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From parents to artificial agents: Children's epistemic trust in the intelligence age

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ABSTRACT

For decades, digital information has been accessed primarily through text-based interfaces, placing it out of reach for young children who cannot yet read or type. As artificial intelligence (AI) gains the ability to speak and listen in a human-like way, these barriers are disappearing. Young children who have traditionally relied heavily on parents for information now gain access to powerful knowledge sources on their own. This raises a pivotal question: Will AI increasingly share parents' role as children's epistemic guides? We examined how 6- and 8-year-olds (N = 70) chose between an advanced conversational AI system and their own parent when seeking answers to questions spanning three knowledge domains with different epistemic structures: factual, social inference, and personal. Children demonstrated a clear pattern of selective epistemic trust. They relied on their parents as privileged sources of personal information but preferred the AI for factual questions and, notably, for social inference questions. Eightyear-olds were less likely than six-year-olds to direct personal questions to the AI. Questionnaire measures further indicated that, with age, children increasingly viewed AI as more knowledgeable than their parents while simultaneously becoming more aware of its fallibility. These findings demonstrate how children may incorporate AI into their epistemic framework as it becomes embedded in daily life. Their willingness to consult AI not only for factual information but also for social inference raises the possibility that AI could become a source through which children make sense of the social world. Determining how robust this pattern is and whether it persists as familiarity increases will be important for understanding AI's emerging role in the ecology of childhood learning.

Questions of trust in information represent a defining challenge of our time, made so by the ever-increasing threats of misinformation and disinformation (Lewandowsky et al., 2017). For children, whose cognitive and social capacities are still developing, the sources they rely on for information shape fundamental processes of learning and socialization. At the same time, today's children are growing up in an Intelligence Age: a time when artificial intelligence (AI) is not only reshaping societies and economies (Maslej et al., 2025; World Economic Forum, 2025) but also transforming the ways in which we seek, evaluate, and interact with information (Liu et al., 2024). And because these systems evolve rapidly, each new generation of AI expands the kinds of interactions that are possible. As AI becomes equipped with natural voice interactivity, even younger children will, for the first time, have direct and effortless access to it (Astor, 2026). This capability shift raises deep questions about how children decide whom to trust, where they seek knowledge, and how technology may influence their developing understanding of the world.

1. Epistemic trust

From an early age, children often treat parents as oracles, relying on them to explain unfamiliar concepts, provide guidance, and scaffold early learning (Callanan & Oakes, 1992; Frazier et al., 2009; Gopnik et al., 1999). Much of this learning occurs through children's frequent and strategic use of questions (Chouinard, 2007; Frazier et al., 2009; Jirout & Klahr, 2020), which deepens their engagement with caregivers' input and helps refine the causal models and cognitive and linguistic skills that such interactions support. Underpinning this process is epistemic trust: the ability to regard others as reliable sources of knowledge (Harris, 2012; Koenig & Harris, 2007). To differentiate between reliable and unreliable testimony, epistemic trust develops in parallel with epistemic vigilance: the mechanisms that monitor both the

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source (knowledge and intent of the informant) and the content (plausibility of the message) (Shafto et al., 2012; Sperber et al., 2010). By ages 3 to 4, children track agents' intentions across contexts and continuously update their trust (Hoicka et al., 2017), and by age 4, they favor epistemic characteristics over social ones (Tong et al., 2020). These mechanisms have positioned parents and close caregivers as children's primary epistemic guides, a role that has historically been taken for granted.

2. AI interactive capabilities: State-of-the-art

The increasing presence of always-available, socially responsive, and knowledgeable artificial agents now places this child-parent dynamic in question. The release of ChatGPT in late 2022 marked a qualitative shift in AI capabilities and a milestone in the evolution of AI. By late 2024, native multimodal capabilities (Hurst et al., 2024) further advanced human-AI interaction by making fluid, natural spoken interaction widely accessible. This represents a second qualitative shift in AI interactivity, removing the barriers inherent to text-based interfaces and, for the first time, making the most advanced AI systems directly accessible to children (Astor, 2026).

3. Trust in artificial intelligence

Existing research on children's trust in AI has offered important early insights into how children evaluate artificial and human sources of information. By early elementary school, voice assistants are frequently treated as reliable sources of factual knowledge (Girouard-Hallam & Danovitch, 2022; Lovato et al., 2019; Oranç & Ruggeri, 2021), and children sometimes rely more on AI than on humans when evaluating factual claims (Stower et al., 2024). At the same time, they distinguish between domains of knowledge, preferring human informants for information grounded in personal experience (Girouard-Hallam & Danovitch, 2022).

Beyond source preferences, related work suggests that children possess a nuanced understanding of AI systems. Children often view these systems as knowledgeable and socially meaningful (Girouard-Hallam et al., 2021), readily anthropomorphize them (Epley et al., 2007; Złotowski et al., 2018), and attribute mental states and cognitive capacities to them (Dietz et al., 2023). Such attributions resemble aspects of Theory of Mind reasoning, the process through which people interpret others in terms of beliefs, knowledge, intentions, and mental states (Rakoczy, 2022; Wellman, 2014). These mind-related judgments also matter for trust: children's trust in robots is positively associated with the extent to which they attribute psychological agency to them (Brink & Wellman, 2020; Hoehl et al., 2024). At the same time, children do not view AI as fully equivalent to human agents. They attribute fewer emotional characteristics and less moral standing to AI than to humans (Girouard-Hallam et al., 2021) and may sometimes prefer AI as an information source precisely because it is perceived as less influenced by intentions, motives, or other social characteristics that can shape human testimony (Flanagan et al., 2024). Together, these findings suggest that children view AI as both a knowledgeable source of information and a socially valuable but distinct type of agent, making it a distinctive test case for how children calibrate epistemic trust toward artificial and human sources, leaving open the question of how they will evaluate AI in domains that require interpreting human minds and behavior.

