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Robot Social Skills: Influencing Children's Performance and Robot Perception Through a Robot Math Tutor's Scaffolding and Personalization

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Abstract

Robot tutors can add value in education, but their impact usually differs depending on their social interaction skills. This study disentangled the effect of two specific robot social interaction skills on children's math performance and their social perception of the robot. The first is to scaffold the explanations to children's evolving math, and the second to personalize the math conversations to children's preferences and interests. In a 2 (scaffolding: without vs. with) x 2 (personalization: without vs. with) between-subjects design, 113 children (9–12 years) were randomly assigned to one of the four conditions. Findings after 4 child-robot interactions showed that scaffolding improved children's response time but not the correctness of their answers, while personalization increased relationship formation. Examination of the underlying explaining mechanisms revealed that both social skills must be salient enough to have the indented effect, that personalization satisfies children's need to be understood, and that social presence influences feelings of friendship.

Keywords Child-Robot interaction · Friendship · Math performance · Personalization · Scaffolding · Social presence

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1 Introduction

Mathematics is a core subject at primary schools [1, 2]. Being proficient in math is important for everyday life and for future careers [2, 3]. Yet many children underperform in math, possibly due to low interest, negative attitudes and sometimes even anxiety [2, 3]. At the same time staff shortages, overcrowded classrooms, and increased demand for special education decrease the time teachers have to address these issues [4, 5]. UNESCO estimates that an additional 24.5 million teachers are needed in primary education worldwide to achieve universal basic education by 2030, and calls for unique classroom innovations [6]. Most potential are technical solutions that can mimic human interactions, such as social robots [4, 5]. According to Vygotsky, social interaction plays a fundamental role in learning. It is often under the guidance and encouragement of knowledgeable tutors that children progress from a level where they can comfortably solve problems independently to a more challenging level. Through collaborative dialogues, children seek to understand the tutor's instructions, then internalize it and use this information in similar future occasions [7, 8].

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While the use of social robots has shown to result in learning outcomes similar to those of human tutoring, choosing the appropriate social interaction skills that enhance children's learning remains challenging, and the skills should be carefully designed for the specific task at hand [5].

There are numerous ways in which robot interactions can contribute to a child's learning. Davidson et al. [8] grouped the social interactions (and their related social skills) that take place in educational environments into three categories: educational interactions (focused on helping and explaining), collaborational interactions (focused on alignment), and relational interactions (focused on bonding). For the development of a social robot math tutor, the present study focused on educational and relational interaction skills. This focus was informed by our initial focus groups with teachers and students, who helped to identify key design elements for social robots to support mathematics education in primary school classrooms [9]. First, the focus groups indicated that for a robot math tutor to be helpful, it is required to give step-by-step instructions and explanations, adapted to the child's math level [9]. The *educational* interaction skill here is *scaffolding*. Second, to make math fun, the robot tutor is also required to have prior knowledge of the child (e.g., name, preferences, interests) and to adapt the math activities to this information accordingly [9]. This requires the robot to get to know the child through small talk and to use this information to create pleasant, engaging and friendly interactions [8]. The *relational* interaction skill here is *personalization*.

Adaptivity through scaffolding and personalization is particularly important for long-term child-robot interactions. Because learning takes time [10], robot math tutors need to remain compelling over a long period to help children progress to higher math levels [11]. It requires the robot to remain meaningfully relevant by scaffolding the explanations and instructions to a child's evolving learning abilities (Zone of Proximal Development [7]), and to remain socially relevant as an interesting and safe learning partner by personalizing the conversations with both familiar and novel aspects [8, 12]. These type of interaction skills have shown to foster child-robot relationships, which in turn increased children's willingness to continue the interactions [8, 12, 13]. Thus, while the impact of robot tutors' social skills on children's learning gains is essential to warrant its value in educational environments, their impact on children's social perception of the robot (and thus whether it is a compelling long-term learning partner) is essential for the sustainability of robots in educational environments.

For this reason, the aim of the present study was to investigate the impact of a robot math tutor's social interaction skills (i.e., scaffolding and personalization) on both children's math performance and their robot perception after 4 interactions with the robot over an 8-9-month interval. The study also investigated the underlying psychological mechanisms that could explain this impact. Figure 1a and b provide a summary of all the independent, mediator, and dependent variables, along with their expected relationships, which will be further explained in the next section.

2 Related Work

2.1 Outcomes of Robot Tutors

2.1.1 Math Performance

Social robots are embodied computers specifically designed to interact with people in a human-like way [14]. They are increasingly developed and used for education, mostly in primary education for language learning and for children with autism [5, 11, 15]. Often introduced as learning companions, children tend to treat them as social beings and value them for their physical presence, human-like features and behaviors, individual attention, patience, and non-judgmental demeanor [11, 16, 17]. Educational reviews that examined the learning gains of social robots indicated that they are particularly effective for tutoring well-defined lessons and specific skills, such as mathematics [5].

However, studies on the impact of social robots on children's math performance (e.g., math knowledge, test completion time, response correctness) remain limited, and their findings are mixed [18–22], with some finding positive effects on math learning outcomes [18] and others negative or no effects [19–22]. These mixed findings are the result of studying various aspects of robot-assisted math tutoring. For instance, Brown and Howard [18] investigated how a socially interactive humanoid robot engages children in math education, while Kennedy et al. [19] examined the negative effects of excessive social behaviors on learning outcomes. Other studies focused on gender differences in robot-assisted math learning [20], the role of robot-provided feedback [21], and how a robot tutor can support basic arithmetic skills such as times tables [22].

Many of these studies looked at the role of a robot's social skills, examining the effects of verbal encouragement [18], appropriate gestures and gaze [18, 19, 22], personalized speech [19, 22], and feedback strategies [21]. But because most either focused on a single social cue or combined multiple social cues without isolating their individual effects, it remains unclear how specific social behaviors influence children's math learning outcomes, leading to these mixed findings. To address this gap, this study systematically isolates and analyzes different social skills of a robot math

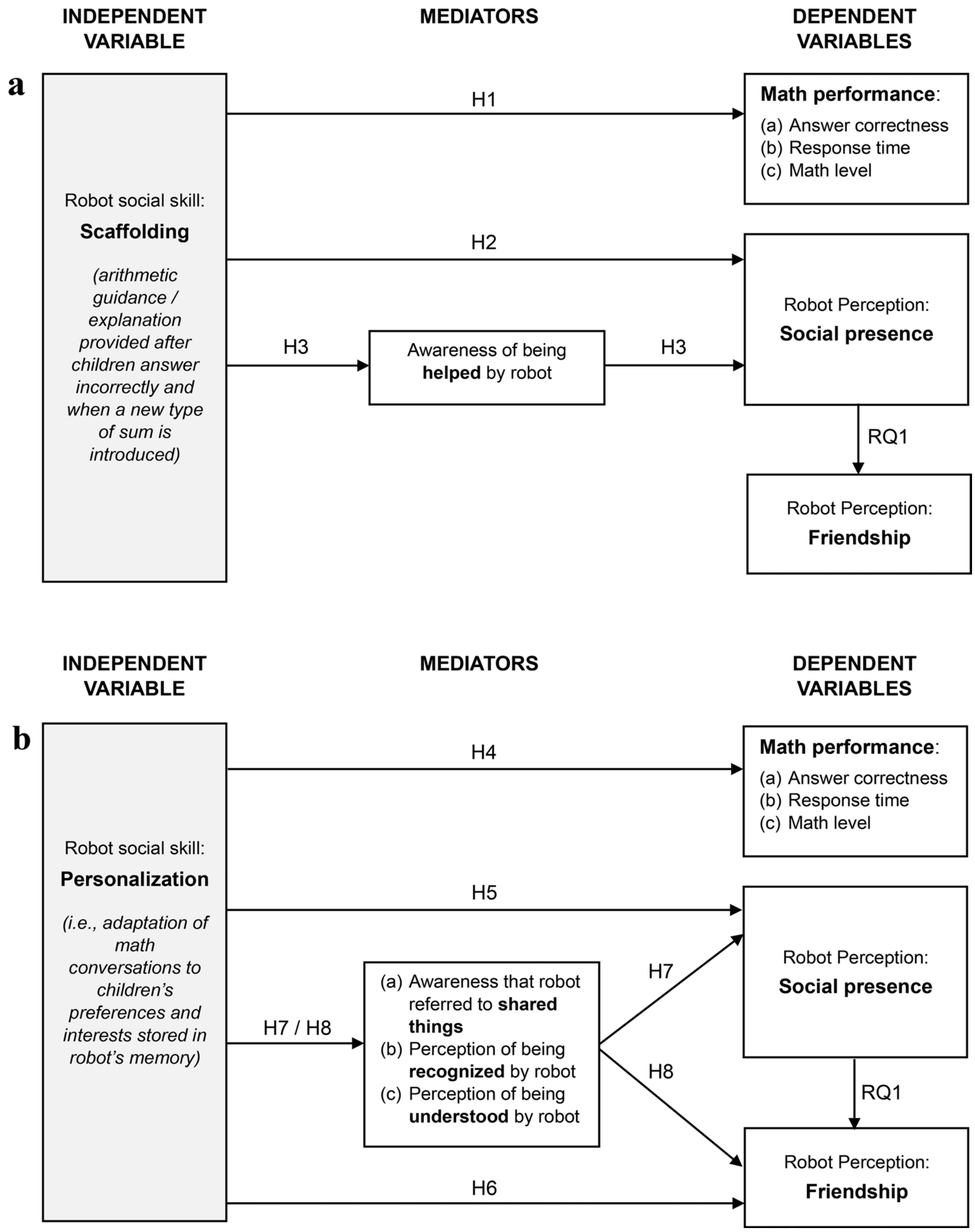

Fig. 1 **a** Conceptual model of the impact of the robot math tutor's scaffolding on children's math performance and their social perception of the robot. **b** Conceptual model of the impact of the robot math tutor's personalization on children's math performance and their social perception of the robot

tutor, allowing for a clearer understanding of the distinct impact each skill has on children's math performance.

