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Can social robots affect children's prosocial behavior? An experimental study on prosocial robot models

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ABSTRACT

The aim of this study was to investigate whether a social robot that models prosocial behavior (in terms of giving away stickers) influences the occurrence of prosocial behavior among children as well as the extent to which children behave prosocially. Additionally, we investigated whether the occurrence and extent of children's prosocial behavior changed when being repeated and whether the behavior modeled by the robot affected children's norms of prosocial behavior. In a one-factorial experiment (weakly prosocial robot vs. strongly prosocial robot), 61 children aged 8 to 10 and a social robot alternately played four rounds of a game against a computer and, after each round, could decide to give away stickers. Children who saw a strongly prosocial robot gave away more stickers than children who saw a weakly prosocial robot. A strongly prosocial robot also increased children's perception of how many other children engage in prosocial behavior (i.e., descriptive norms). The strongly prosocial robot affected the occurrence of prosocial behavior only in the first round, whereas its effect on the extent of children's prosocial behavior was most distinct in the last round. Our study suggests that the principles of social learning also apply to whether children learn prosocial behavior from robots.

1. Introduction

Social robots – robots that are made to engage in meaningful social interactions with humans (e.g., Lee et al., 2005) – are currently seen as one of the crucial future technologies (e.g., Eberl, 2016; Ross, 2016). Against this background, scholars have started to study an important process in human social interaction – persuasion – in the context of social robots (e.g., Chidambaram, Chiang, & Mutlu, 2012; Ghazali, Ham, Barakova, & Markopoulos, 2019; Siegel, Breazeal, & Norton, 2009). More specifically, researchers have focused on whether social robots can persuade humans to engage in prosocial behavior (e.g., Chernyak & Gary, 2016; Martin et al., 2020; Zaga, Moreno, & Evers, 2017), that is, "voluntary behavior intended to benefit another" (Eisenberg, Spinrad, & Knafo-Noam, 2015, p. 610). As a recent review has shown (Oliveira, Arriaga, Santos, Mascarenhas, & Paiva, 2021, notably pp. 7–8, 10), studies have typically dealt with the influence of robots' appearance, emotional adaptation, awareness, and agency on prosocial behavior, such as helping a robot or donating money. In terms of results, however, the review concluded that the effects of social robots on eliciting prosocial behavior are "mixed, with only approximately half of the studies…reporting positive results" (Oliveira et al., 2021, p. 9).

In this context, it is striking that we know still little about whether robots that *model* prosocial behavior can persuade others to also engage in that behavior. Not only theoretical frameworks (Bandura, 1986) but also empirical evidence of the influence of human role models on engagement in prosocial behavior (for a review, see e.g., Rushton, 1976) suggest that a social robot model may prompt prosocial behavior in humans. It is, therefore, the main goal of the current study to investigate whether prosocial behavior modeled by a social robot elicits this behavior in humans. More specifically, based on an experimental paradigm used in early research on human influence on children's prosocial behavior (e.g., Bryan & Walbek, 1970a; for a review, see Rushton, 1976), we study whether a robot that models prosocial behavior in terms of giving away stickers prompts this prosocial behavior in children. We center on children because they are still somewhat underrepresented in research on social robots and prosocial behavior (for notable exceptions, see Beran, Ramirez-Serrano, Kuzyk, Nugent, & Fior, 2011; Chernyak & Gary, 2016; Martin et al., 2020; Zaga et al., 2017). Moreover, as children encounter robotic technology already relatively often (Mascheroni & Holloway, 2019; Peter, Kühne,

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Barco, De Jong, & Van Straten, 2019) and research on child-robot interaction (CRI) has generally been thriving (e.g., Belpaeme, Kennedy, Ramachandran, Scassellati, & Tanaka, 2018; van Straten, Peter, & Kühne, 2020), it seems timely that we try to understand better to what extent social robots can trigger prosocial behavior in children.