Addressing this question is challenging because existing research is constrained by the technologies and experimental designs on which it relies, limiting its potential relevance for the more advanced AI available today (Astor, 2026). Most studies are based on earlier generations of less interactive systems, such as smart speakers or rule-based voice assistants, and many employ pre-scripted, pre-recorded, or narrative scenarios rather than real-time interaction with autonomous AI. Further, existing designs also typically compare AI with an unfamiliar adult rather than someone with whom the child has an established relationship. Although some studies distinguish between factual and personal information, personal questions often concern another person's experiences rather than the child's own life. Together, these limitations constrain the ecological validity and generalizability of existing findings, particularly in the context of today's conversational, multimodal AI systems.

Broader societal trends underscore the relevance of these questions. As adults increasingly use generative AI not only for information but also for companionship and emotional support (Zao-Sanders, 2025), AI systems are being positioned as quasi-social partners. This matters developmentally: epistemic trust in childhood is deeply rooted in relational and affective connections (Fonagy & Allison, 2014). As AI becomes more socially responsive and conversationally attuned, it may engage these mechanisms of trust in ways earlier technologies never could.

While such socially responsive interactions open new directions for learning and exploration, they simultaneously amplify longstanding concerns about digitally mediated social relations (Turkle, 2011). One concern is that AI systems may project unwarranted confidence (Sun et al., 2025) while lacking the empathy and contextual sensitivity that characterize appropriate communication with children (Kurian, 2023). This tension highlights both opportunities and risks that AI presents for children's social and cognitive development, bringing us back to a central developmental issue: Will parents continue to serve as children's primary epistemic guides, or will AI increasingly assume that role? As AI becomes more conversational and socially responsive, a key question is whether children will treat it merely as a source of objective information or also as a source of insight into human minds, relationships, and social behavior.

4. This study

To address this, we place the child at the center of the interaction, examining how they negotiate trust between an advanced multimodal AI and their own parent rather than a stranger. For each question, children made a forced choice between having the AI or their parent provide the answer. Personal questions concern the child's own life, not that of an unfamiliar adult, and the AI engages in live, natural-voice conversation rather than pre-scripted or narrative-based exchanges. We adopt a broader definition of information and distinguish between domains that differ in epistemic structure: personal-history questions, stable factual knowledge, and social inference. Together, features allow us to examine how children balance human and artificial sources of information in natural, voice-based interactions that center on their own experiences and close social relations, providing insight into how they evaluate sources (AI or parent) across the kinds of information they encounter in everyday life.

Based on prior work, we expected children to prefer their parents for personal information (H1) and the AI for factual questions (H2). For the social-inference domain we had no directional hypothesis. Previous findings suggest that children often view humans as uniquely positioned to understand emotions, relationships, and social experience, yet they readily anthropomorphize AI systems. Two outcomes therefore seemed possible: children might regard humans as privileged sources for questions concerning human thoughts, feelings, and social interaction, or they might view social inference as a domain in which answers can be more or less objectively correct. In the latter case, they might prefer AI, much as they do for factual information. Finally, because trust judgments do not always align with behavior (Kotaman & Aslan, 2024), we examined both children's source choices and their explicit evaluations of AI and parental knowledge.

5. Methods

This research was conducted in accordance with the Declaration of Helsinki and approved by the local ethics authority (DNR: 2025-04400-

02). Informed consent was obtained from all participants prior to data collection.

5.1. Transparency and openness

We first conducted a study with 8-year-olds, which revealed striking evidence of epistemic vigilance: children distinguished clearly between parents and AI, applying different trust strategies across information domains. To complement and extend these findings, we conducted a second data collection with 6-year-olds, allowing us to test whether similar patterns emerge earlier in development. This was preregistered and is available at https://osf.io/3m5dw/overview?view_only=ea937105dc9d49a8be62bae3c19ed098. An a priori power analysis indicated that a minimum of 34 participants would be required to detect a medium effect size ($d = 0.5$) with 80% power ($\alpha = .05$) in a within-subjects design. Based on the already collected 8-year-old cohort, the correlations among the three repeated domain scores indicated that assuming the conventional correlation of 0.50 among repeated measures would be overly optimistic. A sensitivity analysis for the planned 2 × 3 mixed design (N = 70), using the repeated-measures correlation structure observed in the initial cohort, indicated approximately 80% power to detect an Age × Question Type interaction of Cohen's f ≈ 0.26. Thus, the design was adequately powered for moderate interaction effects, although smaller developmental differences may have gone undetected.