2.1.2 Robot Perception: Social Presence and Friendship

While the overall learning gain of robots is well-documented in several reviews [e.g., [5, 13, 15, 16], the literature on children's social perception of robots is more scattered due to its broader context and less-defined multidimensional meaning. A majority of these studies looked at precursors of relationship formation that measure whether children perceive the robot suited for relationship formation [23]. They are indications of children's willingness to initiate a robot relationship, such as physical attraction, similarity, reciprocal liking, anthropomorphism, and social presence [23–25]. Other studies have focused more on the relationship itself and looked at factors that measure whether children perceive the robot as someone they have formed a relationship with, such as a friend or companion [23, 26]. Indications of a child-robot relationship are usually derived from human relationship characteristics such as feelings of connectedness, intimacy, reliance on another, attachment, and a desire for continued interactions [23, 25, 27, 28]. The present study focuses on social presence (as precursor) and friendship (as relationship).

Social presence is the perception that the other entity taking part in the interaction is a social being, thereby disregarding its artificiality [29]. This perception is crucial for experiencing true ‘social’ interactions with a robot [29]. In learning contexts, social presence has shown to foster positive learning experiences and improved learning by increasing children’s interest in the learning material, compliance, and persistent motivation [HRI: [17], media characters: [30]]. More importantly, social presence has shown to elicit social responses toward the robot that indicate that the robot was treated more as an embodied social actor rather than a mere machine [29–31]. It is these social responses that potentially stimulate feelings of connectedness and relationship formation with the robot [17].

Friendship was selected to define the relationship children may form with the robot math tutor, because this term is widely used in both child-robot interaction and child-media studies and entails most of the key concepts that characterize relationships with various nonhuman entities, such as parasocial interaction, closeness, and trust [HRI: [26]], media characters: [30, 32]. Research has demonstrated that children can develop close relationships with robots, as reflected in friendship feelings, making them powerful learning tutors [17, 26, 33]. Children usually learn more from these socially and meaningfully relevant tutors because they trust information presented by someone they have bonded with [media characters: [30]]. In addition, relationships in learning contexts have shown to increase the motivation to attend to the educational content, foster emotional engagement, and elicit the willingness for ongoing interactions [media characters: [30], HRI: [33], AI agents: [34]].

Both social presence and friendship require the robot to exhibit human-like qualities, including appropriate social skills that lead to meaningful social interactions [12, 28]. Specifically, the need-to-belonging theory stipulates that robots must be sufficiently social to satisfy the needs that children have in repeated social interactions [HRI: [28], HHI: [35]]. Nonetheless, there is a lack of systematic knowledge on the kind of social skills a robot should have in educational settings. In addition, little is known about the underlying psychological mechanisms that explain the impact of a robot’s social skills [25]. Therefore, the present study investigates the impact of social skills that meet children’s needs in robot math tutor interactions, while also uncovering the underlying mechanisms that explain the impact of these social skills on children’s robot perception. Finally, although many studies hint on a potential relationship between social presence and friendship (e.g., HRI: [11, 24, 25, 36], media characters: [27]), empirical evidence is lacking. Presumably social presence is the first-degree social response that identifies and interprets the social dimensions of a robot which, in turn, determines the second-degree response, namely relational feelings for the robot [14, 25]. The present study will therefore explore **(RQ1)** whether perceiving the robot math tutor as socially present will, in turn, increase children’s feelings of friendship for the robot (see Fig. 1a and b).

2.2 Robot Social Interaction Skills

2.2.1 Scaffolding

Scaffolding refers to any kind of guidance that helps children achieve new skills or levels of understanding they would not reach on their own [37]. The guidance by the tutor consists of supporting actions (i.e., scaffolds), such as providing hints, modelling, highlighting important aspects, or breaking the task into simpler sub-tasks [37, 38]. In response to a child’s progressive skill competence, the scaffolds should be gradually reduced or adapted to move toward skills that should be acquired next [37]. Although scaffolding differs depending on the educational content and specific learning needs, robot studies have provided some general guidelines for the successful design of a robot’s scaffolding skills. Insufficient is to solely adapt the difficulty of the task [39], hint that the answer is wrong [38] or provide the correct answer [40]. In educational social interactions, children have a specific need for content-related feedback, where the robot explains why the answer is wrong and what the correct way is to approach the problem [8, 37, 38, 40]. This kind of detailed feedback helps children to judge the outcome of the tasks, internalize new information, and avoid making the same mistake next time [8, 40]. Preferably, the robot automatically recognizes when a child needs guidance and uses additional physical tools to visualize the verbal explanations [8].

In the context of mathematics, meta-analyses on the impact of digital math tools indicated that explanatory feedback is indeed more beneficial than corrective feedback alone [41, 42]. Particularly intelligent tutoring systems that use adaptivity, scaffolding and feedback seem to create strong learning effects [41, 42]. Intelligent agents can support children’s learning by practicing content knowledge to foster mathematical principles, while at the same time providing immediate individual feedback to help discover new knowledge and avoid typical misconceptions [41]. This type of guidance is in line with the ideology of realistic mathematics education (RME) that perceives the learner as a reflective practitioner that organically develops models for mathematical concepts [43, 44]. During learning processes, children look back on their action and review its outcomes with the aim to discover new patterns or procedural rules and to modify future actions [45]. Progressive schematization is an RME method whereby a tutor guides the child through hierarchically ordered steps that help solve the sum [46, 47]. For instance, the ‘small sum’ guided strategy for 3 × 400 could be: 400 is 100 times bigger than 4, first solve

3×4 (small sum), then multiply the answer with 100 to get 3×400. It is especially important that children understand and internalize the steps (rather than simple automatization), as they are applicable in a wide variety of realistic situations [43, 44].

The robot math tutor in the present study is designed to apply progressive schematization. Guidance is automatically provided by the robot after children answer incorrectly and when a new type of problem (that might need a new approach) is introduced. The robot uses various guidance strategies (e.g., small sum, support sum, double). It goes through the informal strategy that children could use to solve the sum, without providing the answer, helping them create their own math models. More details on the guidance strategies and design of the robot are provided in the method and in [48]. Because progressive schematization has been shown to improve children's math performance in both human [47] and computer [46] tutoring settings, we hypothesize that after 4 child-robot interactions, scaffolding will increase children's math performance, meaning they will give more correct answers **(H1a)**, respond faster **(H1b)**, and increase in math level **(H1c)** (see Fig. 1a). By providing guidance, a robot demonstrates its ability to empathize with a child's learning needs as a human tutor would, thereby increasing its social presence [49]. However, it is required that children experience the support multiple times and perceive the support as helpful [HRI: [49], HHI: [50]]. Children with a lower need for guidance are unlikely to experience much of the robot's scaffolding skills, and are more likely to consider the scaffolds redundant [41] or not notice them as an aid. Therefore, we hypothesize that scaffolding will increase the robot's social presence **(H2)**, but that this impact of scaffolding on social presence is mediated by children's awareness of being helped by the robot **(H3)** (see Fig. 1a).

2.2.2 Personalization

The general assumption in education is that a good tutor provides personalized education, even though it is not clearly defined what personalization is [HHI: [51]]. Students perceive education personalized when a tutor is accessible (e.g., socializes, talks about non-professional issues), interpersonal competent (e.g., knows student name, is a skilled communicator, promotes teacher-student equality and friendship), and personalizes the course-related practices (e.g., designs course activities/content based on student's interests) [51]. These dimensions of personalization align with what Davison et al. [8] refer to as relational interactions within educational environments. A healthy, pleasant working relationship requires the 'allies in learning' to know each other's interests and skills, interact and understand each other on a personal level, and maintain common ground and a strong bond through mutual shared experiences [8]. For robots to engage in these type of relational interactions, they need to simulate having memory by obtaining, storing and recalling personal information, such as using the child's name in greetings, storing the child's interests, recalling previously discussed topics, and adapting behaviors to the child's needs [HRI: [17, 28], AI agents: [52]]. The personal information is often naturally obtained during small talk by asking children direct questions or eliciting information via self-disclosure [HRI: [12, 53], AI agents: [52]]. The robot is then programmed to apply this information with the aim of making child-robot interactions feel more intimate and substantively engaging for a longer period of time [12, 28].

Studies have demonstrated that robots applying personalization (as in having a persistent memory) are perceived as more intelligent [53] and treated as an embodied social actor [12] as if they have a social presence. Children also feel more close to these type of robots and perceive them as friends [28, 33, 53, 54]. This could be because persistent memory in robots fulfills children's interpersonal needs to be recognized and understood [28]. First, being recognized indicates that the relationship means something and might go somewhere [28]. Using the child's name, personal greetings, and details from previous interactions signal to a child that he/she is being remembered by the robot [12, 53]. Already after the first interaction children have a tendency to attribute animistic characteristics to the robot, like having a recognition brain, and come to expect robots to recognize them in future interactions [55, 56]. Second, feeling understood is a characteristic of intimate friendships, which becomes increasingly important during middle childhood [HHI: [57], HRI: [58]]. By self-disclosing personal information, friends come to understand each other on a personal level, meaning that they know and empathize with the other person's thoughts, emotions, interests, needs, and actions [HHI: [57]]. Recalling previously disclosed information and tailoring the interaction accordingly signals to a child that he/she is being heard and understood by the robot [12, 59].