Next to the inconsistent results of research on social robots and prosocial behavior (Oliveira et al., 2021), there are at least three more reasons why more research on social robots and (children's) prosocial behavior is needed. First, dealing with social robots as potential influences on children's prosocial behavior may extend our notion of agents in children's socialization toward prosocial behavior. To date, research has at least implicitly assumed that socialization agents are human, either in direct (Eisenberg et al., 2015) or mediated form (Mares & Woodard, 2005) (for a similar reasoning, see also Oliveira et al., 2021). However, if it can be shown that social robots as role models may also affect children's prosocial behavior, we may have growing evidence that non-human agents may contribute to an important aspect of human socialization, as suggested by related research (Beran et al., 2011; Chernyak & Gary, 2016; Martin et al., 2020; Zaga et al., 2017). Second, the emphasis on pro-social behavior in the present study responds to a more general call by Paiva, Santos, and Santos (2018) for more research on 'Pro-social Computing,' which they define as "computing directed at supporting and promoting actions that benefit the society and others at the cost of one's own" (p. 7995). Third and finally, similar to persuasive technology (Fogg, 2003) more generally, robots that persuade humans to engage in desirable behavior may also persuade humans to engage in undesirable behavior. Assessing the impact of socially desirable modeled behavior of social robots may thus help us judge the potential effect of socially undesirable modeled behavior.

2. Social robots and the occurrence and extent of children's prosocial behavior

A prominent theory that can explain why social robot models may affect children's behavior is Bandura's (1986) Social Cognitive Theory, which has been described as "explicitly persuasive in orientation" (Holbert & Tchernev, 2013, p. 45). Social Cognitive Theory is "founded in an agentic perspective…. [in which] [p]eople are self-organizing, proactive, self-reflecting, and self-regulating, not just reactive organisms shaped and shepherded by environmental events or inner forces" (Bandura, 2001, p. 266). A basic tenet of Social Cognitive Theory is that humans not only learn from direct experience, but also vicariously, through the observation of others (Bandura, 2001). Although Social Cognitive Theory does not explicitly preclude non-human agents as behavioral models, it tends to assume that they are human: Social learning is essentially interpersonal and behavioral models are typically assumed to be human social actors. However, similar to technology more generally (Nass & Moon, 2000), social robots can be perceived as social actors (Fong, Nourbakhsh, & Dautenhahn, 2003) and thus potentially function as behavioral models. As a result, Social Cognitive Theory is also applicable to the effects that social robots modeling prosocial behavior may have on children.

According to Social Cognitive Theory, social learning is governed by four processes (Bandura, 2001). The first process implies that people pay attention to a behavioral model. Because children are typically interested in social robots, at least initially (Kanda, Hirano, Eaton, & Ishiguro, 2004; Ros Espinoza et al., 2011), they can be expected to attend to a social robot. In a second process that governs social learning, people need to retain the modeled behavior by transforming and organizing the modeled behavior such that it can be stored in memory (Bandura, 2001). Amongst other things, retention improves through cognitive and enactive rehearsal of the modeled behavior. In a third process that guides social learning, people perform the remembered modeled behavior (Bandura, 2001). The performed behavior does not have to be identical with the modeled behavior and can be adapted to the match situational requirements. Early studies on children's social learning of prosocial behavior (for a review, see Rushton, 1976) have already shown that children are able to retain and perform modeled behavior if the behavior is developmentally appropriate. This may also apply to prosocial behavior modeled by a social robot.

A fourth and final process that guides social learning refers to incentives for performing an acquired behavior (Bandura, 2001). These incentives consist of rewards for a performed behavior that are either experienced directly or observed with others. Personal standards can also present incentives and influence the performance of a given behavior most when they merge with social standards. Prosocial behavior inherently reflects social standards; it may also be linked to personal standards, notably when it concerns behavior that is rewarded directly or vicariously in real life (Elliott & Vasta, 1970) and that is salient and relevant for individuals, as sharing, which is investigated in the present study, is for children. In this view, performing a given prosocial behavior may be 'self-reinforcing' and accordingly not hinge on reinforcement by others or the observation of others being rewarded (Rosenhan, 1972). Thus, even if a model is not rewarded when performing prosocial behavior, people may still be likely to perform the behavior upon observing the model.