5.2. Participants

The study included a total of 70 children, divided equally into 35 six-year-olds (19 girls, 16 boys) and 35 eight-year-olds (18 girls, 17 boys). The age range was birthday ± 3 months. At the time of testing, the six-year-olds had a mean age of 2192 days (≈6.0 years, SD = 22 days), while the eight-year-olds had a mean age of 2922 days (≈8.0 years, SD = 35 days). Data was collected between February and July 2025 (8-year-olds), and between September and October 2025 (6-year-olds). Children were recruited through BLINDED Labs participant database and received a movie ticket as compensation. Additional demographic data can be found in the Supporting Information.

5.3. Design

The study employed a 2 (Age: 6 vs. 8 years; between-subjects) × 3 (Knowledge domain: Factual, Social inference, Personal; within-subjects) mixed design. Each child was presented with 21 questions (7 per category), one at a time, and was asked to decide for each whether the AI or their parent should answer. Thus, the task used a forced-choice source-selection paradigm in which only the selected source answered each question. Question order was pseudorandomized with six counterbalanced question protocols to present items in varied sequences. The dependent variable; source preference, was operationalized as a difference score reflecting the number of questions directed to the AI versus the parent (coded +1 for AI, −1 for parent), aggregated within each question type. This scoring produced a range from −7 to +7 per knowledge domain, with positive values indicating a preference for the AI. Children's source choices were recorded by the experimenter during testing. To assess coding reliability, a second coder independently coded 20% of the video recordings without access to the original coding. Interrater agreement for children's source choices was 100%.

5.4. Materials

The AI system used was ChatGPT (Advanced Voice Mode, GPT-4o architecture, OpenAI) accessed through a university licensed ChatGPT Business account). No custom instructions or other study-specific configurations were applied beyond the age-specific instruction described in the Experimental procedure below. The voice used was Breeze and is described as animated and earnest. Breeze's perceived gender was ambiguous within the research team, with half of the team coding the voice as female and the other half as male. Though data collection did not occur simultaneously between the two groups, the same model and voice were used. An iPad tablet was used for AI interaction, and a regular iPhone smartphone for the parent. All sessions were video-recorded. The 21 questions spanned three knowledge domains:

- Factual, involving stable, general knowledge (e.g., “How far is it to the moon?”).
- Social inference, requiring interpretation of others (e.g., “What does it mean if someone looks at you a lot but doesn't say anything?”).
- Personal, referring to information about the child's own life (e.g., “What was your first word as a baby?”).

The full set of questions is documented in the Supporting Information.

The following questions about AI were asked to children in the questionnaire:

- Who do you think knows the most about things: the AI or your parents?
- On a scale from 1 to 5, how much do you trust the AI's answers?
- Do you think the AI can make mistakes?

Parents were asked how often their child interacts with smart devices or AI. All questions and their scales can be found in the Supporting Information.

5.5. Procedure

5.5.1. Familiarization

Children were introduced to the AI be the experimenter who told the AI the child's name and some of the child's interests. The AI was then prompted to chat with the child. Children spent approximately 5 min in open ended conversation with the AI, followed by a 2-min demonstration in which the experimenter highlighted the AI's interactive capabilities, ensuring that all children experienced examples of its flexibility, breadth of knowledge, and conversational interactivity. Parents waited in a nearby room during the procedure, reducing the possibility that parents' physical presence influenced children's subsequent source choices, as both sources were available exclusively through speaker-mediated communication (AI via tablet in advanced voice mode and parent via smartphone). Children also briefly conversed with their accompanying parent by phone to establish this as the basis for communication. The familiarization procedures were not intended to provide equivalent exposure to the two sources, as children were already highly familiar with their own parent but relatively unfamiliar with the conversational AI. Rather, the aim was to ensure that children had sufficient experience with each source within the setup to prepare them for the experiment and make a meaningful source choice possible.

5.5.2. Experimental procedure

Before the experimental trials, the AI was instructed in Swedish: “Du kommer nu få frågor och du ska svara anpassat för en sex-åring. Du får inte ställa några följdfrågor. Har du förstått?” (English translation: “You will now be asked questions, and you should answer in a way that is appropriate for a six-year-old. You must not ask any follow-up questions. Do you understand?”). For 8-year-old participants, “six-year-old” was replaced with “eight-year-old”; the instruction was otherwise identical. Parents were instructed to respond as they normally would to their child, without any expectation that they should know the answer to every question, and were likewise instructed not to ask follow-up questions.

The experimenter read a question aloud and then asked the child to indicate whether the AI or the parent should answer the question. Once a choice was made, the microphone was activated for the selected source,

the experimenter posed the question, and the selected source provided a live answer (it was not scripted or pre-recorded, with natural variation as a consequence). This procedure was repeated for each of the 21 questions. Microphones and speakers were muted between questions so that neither the AI nor the parent could know when the child had chosen the other source. This ensured that responses were independent across sources and that children's choices carried no social consequences. Children had no information about the question categories.

At the end of the question task, the experimenter briefly left the room, which introduced a mild sense of uncertainty. Children were asked whether they preferred to continue interacting with the AI or with their parent. This end-of-session choice task served as an additional measure of trust. Finally, children completed a short verbal questionnaire about their perceptions of the AI (e.g., ease of use, trust), while parents completed a demographic questionnaire and reported their child's prior experience with AI and digital devices.

5.5.3. Safety monitoring

The experimenter monitored the child's interactions throughout the experimental procedure. In cases where the child was left alone with the AI, the experimenter either listened to the interaction from outside the room or reviewed the video recording immediately afterward. In one session, the AI recommended a food containing an ingredient to which the child was allergic. The experimenter immediately intervened and followed up during debrief. No comparable incidents occurred in any other session.