The robot math tutor in the present study is designed to apply the memory-based personalization strategy of Ligthart et al. [12]. This strategy has shown to foster child-robot relationships through both routine (i.e., using the child's name and a personal greeting) and strategic (i.e., referring to previously shared things and selecting content based on stored interests and preferences) personalization behaviors [12, 59]. Research indicates that initial interactions play a crucial role in shaping engagement and cooperation in human-robot interactions. Specifically, Erel et al. [60] found that positive opening encounters, such as appropriated gestures, enhance the willingness to engage with the robot, while Fischer et al. [61] demonstrated that verbal greetings increase attention and perceived friendliness, which help establish social presence and facilitate interaction. In line with these findings, our robot gathers personal information from the child during chitchat conversations (e.g., interests, hobbies, preferred handshake), which it later uses to personalize greetings and tailor math stories. More details on this memory-based personalization strategy are provided in the method and in [48].

Because personalization has been shown to improve children's learning performance in both human [51, 62] and robot [63] tutoring settings, we hypothesize that after 4 child-robot interactions, personalization will increase children's math performance, meaning they will give more correct answers **(H4a)**, respond faster **(H4b)**, and increase in math level **(H4c)** (see Fig. 1b). We also hypothesize that personalization will increase the robot's social presence **(H5)** and feelings of friendship for the robot **(H6)**. However, the personalization skills of a robot need to be salient and unambiguous enough for a child to notice them [25]. From this perspective, we hypothesize that the impact of personalization on social presence **(H7)** and feelings of friendship **(H8)** will be mediated by children's awareness that the robot referred to things previously shared by them **(a)**. Furthermore, from the perspective of interpersonal need fulfillment, the impact is also anticipated to be mediated by children's perception that the robot recognized them **(b)**, and perception that the robot understood them **(c)** (see Fig. 1b).

3 Method

3.1 Participants

113 children aged 9–12 years (49% boys, 51% girls) completed the experiment. The participants, all from grade 7, were recruited from six different primary schools, situated in both urban and suburban districts of the Netherlands. The respective teachers provided a centralized national math level, ranging from E (lowest) to A (highest), for each child. Most children had the highest math levels A-B (49%), while around 23% had an average C-level, and 28% the lowest D-E levels. Parents signed an informed consent form before participating. The study was approved by the ethical committee of the Amsterdam University of Applied Sciences (ref. number: 2022–054032).

3.2 Experimental Design

The study had a 2 (scaffolding: without vs. with) x 2 (personalization: without vs. with) between-subjects design. Participants were randomly assigned to one of the 4 conditions. Matching procedures were used to ensure balance in gender, age and math level. In the *scaffolding (S)* condition the robot offered guidance after an incorrect answer and when a new type of sum was introduced. In the *non-scaffolding (NS)* condition the robot moved on to the next problem without guidance. In the *personalization (P)* condition the robot used the preferences and interests shared by the child to make the interaction feel personal and to tailor the content of the math stories to children's interests. In the *non-personalization (NP)* condition the interaction was not personal and the robot used math stories with a random topic and fixed content. After 4 complete interactions the distribution per condition was: S-P ($n=30$), NS-P ($n=25$), S-NP ($n=30$), NS-NP ($n=28$).

3.3 Procedure and Robot Specifications

Pairs of researchers conducted the study in parallel at multiple locations. The researchers were trained prior to the study and followed a procedure manual during the experiments to minimize differences between the groups. The experimental sessions took place in two quiet rooms in the school during normal school days: in one room the child-robot interaction took place, in the other room children filled in the survey while being assisted by a researcher unaware of the child's experimental condition. In total, children participated in 4 sessions: 3 sessions on separate days within one week in May or June 2022, and one final session in February or March 2023. During all these sessions, children remained in the same experimental condition. The first three sessions allowed us to examine short-term learning effects (which we published in [64]). However, long-term engagement with tutor robots remains a challenge in educational settings, as children's motivation can decrease once the novelty effect fades [12, 33]. To explore how the child-robot relationship and math learning develop after a prolonged break, we included a fourth session approximately nine months later. This break reflects real-life classroom challenges, such as holidays or inconsistent robot use by teaching staff [65].

The children came to the rooms one by one, starting with a math session with the robot. A 57 cm tall V6 Nao (humanoid) robot was placed on the ground. On one side a 9.9 inch Lenova Tab4 10 tablet was placed in a tablet stand. The tablet visually displayed the sums and could be used by the children as fallback for when the robot could not hear or understand them. On the other side was a BRÄDA lap table with paper and pencil which children could use for calculations. A rug was placed in front of the robot to seat the participants. The robot operated autonomously and was started from a laptop by a researcher. The researcher remained in the room and was positioned far behind the child to avoid unnecessary contact. The researcher only intervened in the event of a system crash. In that case, a reboot was performed, after which the child could continue where it left off.

At the start of the robot math session, children received general instructions about the study and the robot, and were reminded that they could stop at any moment without reasons or consequences. Each session consisted of 4 blocks: introduction/greeting, chitchat, math, goodbye. The differences between the sessions are shown in Table 1. Specifically, the first session started with a short getting acquainted introduction, where names were exchanged and the robot introduced its goals. This was followed by a how-to-talk-to-me tutorial, where the robot and child practiced with the mechanics of the speech recognition, using the tablet as fallback, and solving a math problem. This was the same in all conditions. The second, third and fourth sessions started with a greeting where the robot said "Hi [name], nice to see you again" either with (P) or without (NP) the child's name inserted, followed by either a generic wave (NP) or the personalized secret handshake that children co-created with the robot during the first session (P). After this introduction, all the sessions continued with a chitchat conversation between the child and robot, followed by the math conversation. During each math dialog, the robot presented a math problem in story form. The math conversation consisted of a prespecified amount of math dialogs with either a random topic (NP) or a topic that matched with the child's (from the chitchat conversations) collected interests (P). For example, "Let's talk about your favorite animal, [lions]" versus "Let's talk about the amazing animal, otters". The robot transformed the problem to the A x B format verbally and visually on the tablet. Nineteen different difficulty levels of multiplication sums were defined. To facilitate children with an experience of success, each child started with a low difficulty level in the first session, which changed during all the sessions based on children's performance. The system was programmed in a way that the difficulty level was gradually increased when children performed well and fast decreased when they performed poorly. In case children did not know the answer, the robot gave them guidance (S) or moved on to the next problem (NS). An example of guidance is the small sum strategy given in 2.2.1 (a detailed script of all guidance strategies is provided in the supplemental materials of [64]). This guidance was the same whether it followed an incorrect answer or introduced a new sum. Each robot-interaction session took approximately 15 min. See also [48] for all robot design specifications.

Table 1 Robot interaction blocks per session

Session 1	Session 2	Session 3	Session 4
Introduction & tutorial	Greeting *(P vs. NP)*	Greeting *(P vs. NP)*	Greeting *(P vs. NP)*
Chitchat	Chitchat	Chitchat	Chitchat
Math *(P vs. NP)* *(S vs. NS)*	Math *(P vs. NP)* *(S vs. NS)*	Math *(P vs. NP)* *(S vs. NS)*	Math *(P vs. NP)* *(S vs. NS)*
Chitchat & goodbye (incl. co-creation handshake)	Chitchat & goodbye	Big goodbye	Big goodbye

At the end of the fourth robot math session, children were escorted to the other room to fill in the survey. They were seated behind a laptop to fill in a digital Qualtrics questionnaire. It started with an instruction video and a practice question. The researcher emphasized that there were no right or wrong answers and that their own opinion was valued the most. Children could then fill in the complete 37-item questionnaire, each question displayed separately on the screen together with a 4-point Likert scale. The survey was adapted for this age group by using concrete questions, omitting the neutral response category, and by avoiding complex wording, indirect questions and negations [66]. To aid children with reading problems, each question was also accompanied with a prerecorded video in which the question and answer options were read out loud. The researcher remained in the room but did not intervene, unless the child needed explanation. The researcher did register any verbal comments made by children when filling in the survey. The survey took 10–15 min.

3.4 Measures

3.4.1 Biographical Information

The teachers provided the age, gender, and general math level for each child.

3.4.2 Math Performance

Three variables measured children's math performance during the fourth robot math session (see frequencies and results regarding the first three sessions in our previous publication [64]). First, the *ratio of correct answers* was calculated for each child based on the number of correct answers (during the first answer attempt) and the total number of sums logged by the system (M = 0.71, SD = 0.19, range = [0.20, 1.00]). Second, a child's *average response time* in seconds was calculated (M = 51.26, SD = 16.65, range = [20.00, 99.25]). And third, a child's *math level difference* was calculated based on the difference between their starting level and ending level (M = 0.68, SD = 1.97, range = [-5, 5]).

3.4.3 Robot Perception

Originally two variables measured the robot's social perception: social presence and feelings of friendship. The social presence scale was formed using various adapted items from [31, 67], and [68]. The feelings of friendship scale was formed using various adapted parasocial interaction, closeness and trust items from [69] and [26]. The answer options ranged from (1) no, definitely not, to (4) yes, definitely so. A principle components analysis discovered three distinct factors: in addition to social presence, feelings of friendship split into two factors which we referred to as parasocial interaction (e.g., “Would you like to see the robot more often?”) and trust (e.g., “Do you think the robot can keep one of your secrets?”). The term parasocial interaction was chosen for the first set of items, because they correspond to a one-sided perceived friendship characterized by feeling comfortable around the nonhuman entity, looking forward to seeing/meeting it, and having the desire for repeated interactions [32]. The final scale items are presented under Appendix A.

