they interact and describe different connected toys in front of their children. We also hope that families will engage more often in conversations about the inner workings of these devices and their influence in their daily life. Therefore, in addition to building children's understanding of technology it is also important to prepare parents so that they can better assist their children.

STUDY LIMITATIONS

Our task was well-defined and didn't allow for richer variation in the attributional judgments that children and parents expressed. We chose to start with a goal-driven, well-defined scenario to make it easier for children to recognize the agent's success and strategies. We also recognize that a larger sample size and a more diverse population would have potentially provided us with more insights. For example, looking at participants with varying levels of domain-knowledge, experience with technology, and cultural backgrounds would produce very different results in this study. Despite these limitations, we believe that this work represents an important first look at parent and child interactions and intelligence attribution towards different types of agents. We hope that it will inspire future and ongoing work in children's technology education and child-agent interaction.

FUTURE WORK

Next, we would like to further explore if we see similar attributions and arguments when agents are completing more complex problem-solving tasks or tasks without a clear goal, such as social interaction tasks. The views of teenagers and young adults may also be interesting perspectives. Building on this initial study, we also plan to further explore long term effects of attributing agency, intelligence to 'smart toys'. Additionally, we consider it would be important to investigate the potential implications for different models of schooling and potential constant interaction with 'smart toys' instead of animals. We also wish to further explore the causal relationship between how children imitate their parents and understand other minds ("Like me hypothesis")[33].

CONCLUSION

Based on our findings, we see an opportunity for a new way to introduce intelligent agents with more transparent mental models for this class of ontological entities. We observe that older children (8-10 years old) and parents are similar in how they tend to evaluate which agent is smarter while younger children (4-8 years old) are more open to build meaning through play and experience. This suggests the importance of early interventions which would equip young children to better understand the mind of the robot through making, experiencing and perspective taking. Here we see an opportunity to create new toolkits for young children and parents to interact with intelligent agents in ways that reveal their inner workings and invite families reflections and conversations.

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