6. Results

6.1. Preregistered analyses

6.1.1. Mixed-design ANOVA on source preferences

A 2 (Age group: 6-year-olds, 8-year-olds) × 3 (Question type: Factual, Social inference, Personal) mixed-design ANOVA was conducted on children's source preferences. Mauchly's test indicated that the assumption of sphericity was violated for the within-subjects factor of question type, $\chi^2(2) = 12.48$, $p = .002$. Therefore, Greenhouse–Geisser corrected values are reported.

The analysis revealed a significant main effect of question type, $F(1.71, 116.25) = 55.44$, $p < .001$, partial $\eta^2 = 0.45$, indicating that children's preferences varied across Factual, Social inference, and Personal questions (see Table 1). The main effect of age group was not significant, $F(1, 68) = 1.59$, $p = .212$, partial $\eta^2 = 0.02$. Likewise, the interaction between question type and age group was not significant, $F(1.71, 116.25) = 1.06$, $p = .340$, partial $\eta^2 = 0.02$ (see Fig. 1). A complementary trial-level logistic mixed-effects analysis yielded a similar overall pattern of results and is reported below. Levene's tests for homogeneity of variances were non-significant for each question type, suggesting that the assumption of equality of error variances was met. Additional robustness tests revealed no effect of age when assessed as a continuous variable within each age group or when examining the difference in source preference for personal questions (as shown in Fig. 1), and no gender effect on overall source preference (see Supporting Information).

Table 1
Post hoc t-tests following the mixed ANOVA.

Age group	Comparison	*t*(df)	*p*Holm	Cohen's *d*	95% CI [LL, UL]
6 years	Factual – Social	−0.81(34)	0.704	−0.14	−0.47, 0.20
6 years	Factual – Personal	5.02(34)	< 0.001	0.85	0.46, 1.23
6 years	Social – Personal	6.19(34)	< 0.001	1.05	0.63, 1.46
8 years	Factual – Social	−0.94(34)	0.704	−0.16	−0.49, 0.18
8 years	Factual – Personal	5.65(34)	< 0.001	0.96	0.55, 1.35
8 years	Social – Personal	6.70(34)	< 0.001	1.13	0.70, 1.55

Note. Values represent paired-samples t-tests conducted as post hoc analyses following the mixed-design ANOVA. Comparisons between question types (Factual, Social inference, Personal) within each age group were made. *p*-values are two-tailed and Holm-adjusted across the six tests reported in the table.

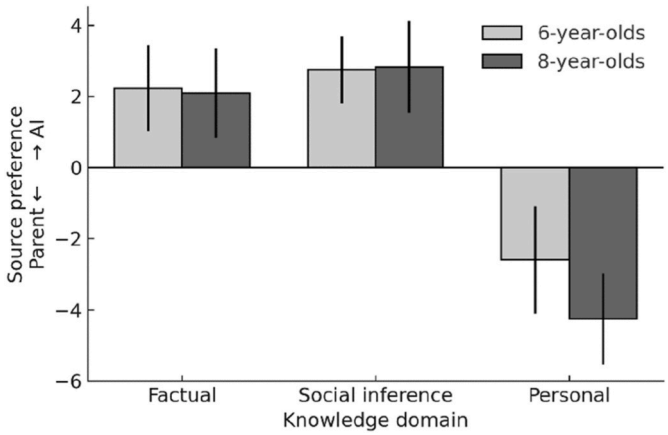

Fig. 1. Difference score per question type across age groups (95% CI).
Note. Mean AI-parent preference scores (−7 to 7 scale) across question types for six- and eight-year-olds. Positive scores indicate a preference for AI, and negative scores indicate a preference for the parent. Error bars represent 95% confidence intervals. Differences between 6- and 8-year-olds in the personal question domain are non-significant (see Supporting Information).

6.1.2. One-sample t-tests by age group

To examine whether children's preferences differed from chance (0), one-sample t-tests were conducted separately for each age group and question type. One-sample t-tests against chance revealed that both six- and eight-year-olds preferred the AI for Factual and Social inference questions but preferred their parent for Personal questions (see Table 2).

6.1.3. Correlations between self-reported trust in AI and source preference

Across both age groups, children's overall preference to ask the AI (collapsed across question types) was positively correlated with their reported trust in the AI's answers, $r(67) = 0.25$, $p = .042$, 95% CI [0.01, 0.46]. When examined separately by age, this relationship was stronger and statistically significant for eight-year-olds, $r(32) = 0.37$, $p = .034$, 95% CI [0.03, 0.63], but non-significant for six-year-olds, $r(33) = 0.20$, $p = .246$, 95% CI [–0.14, 0.50].

6.1.4. Association between source preference and preferred interaction partner

Lastly, we explored whether children's overall preference to ask the AI was associated with their end-of-session choice of companion when the test leader left the room (AI vs. parent). Across the full sample, children who chose the AI ($M = 3.06$, SD = 5.56) displayed significantly higher overall AI preference scores than those who chose their parent ($M = −0.70$, SD = 4.50), $t(66) = 3.05$, $p = .003$, $d = 0.74$, 95% CI [0.25, 1.23].