Of the original 7-item *social presence* scale, 2 items were removed (SP2,5) because they loaded on a different (fourth) factor. Observations during survey administration indicated that some children did not grasp the ‘living creature’ concept (SP5) and/or suddenly shifted their robot perception from a somewhat human-like entity to a mechanical tool “with a camera” when asked if the robot could see them (SP2). The question whether the robot could be a playfellow (SP6) turned out to be a measurement of parasocial interaction. The 4 other scale items (SP1,3,4,7) were averaged to create a single measure of social presence (α=0.72, M=2.94, SD=0.59).

Of the original 10-item feelings of friendship scale, 3 items measured *trust* and 7 items measured *parasocial interaction*. These groups of items were averaged to create a single measure of trust (F8-10: α=0.75, M=3.47, SD=0.59) and parasocial interaction, the latter also including item SP6 from the social presence scale (F1-7, SP6: α=0.88, M=3.46, SD=0.46). A scan for outliers indicated that 3 children scored very negative on the parasocial interaction scale compared to other children. Only in analyses with this scale were these children removed from the analyses.

3.4.4 Mediators

Four potential meditators were measured with single items. Children had to indicate whether the robot helped them with difficult or new sums (*awareness of being helped by robot:* M=3.00, SD=0.94), whether the robot used things they said during chatting to create a math story (*awareness that robot referred to shared things:* M=3.08, SD=0.85), whether the robot recognized them from last time (*perception of being recognized by robot:* M=3.31, SD=0.87), and whether the robot could understand them well (*perception of being understood by robot:* M=2.94, SD=0.67). The answer options ranged from (1) no, definitely not, to (4) yes, definitely so.

3.4.5 Covariates

Correlation analyses were performed to investigate whether the dependent variables significantly related to a child’s gender, age, math level, math motivation, total number of math problems, total number of correct answers, and highest / average / last math level reached. Math motivation was measured at the end of the online survey using the Mathematics Motivation Questionnaire for Children (MMQC) of [70, 71]. Only the subscales Task Value (6 items, e.g. “Do you like math?”; α = 0.91) and Perceived Competence (6 items, e.g. “Are you good at math?”; α = 0.85) were included in the study.

The following covariates were identified for specific dependent variables (p-values ranging from .046 to <.001) and will be included in the analyses: *average response time*: math level (r=.41), math motivation Perceived Competence (r=.25), total number of math problems (r=−.44), total number of correct answers (r=−.36); *math level difference*: math level (r=−.10), total number of math problems (r=.31), total number of correct answers (r=.55); *social presence*: gender (r=.28), math level (r=−.21); *parasocial interaction*: gender (r=.29), math level (r=−.32); *trust*: math level (r=−.29).

3.4.6 Technical and Design Checks

To ensure the robot functioned correctly and the math stories were engaging and appropriately tailored to the children, participants answered four single-item questions. These questions assessed whether they could hear the robot well, understood what the robot said, felt that the robot matched the sums to their math level, and whether they found the math stories interesting. The answer options ranged from (1) no, definitely not, to (4) yes, definitely so. The frequencies of these responses are reported under 4.1 (Descriptives).

4 Results

4.1 Descriptives

Overall, the robot performed good: children could hear the robot well (M=3.48, SD=0.66), could understand what the robot said (M=3.58, SD=0.56), and felt that the robot matched the math level of the sums to their personal math level (M=3.32, SD=0.72). Furthermore, the math stories were found interesting (M=3.45, SD=0.61), particularly among children with a lower math level (r=−.21, p=.023).

4.2 Direct Effects of Scaffolding and Personalization on Math Performance

To investigate whether scaffolding (H1) and personalization (H4) increased children's math performance, three analyses of covariance (ANCOVAs) were performed with scaffolding and personalization as between-subject factors, and either (a) ratio of correct answers, (b) average response time or (c) math level difference as dependent variable. Each analysis included their own identified covariates (see Method). As anticipated, children receiving guidance from the robot (S) responded faster to the math problems ($M=48$ s, $SD=1.91$) than children who did not receive guidance (NS) ($M=55$ s, $SD=2.08$), $F(1,105)=5.472$, $p=.02$. Children receiving guidance from the robot (S) also increased in math level ($M=1.59$, $SD=1.94$), while children not receiving guidance (NS) actually decreased in math level ($M=-0.36$, $SD=0.21$), $F(1,106)=37.393$, $p<.001$. No main effects were found for scaffolding on correct answers, nor for personalization on all math performance measures. Additionally, no interaction effects between scaffolding and personalization were found.

4.3 Direct Effects of Scaffolding and Personalization on Robot Perception

To investigate whether scaffolding (H2) and personalization (H5-6) increased the robot's social perception, three analyses of covariance were performed with scaffolding and personalization as between-subject factors, and either social presence, parasocial interaction or trust as dependent variable, each with their own identified covariates. The analyses only yielded one main effect for personalization, $F(1,104)=5.676$, $p=.02$, with children in the personalized condition (P) parasocially interacting more with the robot ($M=3.59$, $SD=0.05$) than children in the non-personalized (NP) condition ($M=3.42$, $SD=0.48$). No main effects were found on social presence and trust, nor for scaffolding on social presence. Additionally, no interaction effects between scaffolding and personalization were found.

4.4 Indirect Effects of Scaffolding and Personalization on Robot Perception

To explain the impact of personalization on parasocial interaction (H8-PI-a-b-c), three mediation analyses were performed (model 4, 5000 bootstrap samples) in PROCESS (Version 4.2) [72]. As anticipated (see Fig. 2a), children in the personalized condition more often indicated that the robot referred to things previously shared by them ($a = 0.95$, $SE = 0.14$) and, in turn, parasocially interacted more with the robot ($b = 0.10$, $SE = 0.05$), $B = 0.09$ $SE = 0.05$, 95% $CI = [0.005, 0.189]$. Children in the personalized condition also more often thought that the robot understood them ($a = 0.28$, $SE = 0.13$) which, in turn, lead to more parasocial interaction with the robot ($b = 0.12$, $SE = 0.05$), $B = 0.03$ $SE = 0.02$, 95% $CI = [0.007, 0.086]$ (see Fig. 2b). However, children's perception that the robot recognized them from last time did not explain the impact of personalization on parasocial interaction. No indirect effects were found for the impact of personalization on trust (H8-Trust-a-b-c) and social presence (H7a-b-c).

Although scaffolding had no direct effect on social presence, the effect could be completely indirect (as explained in [72]). For this reason, another mediation analysis (model 4, 5000 bootstrap samples) was performed to investigate whether children needed to be aware of the robot helping them in order for them to perceive the robot as socially present (H3). As anticipated (see Fig. 3a), children receiving

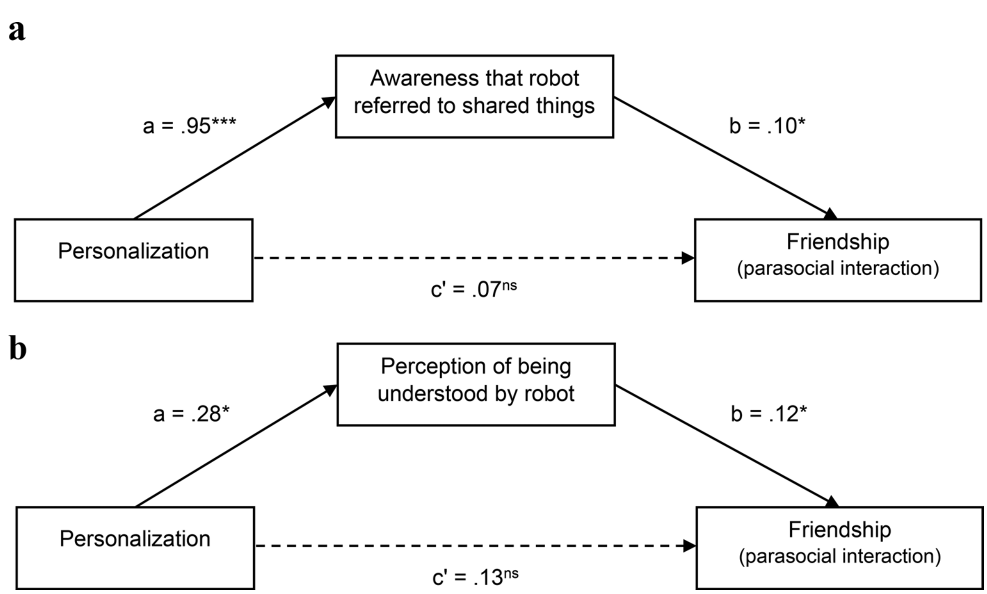

Fig. 2 Mediation models for the effect of personalization on parasocial interaction via children's awareness that the robot referred to things previously shared by them (**a**: upper model) and via perception that the robot understood them (**b**: lower model); *$p<.05$, **$p<.01$, ***$p<.001$, *ns*=nonsignificant