When analyzed separately by age group, the effect was significant for six-year-olds, $t(32) = 2.43$, $p = .021$, $d = 0.85$, 95% CI [0.13, 1.56], but not for eight-year-olds, $t(32) = 1.61$, $p = .117$, $d = 0.56$, 95% CI [-0.14, 1.24]. These results suggest that the link between overall AI preference during the task and end-of-session choice was stronger in the younger group. Descriptively, 20 of the six-year-olds chose the AI and 14 chose their parent (with one choosing neither), whereas among eight-year-olds, 15 chose the AI and 19 chose their parent (with one choosing neither). The difference was not significant.

Table 2
One-sample t-tests against 0 for AI preference scores by age group and question type.

Age group	Question type	*M*	SD	*t*(df)	*p*Holm	Cohen's *d*	95% CI [LL, UL]
6 years	Factual	2.23	3.53	3.73(34)	0.002	0.63	0.26, 0.99
6 years	Social	2.74	2.76	5.88(34)	< 0.001	0.99	0.58, 1.40
6 years	Personal	−2.60	4.39	−3.51(34)	0.003	−0.59	−0.95, −0.23
8 years	Factual	2.09	3.64	3.39(34)	0.003	0.57	0.21, 0.93
8 years	Social	2.83	3.77	4.44(34)	< 0.001	0.75	0.37, 1.12
8 years	Personal	−4.26	3.73	−6.76(34)	< 0.001	−1.14	−1.56, −0.71

Note. Values represent one-sample t-tests against 0 (chance level). Positive Cohen's d values indicate preference for the AI, while negative values indicate preference for the parent. Social refers to the knowledge domain named: Social inference. *p*-values are two-tailed and Holm-adjusted across the six tests reported in the table.

6.2. Additional analyses (not preregistered)

6.2.1. Trial-level robustness analysis

As a robustness check, we conducted a trial-level logistic mixed-effects analysis predicting source choice (AI vs. parent) from knowledge domain, age group, and their interaction, with random intercepts and random slopes for knowledge domain by participant. The model converged without convergence or singular-fit warnings. The model revealed a significant effect of knowledge domain, $\chi^2(2) = 59.58$, $p < .001$, but no significant main effect of age, $\chi^2(1) = 2.54$, $p = .111$, or Age × Domain interaction, $\chi^2(2) = 4.00$, $p = .135$. An earlier random-intercept-only specification yielded a significant Age × Domain interaction. During peer review, the model was respecified to include random slopes for knowledge domain, thereby accounting for participant-level variation in this within-subject effect. The random-slopes specification provided better model fit, and the Age × Domain interaction was no longer significant. Thus, the trial-level analysis corroborated the domain-specific pattern observed in the primary aggregated analyses.

6.2.2. Perceptions of AI and parental knowledge

Children were asked who they thought knew most about things: the AI, their parent, or both equally. Across the full sample, 36 children (51%) said that AI knows more, 18 (26%) said both know equally, and 16 (23%) chose parents. Responses differed significantly by age group, $\chi^2(2, N = 70) = 16.81$, $p < .001$. Six-year-olds were relatively evenly divided between AI and parents, whereas eight-year-olds most often selected the AI or both sources equally; 97% thought that AI knew at least as much as their parents (see Table 3 and Fig. 2). Several children elaborated on their answers, emphasizing that AI and parents have different domains of knowledge. Three children expressed the same idea, one of whom stated: "The AI knows more about everything, but my mom knows more about me."

6.2.3. Relationship between perceived knowledge and source preference

We examined whether children's general source preference (AI vs Parent) was associated with their answer to the "Who knows most?" question (AI, parent, or both, see Table 3). A one-way ANOVA indicated no significant effect of perceived knowledge source on overall preference, $F(2, 67) = 0.26$, $p = .770$. This suggests that children's judgments about who knows most were unrelated to their tendency to direct questions to the AI versus their parent.

Table 3
Children's perceptions of AI by age group.

AI perception measure	6 years	8 years	Total
Trust in AI answers, *M* (SD)	3.93 (1.31)	4.00 (0.98)	3.96 (1.15)
AI knows most, *n* (%)	15 (43%)	21 (60%)	36 (51%)
Both know equally, *n* (%)	5 (14%)	13 (37%)	18 (26%)
Parent knows most, *n* (%)	15 (43%)	1 (3%)	16 (23%)
AI can make mistakes: Yes, *n* (%)	24 (69%)	33 (94%)	57 (81%)
AI can make mistakes: No, *n* (%)	11 (31%)	2 (6%)	13 (19%)

Note. Trust ratings were provided on a 1–5 scale, with higher scores indicating greater trust in the AI's answers, and are reported as *M* (SD). Responses to perceived relative knowledge ("Who knows most?") and AI fallibility ("Can the AI make mistakes?") are reported as *n* (%). One trust rating was missing for the 8-year-old group ($n = 34$); all other measures had complete data ($n = 35$ per age group).

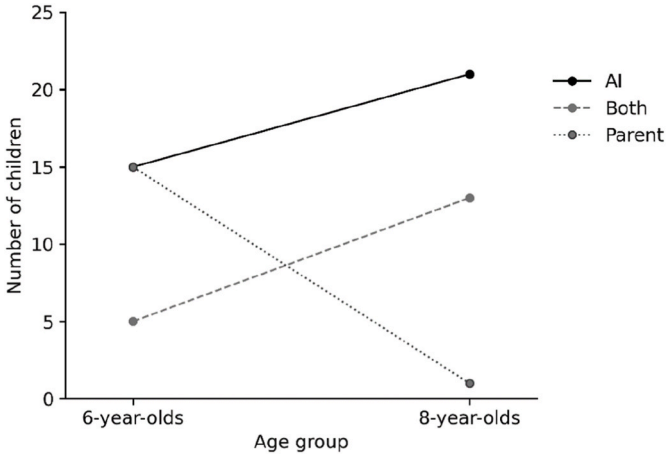

Fig. 2. Children's ratings of "Who knows most?" (AI, both, or parent), by age group (6 vs. 8 years).
Note. Values represent the raw number of children selecting each response option. The solid black line depicts children who indicated that AI knew the most, the dashed gray line depicts children who indicated that both knew equally much, and the dotted gray line depicts children who indicated that their parent knew the most. Whereas 6-year-olds showed no clear preference between AI and parents, 8-year-olds demonstrated a marked preference for the AI, with only one child indicating that their parent knew more than the AI. Also note that the responses shown here are reported numerically in Table 3 below.

6.2.4. Belief about AI's fallibility

When asked whether they believed the AI could make mistakes, 57 children (82%) responded "yes," whereas 13 children (18%) answered "no." Thus, the majority of children recognized that the AI could be fallible. However, responses differed significantly by age group, $\chi^2(1, N = 70) = 6.05$, $p = .014$. Among six-year-olds, 24 said the AI could make mistakes and 11 said it could not, whereas among eight-year-olds, nearly all (33 of 35; 94%) judged that the AI could be fallible (see Table 3). Adding a qualitative dimension to these results, one six-year-old spontaneously commented on this question: "Everyone can make mistakes". This illustrates that children may interpret the AI's fallibility in terms of general human error, framing the agent as socially comparable to a person. Another six-year-old said: "Yes, he just lied", suggesting attributed intentionality to the AI's errors, interpreting them not merely as mistakes but as deliberate acts.

6.2.5. Does experience of AI relate to source preference?

A Pearson correlation between children's overall preference for the AI as an information source and prior experience of AI/smart devices was negative but non-significant, $r(68) = -0.22$, $p = .066$, 95% CI [–0.43, 0.01], indicating that more frequent experience with AI is not

related to greater preference for the AI as a source of information. Similarly, for an independent binary measure of prior experience with AI or smart devices, an independent-samples *t*-test showed no significant difference between those choosing AI vs Parent more frequently as a source of information, $t(58) = -0.94$, $p = .352$.

7. Discussion

When a new generation of children seeks information, to whom will they turn: their own parents or an advanced conversational AI? In this study, 6- and 8-year-olds demonstrated a systematic pattern of selective epistemic trust that varied across knowledge domains. They preferred their parents for personal information but turned to the AI with both factual and social-inference questions. These findings extend classic accounts of selective trust (Harris, 2012) into an emerging developmental context in which children must navigate between human and artificial sources of knowledge.

Prior work has shown that children direct factual questions to voice assistants such as Alexa and Google Home (Lovato et al., 2019; Oranç & Ruggeri, 2021)[2] and can selectively allocate information-seeking across human and artificial informants (Girouard-Hallam & Danovitch, 2022). However, this literature has largely relied on earlier-generation technologies, prerecorded or highly scripted interactions, unfamiliar adult comparison targets, and limited information domains. Consequently, it remained unclear whether these findings generalize to contemporary conversational AI systems that engage children in natural spoken dialogue and increasingly resemble human interlocutors.

The present study addressed this uncertainty by placing a state-of-the-art conversational AI in direct competition with the child's own parent. Unlike previous studies, personal questions concerned the child's own life rather than another person's experiences, making the parent a genuinely privileged source of information. The study also extended previous work by including a social-inference domain, allowing us to examine whether children viewed AI as a suitable source not only for factual knowledge but also for interpreting human thoughts, emotions, intentions, and social behavior.

This design revealed a clear pattern of domain differentiation. Children treated AI as a competent source for both factual and social-inference questions, despite the fact that these domains differ substantially in epistemic structure: factual questions are relatively objective and verifiable, whereas social-inference questions require interpretation of human minds and behavior. At the same time, children consistently relied on their parents when the information concerned their own lives, maintaining parents as the privileged source of personal knowledge. Thus, children did not simply prefer AI or parents overall; rather, they calibrated their source choices according to the kind of information being sought.

7.1. AI as a source for social inference

The most theoretically striking finding was children's preference for AI in the social inference domain. Unlike factual questions, social inference questions do not have a single verifiable answer. They require interpreting intentions, emotions, sincerity, and interpersonal behavior. These are domains traditionally associated with human social understanding and with the kind of contextual sensitivity that caregivers provide. Children's willingness to direct such questions to AI, therefore, shows that they were willing to treat AI not only as a source of factual information, but also as a source for making sense of people. Although the present study cannot establish why children made these choices, the finding identifies a potential pathway through which AI could become relevant to children's developing social understanding. This finding connects to the broader shifts in how AI is being used. Recent mappings of adult AI use suggest a rapid increase in use cases involving companionship, emotional support, and interpersonal guidance (Zao-Sanders, 2025). In parallel, emerging work shows that AI-mediated communication can shape the language people use and how social exchanges are evaluated (Hohenstein et al., 2023), with early evidence that large language models may also influence patterns in spoken communication (Yakura et al., 2024). This has developmental significance because conceptual development depends in part on the representational and linguistic resources through which children organize new domains of thought (Carey, 2009). If children increasingly turn to AI for explanations of thoughts, emotions, and interpersonal behavior, AI may influence not only the social guidance they receive but also the conceptual language through which they learn to understand others.