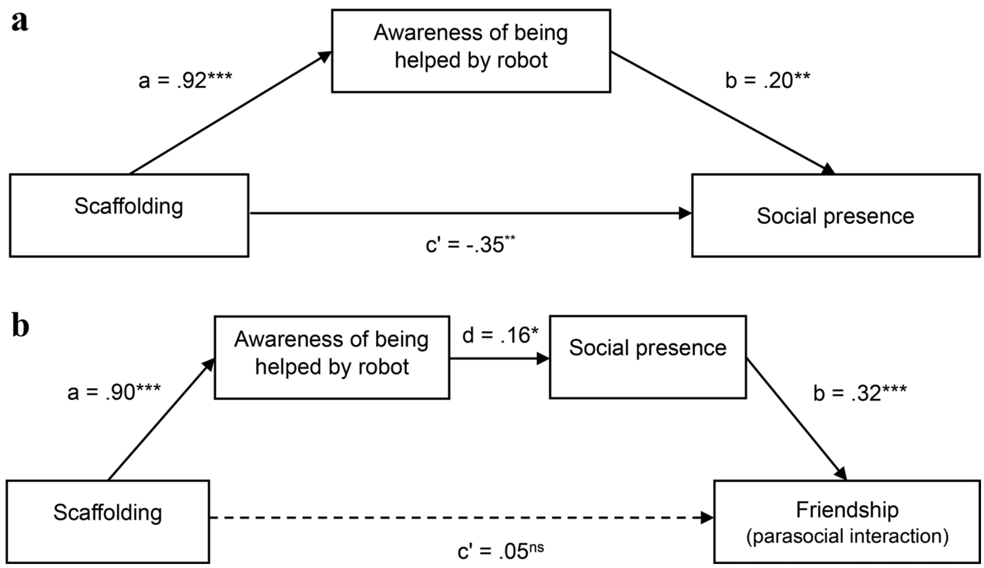

Fig. 3 Mediation models for the effect of scaffolding on social presence via children's awareness of being helped by the robot (**a**: upper model) and for the effect of scaffolding on parasocial interaction via awareness of being helped and social presence (**b**: lower model)

guidance from the robot more often indicated that the robot helped them with difficult or new sums ($a = 0.92$, $SE = 0.15$) and, in turn, perceived the robot as more socially present ($b = 0.20$, $SE = 0.06$), $B = 0.18$, $SE = 0.07$, 95% CI = [0.052, 0.336]. This mediated path was extended with parasocial interaction as dependent variable to investigate whether social presence increases children's feelings of friendship with the robot (RQ1). A serial mediation analysis (model 6, 5000 bootstrap samples) indicated that this indirect effect of scaffolding on parasocial interaction via children's awareness of being helped by the robot and social presence was indeed significant: $B = 0.05$, $SE = 0.02$, 95% CI = [0.007, 0.097] (see Fig. 3b).

5 Conclusions and Discussion

The aim of this study was to investigate the impact of a robot tutor's social interaction skills on children's math performance and robot perception after 4 child-robot interactions. By using a recurring interactions experimental design, we disentangled the effect of two specific social skills: *scaffolding* the explanations to children's evolving math performances (by use of progressive schematization), and *personalizing* the math conversations to children's preferences and interests (by use of the memory-based personalization strategy). We also specifically investigated the underlying psychological mechanisms that explain the impact of these robot's social skills. See Table 2 for a summary of all the results.

Regarding the robot social skill **scaffolding**, the results indicated that children receiving guidance from the robot responded faster and increased in math level compared to children who did not receive guidance. However, scaffolding did not affect the correctness of children's answers. This is most likely an effect of our design. To make a fair comparison, the rate of correct answers in all conditions is based on the first answer attempt. However, in the scaffolding condition, children received a second attempt, which could have influenced learning outcomes. Research suggests that repeated attempts can enhance learning by reinforcing memory retrieval and providing additional opportunities for practice and self-correction [73, 74]. Thus, the increase in math level in the scaffolding condition may partially stem from the fact that children had an extra opportunity to arrive at the correct answer. While this design choice aligns with real-world educational scaffolding, where learners often receive guided support, it also introduces a potential confound that should be considered in future research.

Furthermore, we found that between 10 and 25% of the incorrect answers were actually robot errors: the child gave the correct answer, but the robot did not recognize it correctly. In many cases, the child did not correct the robot, meaning that the robot processed it as an incorrect answer. In the scaffolding condition, children used the second chance as an opportunity to correct the robot, increasing the difference between both conditions even more. Thus, while the robot tutor in our study primarily improved children's response time, the additional attempt in the scaffolding condition likely contributed to the observed math level increase. Future studies should consider isolating the effects of scaffolding from the effects of repeated attempts to disentangle their individual contributions to learning.

Although log checks showed that the robot speech-recognition errors happened just as often in every condition, recent work suggests that children are more forgiving of a robot's mistakes when it first builds a warm, personalized bond [75, 76]. In our study, the personalization and

Table 2 Overview results (see Fig. 1a and b for more details)

Expectations	Results	Key takeaways
Scaffolding		
H1	*Direct* effect on **math performance** • Accepted for: (b) response time, (c) math level • Rejected for: (a) answer correctness	Scaffolding improves speed and level (though this may reflect the second-attempt design), not accuracy.
H2	*Direct* effect on **robot perception** • Rejected for: social presence	No direct scaffolding effect on the robot's social presence.
H3	*Indirect* effect on **robot perception** • Accepted for social presence via: awareness of being helped by robot	Scaffolding raises the robot's social presence *only* when help is noticed.
RQ1	Relationship between social presence and friendship • Supported for friendship (parasocial interaction) via: awareness of being helped by robot	Social presence predicts parasocial friendship with the robot, especially when scaffolding is noticed as helpful.
Personalization		
H4	*Direct* effect on **math performance** • Rejected for all (a, b, c)	Personalization does not improve math performance (accuracy, speed, or level).
H5-H6	*Direct* effect on **robot perception** • Accepted for: friendship (parasocial interaction) • Rejected for: social presence	Personalization increases parasocial friendship with the robot, not the robot's social presence.
H7-8	*Indirect* effect on **robot perception** • Accepted for friendship (parasocial interaction) via: (a) awareness that robot referred to shared things, (c) perception of being understood by robot • Rejected for friendship (parasocial interaction) via: (b) perception of being recognized by robot • Rejected for social presence via: all (a, b, c)	Parasocial friendship with the robot increases when personalization is noticed and conveys understanding, not via perceived recognition.
RQ1	Relationship between social presence and friendship • Not supported	Social presence does not explain personalization-driven friendship effects.

scaffolding features may likewise have made some errors feel less serious or even more annoying, depending on the child. Because we did not track those reactions, we cannot rule out an undetected influence on learning or robot perception-related measures. Future work should therefore log every interactional error, observe children's responses to these errors, and test whether specific social skills (such as personalization or scaffolding) can mitigate the impact of robot mistakes. Being transparent about these flaws will make robot tutor research more realistic and help designers build systems that match children's expectations and error forgiveness thresholds.

Importantly, the observed math level decrease in the non-scaffolding condition does not imply that robots negatively impact learning but rather highlights the necessity of explanatory feedback in educational interactions. This effect is commonly observed in human tutoring as well [73, 74], where the absence of guidance may lead to reinforcement of incorrect strategies, resulting in stagnation or even a decline in performance rather than conceptual growth.

Beyond its impact on learning, scaffolding also influenced how children perceived the robot socially, though only indirectly. Specifically, when children recognized that the robot helped them, scaffolding increased social presence. This aligns with the argument that children must perceive scaffolding as beneficial for it to enhance their perception that the robot is a social entity [41, 49, 50]. In our study, scaffolding was operationalized as arithmetic explanations provided after an incorrect answer and when a new type of sum was introduced, and we captured children's perceived helpfulness via a single-item measure ("the robot helped me with difficult or new sums"). We did not directly assess whether the amount, timing, or content of explanations optimally matched each child's moment-to-moment expertise or informational needs. Prior work suggests that when support is experienced as appropriately targeted and non-redundant, a tutor is perceived as more intelligent and socially present [49], whereas overly detailed or unnecessary explanations can be experienced as mechanical and reduce social presence [e.g., [21, 77–80]. This highlights the need for more sophisticated robot tutoring systems that are not only designed around the robot's technical capabilities (i.e., a robot-centered perspective) but also prioritize the child's needs (i.e., a child-centered perspective) [81]. Future research should therefore examine adaptive scaffolding that adjusts in real time, while explicitly measuring scaffolding fit (e.g., perceived too much/too little help, relevance, and timing) to test when pedagogical support also fosters social engagement [81, 82]. By tailoring support to the child's needs, the robot can maintain its role as an engaging and intelligent social partner.

Interestingly, social presence increased children's feelings of friendship for the robot, as indicated by higher parasocial interaction. This supports the theory that when the robot is perceived as a social being, it becomes more suitable for relationship formation, and children are more willing to initiate a friendship with it [14, 23, 25]. This is a first step in understanding how children's internal states are interconnected and what processes underlie the impact of robots. Nevertheless, these two robot perception responses are not always expected to be related [14]. For instance, in the current study, social presence was an important precursor to friendship when scaffolding was used, but not when personalization was used. One possible explanation is that scaffolding behaviors are experienced as a supportive act by the robot. Some children appreciate this support more than others, for example, because they need it more or because they are naturally more appreciative. It is this level of perceived relevance and appreciation that could determine how socially meaningful the supportive act is, resulting in different social presence scores and, in turn, stronger feelings of friendship. This would align with the broader idea that children's pre-existing robot attitudes (e.g., its personal worth, alignment with personal goals) play an important role in child-robot relationships [83, 84]. Additionally, this finding supports the 'Relevant Needs' proposition of Konijn et al. [85], which suggests that children are more likely to form bonds with artificial others when the interaction serves their needs. According to this theory, an affective bond emerges when a social entity – such as a robot – responds to an individual's goals, desires, or tasks in a way that is subjectively significant. Our results provide empirical support for this theoretical proposition by demonstrating that scaffolding fosters social presence and friendship only when it is perceived as relevant to the child. This highlights the importance of designing robot interactions that are not just socially engaging but also meaningfully aligned with children's individual needs and learning contexts. Further research is needed to determine under which circumstances social presence is a key precursor to friendship and how adaptive scaffolding can optimize child-robot relationships.