7.2. Perceptions of knowledge and trust

Prior work with four-to eight-year-olds found that children's preferences for seeking information from a voice assistant versus a human informant were largely unrelated to the epistemic capacities they attributed to those informants (Girouard-Hallam & Danovitch, 2022). In contrast, our findings suggest a possible developmental pattern: among eight-year-olds, but not six-year-olds, AI source preference was linked to higher self-reported relative trust in AI informants – a difference that may reflect the more natural and interactive qualities of the AI used here. The finding also aligns with research showing that children become increasingly critical of unreliable AI with age (Cao et al., 2025; Flanagan et al., 2024). When the experimenter left the room, six-year-olds who had shown higher AI preference were more likely to choose to stay with the AI, whereas this association was not significant for eight-year-olds. Taken together, these findings raise the possibility of a developmental shift from younger children's social preferences shaping their reliance on AI information (possibly reflecting stronger anthropomorphism at lower ages; Girouard-Hallam et al., 2021) to older children's reliance being guided more by explicit evaluations of informational reliability. Such convergence of explicit judgments and spontaneous choices could point to a broader developmental reorganization in how children evaluate AI as an informant, aligning well with the broader trust literature (Tong et al., 2020).

Children's judgments about "who knows most" revealed another developmental shift. While six-year-olds were evenly divided between parent and AI, eight-year-olds predominantly judged that the AI knew more (only one eight-year-old judged the parent as more knowledgeable). Children's comments added nuance to these judgments, with several noting that "the AI knows more about everything, but my mom knows more about me". Such distinctions suggest that children explicitly differentiate between general and personal domains of expertise, reflecting the study's main finding and revealing a developing theory of mind that extends to AI (Dietz et al., 2023).

Most children (82%) also recognized that the AI could make mistakes, with this judgment more common among eight-year-olds (94%) than six-year-olds (69%). Children's interpretations varied: some treated AI mistakes as ordinary human-like errors ("Everyone can make mistakes"), while others viewed them as intentional ("Yes, he just lied"). This pattern reveals a developmental paradox: children's self-reported epistemic trust in AI increases with age (relative to the parent), even as their awareness of its fallibility grows. These findings contrast with prior work showing that children (ages 3–6) tend to interpret AI errors as accidental and human mistakes as deliberate (Stower et al., 2024). This difference may reflect the advanced conversational abilities of the AI used here (Astor, 2026), which allow for more natural social

[2] Oranç and Ruggeri (2021) observed that younger children (ages 3–10) tend to ask more personal questions to voice assistants than older ones. Girouard-Hallam and Danovitch (2022) demonstrated a similar result. In our main analysis, we did not find a significant difference between six- and eight-year-olds, though the trend direction was consistent with theirs. This suggests that this developmental change emerges more clearly across a broader age range.

engagement than earlier systems.

7.3. Prior experience

Prior experience with smart devices has been shown to influence children's engagement with AI (Oranç & Ruggeri, 2021). In the present study, no significant association was found between source preferences and prior experience, although a weak trend was observed. However, the conversational AI used here had only recently been released, making it unlikely that children had prior exposure to a comparable system. This suggests that their judgments were driven less by familiarity and more by their immediate impressions formed during the interaction.

7.4. Implications and risks

The findings raise important questions about how AI may reshape children's everyday information-seeking behavior. As conversational AI becomes increasingly available in homes and educational settings, children may come to rely on it alongside, or in some cases instead of, parents when seeking information. One possible consequence is a redistribution of epistemic roles, in which parents are valued primarily for knowledge of the child's personal history and experiences, whereas AI is preferred for more general questions – a possibility consistent with children's explicit judgments that AI often knows more than their parents. As AI systems become more integrated into everyday life and more personalized, however, even this distinction may become less stable. Systems that remember prior interactions, adapt to a child's interests, and accumulate knowledge about the child's preferences, routines, and experiences may increasingly appear not only broadly knowledgeable but also personally attuned.

Increasing reliance on AI also raises important safety concerns. Conversational AI systems can produce inaccurate, misleading, or contextually inappropriate responses while presenting them with considerable confidence. In the present study, for example, the AI once recommended peanuts to a child with allergies. Such incidents highlight the need for adult supervision and for child-centered AI systems that support appropriate trust calibration. As AI becomes more deeply integrated into children's lives, the key challenge will not be preventing children from trusting AI, but helping them learn when that trust is warranted and when alternative sources of information should be preferred.

7.5. Limitations and future directions

One limitation is that some sources may be objectively better suited to particular types of questions. Parents have privileged access to information about a child's own life, whereas AI systems may be perceived as especially useful for factual information. The present study was not designed to determine whether children explicitly understood such differences in source expertise or whether their choices were guided by them. Future research should directly assess children's beliefs about source expertise across domains and examine how such beliefs relate to source-selection behavior. Notably, whereas personal questions may naturally favor the parent and factual questions may favor AI, the appropriate source for social-inference questions is less clear. Before the emergence of conversational AI, many such questions would likely have been directed to parents or other adults.

Moreover, the study was limited to six- and eight-year-olds, leaving open questions about both younger preschoolers and older children approaching adolescence. The two age groups were also tested in separate data-collection waves rather than concurrently. Although the same AI model, voice, and experimental procedure were used, age was therefore partially confounded with time of data collection, and age-group differences should be interpreted with this design feature in mind. In addition, the Age × Domain interaction in the exploratory trial-level analysis was sensitive to random-effects specification, becoming non-significant when participant-level random slopes for domain were included. The sample was drawn from an academic city and was relatively homogeneous in terms of ethnicity, which may limit generalizability. Future work should therefore examine how epistemic trust in AI develops across childhood and whether similar patterns are observed in more diverse cultural and socioeconomic contexts.

The study was also not designed to identify the mechanisms underlying children's preference for AI on social-inference questions. For example, children may have perceived AI as more objective, less judgmental, or more knowledgeable about social situations, or other characteristics of the interaction may have influenced their choices. Because trial-specific justifications for source choices were not collected, these possibilities cannot be distinguished here.

Finally, the present findings concern one specific conversational AI system and interaction context. Features of the system's presentation, including its voice, response style, and fluency, were not independently manipulated and may have contributed to children's source choices. Replication across different AI systems and interaction contexts will therefore be needed to determine whether the observed pattern generalizes beyond the system used here. This study also cannot determine whether children's source-selection patterns are specific to AI or would similarly emerge with a highly knowledgeable human informant. Distinguishing between these possibilities will be theoretically important for understanding how children represent AI as an epistemic source. However, from a developmental perspective, AI may still become an influential source of information regardless of whether children treat it as categorically distinct from knowledgeable human experts (a possibility is underscored by children's increasing confidence in AI's knowledge when compared with their parents'). A related but distinct limitation concerns children's familiarity with the AI. Although the observed domain-specific pattern argues against an indiscriminate preference for AI, novelty effects cannot be entirely ruled out. The conversational AI used in this study was substantially more advanced than systems most children had likely encountered, raising questions about how these preferences may change with greater familiarity. The familiarization procedures differed by design: because children were already highly familiar with their own parent, only minimal familiarization was considered necessary to establish the parent as a speaker-mediated source, whereas more extensive familiarization with the unfamiliar AI was needed to ensure that children understood how they could interact with it. Nevertheless, the resulting difference in the duration and structure of familiarization may have increased the AI's salience or influenced subsequent source choices.

Future research should examine how children's reliance on AI stabilizes over time, whether similar patterns emerge across different implementations, such as embodied robots and voice-based systems, and whether prolonged experience with reliable AI shifts children's trust from human to artificial informants or vice versa. Here, we observed mixed source-selection strategies: some consistently alternated between AI and parent without clear domain differentiation, others displayed an initial pattern that later changed, and some showed little differentiation at first but developed a clearer pattern over time. Such patterns point to broader questions about how children navigate hybrid human-AI information environments and coordinate multiple sources of knowledge. Because children of this age do not always act strategically within the constraints of a task and may sometimes explore alternatives unlikely to maximize performance, especially when the cost of exploration is low (Astor et al., 2026), future work should examine the strategies children use to balance information across human and artificial sources.

8. Conclusions

By early elementary school, children treat AI as a reliable and often preferred source of information, particularly for factual knowledge and social inference, while continuing to rely on parents for personal insights. This selective pattern of epistemic trust suggests that children do

not simply choose between human and artificial informants, but calibrate their preferences according to the type of information sought. Notably, as children age, they increasingly view AI as a more knowledgeable source than their parents while simultaneously becoming more aware of its fallibility, indicating that critical evaluation, epistemic trust, and real-world reliance may not develop in lockstep.

More broadly, the present findings suggest that AI may be assuming a new epistemic role in children's lives. While future research is needed to establish how robust these patterns are, children's willingness to direct social-inference questions to AI rather than to their own parents shows that they are willing to consult artificial systems not only for factual information but also for questions involving social interpretation. As AI becomes increasingly embedded in children's everyday lives, a central challenge for developmental science will be understanding whether these systems supplement or compete with parents as children's guides to knowledge and social understanding, and how this may influence not only the knowledge children have access to, but also how they think about and relate to other people.

CRediT authorship contribution statement

Kim Astor: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Katja Kallin:** Writing – review & editing, Validation, Methodology, Investigation, Data curation, Conceptualization. **Adam Ströhm:** Writing – review & editing, Validation, Methodology, Investigation, Data curation, Conceptualization. **Gustaf Gredebäck:** Writing – review & editing, Resources, Funding acquisition, Conceptualization.

Ethics declaration

Written informed consent to take part in the study and to publish the article has been obtained from all participants or their legal representatives. The privacy rights of participants have been observed.

This study was performed in compliance with relevant laws, regulatory frameworks and guidelines where the research took place. This study was approved by the Etikprövningsmyndigheten. (Approval No. DNR: 2025-04400-02)

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the authors used generative AI tools (including Grammarly, Microsoft Word AI, and OpenAI ChatGPT) to improve the clarity, grammar, and readability of the manuscript text. The authors reviewed and edited all generated output and take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chbr.2026.101299.

Data availability

Data will be made available on request.

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