Regarding the other robot social skill, results indicated that **personalization** did not increase children's math performance. Human tutoring studies often suggest that personalization enhances children's interest in learning materials, which in turn improves learning performance [62]. However, in our study, most children found the math stories interesting (see 4.1) and frequently mentioned to the researchers that they found them funny. This suggests that the humor in the math stories may have played a key role in capturing their interest. Embedding an educational message (mathematics) within an entertaining narrative (humorous story), also known as 'entertainment education', is a well-established strategy for enhancing children's motivation, engagement, and concentration, leading to better academic performance [86, 87]. Since *all* children were exposed to the humorous stories, this strategy may have already optimized their interest, potentially masking any additional effect of personalization. Notably, the only study to our knowledge that demonstrated a positive effect of memory-based personalization by robots on children's learning performance did not incorporate humor or entertainment elements in its design [63]. Future research should therefore disentangle the individual effects of personalization from those of entertainment education.

As anticipated, personalization did increase children's feelings of friendship as indicated by higher parasocial interaction. First, we found evidence for how this design element functions: children's awareness that the robot referred to things they had previously shared mediated this effect. Alongside our finding that children needed to recognize the robot's scaffolding, this supports Van Straten et al.'s [25] argument that a robot's social skills must be salient and unambiguous enough for children to notice and be influenced by them. Second, personalization fulfilled children's interpersonal need to be understood. Specifically, memory-based personalization increased children's perception that the robot understood them on a personal level which, in turn, increased their parasocial interaction with the robot. This finding aligns with previous research [12, 57, 59], suggesting that recalling disclosed information and tailoring interactions accordingly signals to children that they are being heard and that the robot empathizes with their preferences and interests. Since feeling understood is a core aspect of close friendships [57], this highlights the potential of personalization in fostering social bonds between children and robots.

Unfortunately, the impact of personalization on parasocial interaction was not mediated by children's perception that the robot recognized them from last time. However, we cannot rule out the possibility that personalization fulfilled children's interpersonal need to be recognized. Our results showed positive correlations between personalization, the perception of being recognized, and parasocial interaction. We suspect the indirect effect was weakened because some children in the non-personalized condition mentioned during survey administration that the robot recognized them because it said "nice to see you again". Presumably, without using a child's name or other personal references, a simple polite greeting with the word 'again' can already be interpreted as a sign of recognition. These findings raise three key questions for future research:

• whether a single-item recognition question adequately captures children's full experience,

• whether recognition was assessed at the right moment (since cognitive overload is a risk at the start of the conversation), and

• whether the specific facts remembered by the robot matter to children and are retained by them.

Measuring the child-robot relationship remains a challenging task as studies and domains differ in their conceptualizations and operationalizations, while widely accepted standards of measurement are lacking [25, 88]. Our scale for feelings of friendship captured two distinct concepts, parasocial interaction and trust, with only the former being influenced by the robot's social skills. Parasocial interaction is a well-known phenomenon in child-media studies, where interactions with nonhuman entities often develop into one-sided perceived meaningful interpersonal connections that stimulate a desire to see and continuously interact with the nonhuman entity [32]. There is a plethora of research demonstrating that children form close parasocial relationships with all sorts of animate and inanimate objects, including intelligent characters [27, 30, 34]. Yet many child-robot studies have focused on trust as the dominant measure of relationships, even though its effects are more inconsistent [25]. Trust is defined and measured in many ways [89], and it is unknown whether it is essential to all nonhuman friendships or rather context depended. In the present study, a higher level of social trust was measured even though our robot did not share sensitive information or keep secrets. Perhaps lower levels of social trust (e.g., trusting the robot to treat answers with respect) as well as aspects of competency trust (e.g., trusting the robot's feedback) did play a role in our robot math tutor setting.

While social bonds with robots are well-documented in child-robot interaction research [5, 17], the ethical implications of these relationships remain complex [17]. In educational settings, such bonds may foster engagement and learning, but in other contexts, they could raise concerns about overtrust and emotional dependency [17]. Future studies should explore in which contexts social connections with robots are beneficial to children and where they might introduce risks. This challenge is further underscored by the difficulty of measuring trust in socially assistive robots, as perspectives and expectations vary across stakeholders, interactions evolve over time, and learning environments are often dynamic and unstructured [90]. Developing nuanced frameworks for assessing trust and parasocial bonds will be critical in advancing ethical and effective child-robot interactions.

In light of our findings, we propose several key design recommendations for educational robots. First, scaffolding should be adaptive to a child's evolving skill level, ensuring that feedback remains relevant and beneficial without becoming redundant or frustrating. Second, personalization should be designed to be salient and meaningful, as children must recognize and appreciate the robot's tailored responses for personalization to foster social bonds. Third, robots should employ strategies that enhance social presence, as children are more likely to form connections with robots they perceive as socially engaging and helpful. This includes not only dynamic social interactions but also mechanisms that signal understanding and potentially recognition. Finally, educational robots should be designed with ethical considerations in mind, balancing engagement with safeguards that prevent overtrust or emotional overreliance. Future research should continue refining these elements to optimize both learning and social engagement in child-robot interactions.

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Data Availability The data set is available for download from the Dutch national centre of expertise and repository for research data (DANS) at: https://doi.org/10.17026/SS/73IY7I.

Declarations

Ethical Approval The questionnaire and methodology for this study were approved by the ethical committee of the Amsterdam University of Applied Sciences (Ethics approval number: 2022–054032).

Consent to Participate Written informed consent was obtained from the parents.

Competing Interests The authors have no competing interests to declare that are relevant to the content of this article.

References

1. Suleiman Y, Hammed A (2019) Perceived causes of students' failure in mathematics in Kwara state junior secondary schools:

implication for educational managers. Int J Edu Stud Math 6(1):19–33
2. Chand S, Chaudhary K, Prasad A, Chand V (2021) Perceived causes of students' poor performance in mathematics: a case study at Ba and Tavua secondary schools. Front Appl Math Stat 7:614408. https://doi.org/10.3389/fams.2021.614408
3. Henslee A, Klein B (2017) Using brief guided imagery to reduce math anxiety and improve math performance: a pilot study. J STEM Educ 18:32–36
4. Konijn EA, Jansen B, Mondaca Bustos V, Hobbelink VL, Preciado Vanegas D (2022) Social robots for (second) Language learning in (migrant) primary school children. Int J Soc Robot 14:827–843. https://doi.org/10.1007/s12369-021-00824-3
5. Belpaeme T, Kennedy J, Ramachandran A, Scassellati B, Tanaka F (2018) Social robots for education: a review. Sci Robot 3:1–9. https://doi.org/10.1126/scirobotics.aat5954
6. Unesco UN (2022) Transforming education from within: current trends in the status and development of teachers. UNESDOC Digital Library. https://unesdoc.unesco.org/ark:/48223/pf0000383002. Accessed 14 July 2023
7. Vygotsky LS (1978) Mind in society: the development of higher psychological processes. Harvard University Press, Cambridge
8. Davison DP, Wijnen FM, van der Meij J, Reidsma D, Evers V (2020) Designing a social robot to support children's inquiry learning: a contextual analysis of children working together at school. Int J Soc Robot 12:883–907. https://doi.org/10.1007/s12369-019-00555-6
9. Elloumi L, Bossema M, de Droog SM, Smakman MHJ, van Ginkel S, Ligthart MEU, Hoogland K, Hindriks KV, Ben Allouch S (2022) Exploring requirements and opportunities for social robots in primary mathematics education. In: Proceedings of the 31st IEEE International Conference on Robot and Human Interactive Communication (RO-MAN) pp. 316–322. IEEE. https://doi.org/10.1109/RO-MAN53752.2022.9900569
10. Wittrock MC (1974) Learning as a generative process. Educ Psychol 11(2):87–95
11. Westlund JMK, Park HW, Williams R, Breazeal C (2018) Measuring young children's long-term relationships with social robots. In: Proceedings of the 17th ACM conference on interaction design and children pp. 207–218. https://doi.org/10.1145/3202185.3202732
12. Ligthart MEU, Neerincx MA, Hindriks KV (2022) Memory-based personalization for fostering a long-term child-robot relationship. In: 17th ACM/IEEE International Conference on Human-Robot Interaction (HRI) pp. 80–89. https://doi.org/10.1109/hri53351.2022.9889446
13. Leite I, Martinho C, Paiva A (2013) Social robots for long-term interaction: a survey. Int J Soc Robot 5:291–308. https://doi.org/10.1007/s12369-013-0178-y
14. Xu K, Chen M, You L (2023) The hitchhiker's guide to a credible and socially present robot: two meta-analyses of the power of social cues in human–robot interaction. Int J Soc Robot 15(2):269–295. https://doi.org/10.1007/s12369-022-00961-3
15. Woo H, LeTendre GK, Pham-Shouse T, Xiong Y (2021) The use of social robots in classrooms: a review of field-based studies. Educ Res Rev 33:100388. https://doi.org/10.1016/j.edurev.2021.100388
16. Van den Berghe R, Verhagen J, Oudgenoeg-Paz O, Van der Ven S, Leseman P (2019) Social robots for Language learning: a review. Rev Educ Res 89(2):259–295. https://doi.org/10.3102/0034654318821286
17. Belpaeme T, Tanaka F (2021) Social robots as educators. OECD digital education outlook 2021 pushing the frontiers with artificial Intelligence, blockchain and robots: pushing the frontiers with artificial Intelligence, blockchain and robots. OECD Publishing, Paris, pp 143–147. https://doi.org/10.1787/1c3b1d56-en
18. Brown L, Howard AM (2013) Engaging children in math education using a socially interactive humanoid robot. In: 13th IEEE-RAS International Conference on Humanoid Robots (Humanoids) pp. 183–188. https://doi.org/10.1109/humanoids.2013.7029974
19. Kennedy J, Baxter P, Belpaeme T (2015) The robot who tried too hard: social behaviour of a robot tutor can negatively affect child learning. In: Proceedings of the tenth annual ACM/IEEE international conference on human-robot interaction pp. 67–74. https://doi.org/10.1145/2696454.2696457
20. Huang IS, Hoorn JF (2018) Having an Einstein in class: teaching maths with robots is different for boys and girls. In: 13th World Congress on Intelligent Control and Automation (WCICA) pp. 424–427. https://doi.org/10.1109/wcica.2018.8630584
21. Hindriks KV, Liebens S (2019) A robot math tutor that gives feedback. In: International Conference on Social Robotics pp. 601–610. https://doi.org/10.1007/978-3-030-35888-4_56
22. Konijn EA, Hoorn JF (2020) Robot tutor and pupils' educational ability: teaching the times tables. Comput Educ 157:103970. https://doi.org/10.1016/j.compedu.2020.103970
23. De Droog SM, De Haas M, Ligthart M, Smakman M (2023) Vriendschap met robots: hoe meet je dat? HEMD Missies, Utrecht University of Applied Sciences. https://hemdmissies.nl/vriendschap-met-robots-hoe-meet-je-dat. Accessed 21 July 2023
24. De Graaf MMA, Ben Allouch S (2017) The influence of prior expectations of a robot's lifelikeness on users' intentions to treat a zoomorphic robot as a companion. Int J Soc Robot 9:17–32. https://doi.org/10.1007/s12369-016-0340-4
25. Van Straten CL, Peter J, Kühne R (2020) Child–robot relationship formation: a narrative review of empirical research. Int J Soc Robot 12:325–344. https://doi.org/10.1007/s12369-019-00569-0
26. Van Straten CL, Kühne R, Peter J, De Jong C, Barco A (2020) Closeness, trust, and perceived social support in child-robot relationship formation: development and validation of three self-report scales. Interact Stud 21(1):57–84. https://doi.org/10.1075/is.18052.str
27. Brunick KL, Putnam MM, McGarry LE, Richards MN, Calvert SL (2016) Children's future parasocial relationships with media characters: the age of intelligent characters. J Child Media 10(2):181–190. https://doi.org/10.1080/17482798.2015.1127839
28. Ligthart MEU (2022) Shaping the child-robot relationship: interaction design patterns for a sustainable interaction. Dissertation, Vrije Universiteit Amsterdam
29. Kim KJ, Park E, Sundar SS (2013) Caregiving role in human–robot interaction: a study of the mediating effects of perceived benefit and social presence. Comput Hum Behav 29(4):1799–1806. https://doi.org/10.1016/j.chb.2013.02.009
30. Richards MN, Calvert SL (2017) Media characters, parasocial relationships, and the social aspects of children's learning across media platforms. In: Barr R, Linebarger DN (eds) Media exposure during infancy and early childhood. Springer, London, pp 141–163. https://doi.org/10.1007/978-3-319-45102-2_9
31. Heerink M, Díaz M, Albo-Canals J, Angulo C, Barco A, Casacuberta J, Garriga C (2012) A field study with primary school children on perception of social presence and interactive behavior with a pet robot. In: RO-MAN 21st IEEE international symposium on robot and human interactive communication pp. 1045–1050. https://doi.org/10.1109/roman.2012.6343887
32. Hoffner C (1996) Children's wishful identification and parasocial interaction with favorite television characters. J Broadcast Electron Media 40(3):389–402. https://doi.org/10.1080/08838159609364360
33. Kanda T, Sato R, Saiwaki N, Ishiguro H (2007) A two-month field trial in an elementary school for long-term human–robot interaction. IEEE Trans Robot 23(5):962–971. https://doi.org/10.1109/tro.2007.904904

34. Calvert SL, Putnam MM, Aguiar NR, Ryan RM, Wright CA, Liu YHA, Barba E (2020) Young children's mathematical learning from intelligent characters. Child Dev 91(5):1491–1508. https://doi.org/10.1111/cdev.13341
35. Baumeister RF, Leary MR (1995) The need to belong: desire for interpersonal attachments as a fundamental human motivation. Psychol Bull 117(3):497–529. https://doi.org/10.1037/0033-2909.117.3.497
36. Chen YC, Gamborino E, Fu LC, Yueh HP, Yeh SL (2021) Social presence in evaluations for a humanoid robot and its effect on children-robot relationship. In: Proceedings of the 23rd HCI international conference pp. 191–199. https://doi.org/10.1007/978-3-030-78635-9_27
37. Schodde T, Hoffmann L, Stange S, Kopp S (2019) Adapt, explain, engage: a study on how social robots can scaffold second-language learning of children. ACM Trans Hum-Robot Interact 9(1):1–27. https://doi.org/10.1145/3366422
38. Jones A, Bull S, Castellano G (2018) I know that now, i'm going to learn this next: promoting self-regulated learning with a robotic tutor. Int J Soc Robot 10:439–454. https://doi.org/10.1007/s12369-017-0430-y
39. De Wit J, Schodde T, Willemsen B, Bergmann K, De Haas M, Kopp S, Krahmer E, Vogt P (2018) The effect of a robot's gestures and adaptive tutoring on children's acquisition of second language vocabularies. In: Proceedings of the ACM/IEEE international conference on human-robot interaction pp. 50–58. https://doi.org/10.1145/3171221.3171277
40. Deublein A, Pfeifer A, Merbach K, Bruckner K, Mengelkamp C, Lugrin B (2018) Scaffolding of motivation in learning using a social robot. Comput Educ 125:182–190. https://doi.org/10.1016/j.compedu.2018.06.015
41. Hillmayr D, Ziernwald L, Reinhold F, Hofer SI, Reiss KM (2020) The potential of digital tools to enhance mathematics and science learning in secondary schools: a context-specific meta-analysis. Comput Educ 153:103897. https://doi.org/10.1016/j.compedu.2020.103897
42. Belland BR, Walker AE, Kim NJ, Lefler M (2017) Synthesizing results from empirical research on computer-based scaffolding in STEM education: a meta-analysis. Rev Educ Res 87(2):309–344. https://doi.org/10.3102/0034654316670999
43. Gravemeijer K (2005) Revisiting 'Mathematics education revisited'. Freudenthal 100:106–113
44. Van den Heuvel-Panhuizen M, Drijvers P (2014) Realistic mathematics education. In: Lerman S (ed) Encyclopedia of mathematics education, vol 10. Springer Science+Business Media, Dordrecht, pp 521–525. https://doi.org/10.1007/978-94-007-4978-8
45. Jaworski B (2014) Reflective practitioner in mathematics education. In: Lerman S (ed) Encyclopedia of mathematics education, vol 10. Springer Science+Business Media, Dordrecht, pp 529–532. https://doi.org/10.1007/978-94-007-4978-8
46. Hurts K (2008) Building cognitive support for the learning of long division skills using progressive schematization: design and empirical validation. Comput Educ 50(4):1141–1156. https://doi.org/10.1016/j.compedu.2006.11.008
47. Glade M, Prediger S (2017) Students' individual schematization pathways-empirical reconstructions for the case of part-of-part determination for fractions. Educ Stud Math 94(2):185–203. https://doi.org/10.1007/s10649-016-9716-5
48. Ligthart MEU, de Droog SM, Bossema M, Elloumi L, de Haas M, Smakman MHJ, Hindriks KV, Ben Allouch S (2024) Back to school: Sustaining recurring child-robot educational interactions after a long break. In: Proceedings of the ACM/IEEE International Conference on Human-Robot Interaction. https://doi.org/10.1145/3610977.3635001
49. Leite I, Castellano G, Pereira A, Martinho C, Paiva A (2014) Empathic robots for long-term interaction: evaluating social presence, engagement and perceived support in children. Int J Soc Robot 6:329–341. https://doi.org/10.1007/s12369-014-0227-1
50. Cutrona CE, Suhr JA, MacFarlane R (1990) Interpersonal transactions and the psychological sense of support. In: Duck S & Silver RC (eds.) Personal relationships and social support, London, UK pp. 30–45
51. Waldeck JH (2007) Answering the question: student perceptions of personalized education and the construct's relationship to learning outcomes. Commun Educ 56(4):409–432. https://doi.org/10.1080/03634520701400090
52. Mattar N, Wachsmuth I (2014) Let's get personal: assessing the impact of personal information in human-agent conversations. In: Proceedings of the 16th HCI International Conference pp. 450–461. https://doi.org/10.1007/978-3-319-07230-2_43
53. Leite I, Pereira A, Lehman JF (2017) Persistent memory in repeated child-robot conversations. In: Proceedings of the conference on interaction design and children pp. 238–247. https://doi.org/10.1145/3078072.3079728
54. Kruijff-Korbayová I, Oleari E, Bagherzadhalimi A, Sacchitelli F, Kiefer B, Racioppa S, Pozzi C, Sanna A (2015) Young users' perception of a social robot displaying familiarity and eliciting disclosure. In: Proceedings of the 7th International Conference on Social Robotics (ICSR) pp. 380–389. https://doi.org/10.1007/978-3-319-25554-5_38
55. Beran TN, Ramirez-Serrano A, Kuzyk R, Fior M, Nugent S (2011) Understanding how children understand robots: perceived animism in child–robot interaction. Int J Hum Comput Stud 69(7–8):539–550. https://doi.org/10.1016/j.ijhcs.2011.04.003
56. Ros R, Nalin M, Wood R, Baxter P, Looije R, Demiris Y (2011) Child-robot interaction in the wild: advice to the aspiring experimenter. In: Proceedings of the 13th international conference on multimodal interfaces pp. 335–342. https://doi.org/10.1145/2070481.2070545
57. Papadopoulou M (2016) The 'space' of friendship: young children's Understandings and expressions of friendship in a reception class. Early Child Dev Care 186(10):1544–1558. https://doi.org/10.1080/03004430.2015.1111879
58. Van Straten CL, Peter J, Kühne R, Barco A (2022) On sharing and caring: investigating the effects of a robot's self-disclosure and question-asking on children's robot perceptions and child-robot relationship formation. Comput Hum Behav 129:107135. https://doi.org/10.1016/j.chb.2021.107135
59. Bickmore TW, Picard RW (2005) Establishing and maintaining long-term human-computer relationships. ACM Trans Comput Hum Interact 12(2):293–327. https://doi.org/10.1016/j.chb.2021.107135
60. Erel H, Oberlender A, Khatib J, Freund N, Sadeh O, Waksberg J, Carsenti E (2024) The power of opening encounters in hri: How initial robotic behavior shapes the interaction that follows. In: Proceedings of the ACM/IEEE International Conference on Human-Robot Interaction. https://doi.org/10.1145/3610977.3634996
61. Fischer K, Soto B, Pantofaru C, Takayama L (2014) Initiating interactions in order to get help: Effects of social framing on people's responses to robots' requests for assistance. In: The 23rd IEEE international symposium on robot and human interactive communication. https://doi.org/10.1109/roman.2014.6926383
62. Reber R, Canning EA, Harackiewicz JM (2018) Personalized education to increase interest. Curr Dir Psychol Sci 27(6):449–454. https://doi.org/10.1177/0963721418793140
63. Baxter P, Ashurst E, Read R, Kennedy J, Belpaeme T (2017) Robot education peers in a situated primary school study: personalisation promotes child learning. PLoS ONE 12(5):e0178126. https://doi.org/10.1371/journal.pone.0178126

64. Ligthart MEU, De Droog SM, Bossema M, Elloumi L, Hoogland K, Smakman MHJ, Hindriks KV, Ben Allouch S (2023) Design specifications for a social robot math tutor. In: Proceedings of the ACM/IEEE International Conference on Human-Robot Interaction. https://doi.org/10.1145/3568162.3576957
65. Van Ewijk G, Smakman MHJ, Konijn EA (2020) Teachers' perspectives on social robots in education: an exploratory case study. In: Proceedings of the Interaction Design and Children Conference. https://doi.org/10.1145/3392063.3394397
66. De Leeuw E (2011) Improving data quality when surveying children and adolescents: cognitive and social development and its role in questionnaire construction and pretesting. In: Report prepared for the annual meeting of the academy of Finland: research programs public health challenges and health and welfare of children and young people pp. 10–12
67. Van Straten CL, Peter J, Kühne R, Barco A (2021) The Wizard and I: how transparent teleoperation and self-description (do not) affect children's robot perceptions and child-robot relationship formation. AI Soc 37(1):383–399. https://doi.org/10.1007/s00146-021-01202-3
68. Weiss A, Wurhofer D, Tscheligi M (2009) I love this dog: children's emotional attachment to the robotic dog AIBO. Int J Soc Robot 1(3):243–248. https://doi.org/10.1007/s12369-009-0024-4
69. De Droog SM, Buijzen M (2014) Presenting validated self-report character involvement scales for 4-to 6-year-olds. In: International Communication Association (ICA) conference
70. Prast EJ, Van de Weijer-Bergsma E, Kroesbergen EH, Van Luit JEH (2012) Handleiding voor de rekenmotivatievragenlijst voor kinderen [manual for the mathematics motivation questionnaire for children]. Universiteit Utrecht, Utrecht
71. Prast EJ, Van de Weijer-Bergsma E, Miočević M, Kroesbergen EH, Van Luit JEH (2018) Relations between mathematics achievement and motivation in students of diverse achievement levels. Contemp Educ Psychol 55:84–96. https://doi.org/10.1016/j.cedpsych.2018.08.002
72. Hayes AF (2022) Introduction to mediation, moderation, and conditional process analysis: a regression-based approach, 3rd edn. The Guilford Press, New York
73. Metcalfe J (2017) Learning from errors. Annu Rev Psychol 68(1):465–489. https://doi.org/10.1146/annurev-psych-010416-044022
74. Roediger HL, Butler AC (2011) The critical role of retrieval practice in long-term retention. Trends Cogn Sci 15(1):20–27. https://doi.org/10.1016/j.tics.2010.09.003
75. Cocchella F, Pusceddu G, Belgiovine G, Lastrico L, Rea F, Sciutti A (2022) iCub, we forgive you! Investigating trust in a game scenario with kids. ArXiv Preprint arXiv: 220901694
76. Ceranić HK (2025) It's to, not too! The impact of robot errors on children's learning in a learning–by–teaching paradigm (Doctoral dissertation; April–2025 committee–approved version). https://macsphere.mcmaster.ca/handle/11375/31562
77. Barco A, De Jong C, Peter J, Kühne R, Van Straten CL (2020) Robot morphology and children's perception of social robots: An exploratory study. In: Companion of the ACM/IEEE International Conference on Human-Robot Interaction pp. 125–127. https://doi.org/10.1145/3371382.3378348
78. Oranç C, Küntay AC (2020) Children's perception of social robots as a source of information across different domains of knowledge. Cogn Dev 54:100875. https://doi.org/10.1016/j.cogdev.2020.100875
79. Cameron D, Fernando S, Collins EC, Millings A, Szollosy M, Moore R, Sharkey A, Prescott T (2017) You made him be alive: Children's perceptions of animacy in a humanoid robot. In: Proceedings of Biomimetic and Biohybrid Systems Conference pp. 73–85. https://doi.org/10.1007/978-3-319-63537-8_7
80. Van Straten CL, Peter J, Kühne R, Barco A (2020) Transparency about a robot's lack of human psychological capacities: effects on child-robot perception and relationship formation. ACM Trans Comput Hum Interact 9(2):1–22. https://doi.org/10.1145/3365668
81. Rudenko I, Rudenko A, Lilienthal AJ, Arras KO, Bruno B (2024) The child factor in child–robot interaction: discovering the impact of developmental stage and individual characteristics. Int J Soc Robot 16(8):1879–1900. https://doi.org/10.1007/s12369-024-01121-5
82. Ahmad MI, Mubin O, Orlando J (2017) A systematic review of adaptivity in human-robot interaction. Multimodal Technol Interact 1(3):14. https://doi.org/10.3390/mti1030014
83. Barber O, Somogyi E, McBride AE, Proops L (2021) Children's evaluations of a therapy dog and biomimetic robot: influences of animistic beliefs and social interaction. Int J Soc Robot 13(6):1411–1425. https://doi.org/10.1007/s12369-020-00722-0
84. De Jong C, Peter J, Kühne R, Barco A (2022) Children's intention to adopt social robots: A model of its distal and proximal predictors. Int J Soc Robot 14(4):875–891. https://doi.org/10.1007/s12369-021-00835-0
85. Konijn EA, Preciado Vanegas D, Van Minkelen P (2025) Theory of affective bonding: a framework to explain how people may relate to social robots and artificial others. Commun Theor (in press)
86. Moyer-Gusé E (2008) Toward a theory of entertainment persuasion: explaining the persuasive effects of entertainment-education messages. Commun Theory 18:407–425. https://doi.org/10.1111/j.1468-2885.2008.00328.x
87. Fisch SM (2000) A capacity model of children's comprehension of educational content on television. Media Psychol 2:63–91. https://doi.org/10.1207/s1532785xmep0201_4
88. Stower R, Ligthart M, Van Straten C, Calvo-Barajas N, Velner E, Beelen T (2021, March) Interdisciplinary research methods for child-robot relationship formation. In: Proceedings of the ACM/IEEE International Conference on Human-Robot Interaction pp. 700–702. https://doi.org/10.1145/3434074.3444869
89. Stower R, Calvo-Barajas N, Castellano G, Kappas A (2021) A meta-analysis on children's trust in social robots. Int J Soc Robot 13(8):1979–2001. https://doi.org/10.1007/s12369-020-00736-8
90. Weinberger N, Gerling K, Rixen JO, Bruno B (2024) Trust in the field: Reflections on a real-world lab deploying social robots in childcare settings. In: Proceedings of the SCRITA Workshop on Trust, Acceptance and Social Cues in Human-Robot Interaction at IEEE RO-MAN 2024

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