In line with this, studies on the impact of a prosocial human model on children's sharing behavior have shown that a reward of the model is not necessary for the prosocial behavior to occur among children (Elliott & Vasta, 1970; Harris, 1970). Children generally seem to be able and willing to share their resources, at least up to a certain point and typically when they have reached middle childhood (Benenson, Pascoe, & Radmore, 2007; Blake & Rand, 2010; Fehr, Bernhard, & Rockenbach, 2008; McAuliffe, Raihani, & Dunham, 2017; Smith, Blake, & Harris, 2013). More specifically, early studies on the social learning of prosocial behavior have consistently suggested that a human model that performs prosocial behavior in the form of sharing with others subsequently elicits that prosocial behavior in children (e.g., Bryan & Walbek, 1970a, 1970b; Elliott & Vasta, 1970; Hartup & Coates, 1967; Presbie & Coiteux, 1971; for a review, see Rushton, 1976). Finally, there is at least some evidence that social robots can prompt social behavior in humans (for a review, see Oliveira et al., 2021). Based on Social Cognitive Theory (Bandura, 2001) and empirical research, we therefore expected that the *occurrence* of prosocial behavior differs when children see different types of prosocial models. Occurrence of prosocial behavior refers to the performance of at least one act of prosocial behavior (Benenson et al., 2007; Blake & Rand, 2010). We hypothesized:

H1a. Children who observe a strongly prosocial robot will more frequently behave prosocially than children who observe a weakly prosocial robot.

However, as Blake and Rand (2010) have emphasized, children make two distinct decisions when they perform a prosocial behavior, such as sharing: "(a) *whether* to give or not and (b) *how much* to give" (p. 216, emphasis added). Next to the occurrence of prosocial behavior, the *extent* to which a given prosocial behavior is performed thus also deserves attention. In this context, it is important to note that Social Cognitive Theory posits, as outlined before, that behavior learned from a model does not have to be exactly imitated, but can be adjusted to the circumstances (Bandura, 2001). Children may thus deviate from a prosocial model in the extent to which they perform the prosocial behavior.

Accordingly, studies on the learning of prosocial behavior from a human model have largely suggested that the modeling of prosocial behavior does affect children in their degree of performing a prosocial behavior, but that they hardly copy the modeled behavior exactly (Bryan & Walbek, 1970a; Elliott & Vasta, 1970; Grusec & Skubiski, 1970). The finding that human models can increase prosocial behavior among children has also been documented in different cultural contexts (i.e., India: Blake, Corbit, Callaghan, & Warneken, 2016) and for human models with specific characteristics (e.g., perceived similarity, Owens & Ascione, 1991). In addition, research has shown more generally that also social robots can enhance prosocial behavior in children (Beran et al., 2011; Chernyak & Gary, 2016; Martin et al., 2020; Zaga et al., 2017). Against this background, we hypothesized:

H1b. Children who observe a strongly prosocial robot will to stronger extent behave prosocially than children who observe a weakly prosocial robot.

2.1. Repetition and sharing

Social Cognitive Theory also posits that observed behavior is retained better after being cognitively repeated and performed more adequately after being enacted several times (Bandura, 2001). The repetition of the modeled behavior (Holbert & Tchernev, 2013) and the rehearsal of the behavior itself may thus affect the extent to which a given behavior is performed if situationally appropriate. The importance of repeated modeled behavior dovetails with basic principles from cognitive psychology: The more frequently a given modeled behavior has been encountered, the more accessible the cognitive representation of the behavior becomes (e.g., Higgins, 1996). The importance of rehearsing a given behavior merges with basic insights from the psychology of learning: The more frequently a given behavior is rehearsed, the more easily it will be performed (Baddeley, 1999).

Research has hardly studied the effect of repetition and rehearsal of the modeled behavior in the context of prosocial behavior. The few studies that did so found that prosocial behavior reduces when children rehearse prosocial behavior, either generally (Hartup & Coates, 1967) or only when a prosocial model was observed (Presbie & Coiteux, 1971). None of the studies, however, tested the influence of the model's repetition of the behavior along with the children's rehearsal of the behavior. Children thus saw the model perform the behavior, but model and child did not take repeated alternate turns. Moreover, the studies did not distinguish between the occurrence and the extent of the prosocial behavior. In the light of the tenets of Social Cognitive Theory and insights from cognitive psychology, we therefore hypothesized:

H2. The more often children observe a strongly prosocial robot and the more they have the chance to enact the prosocial behavior, (a) the more frequently they will behave prosocially and (b) the stronger the extent will be to which they behave prosocically, compared to children who observe a weakly prosocial robot.

2.2. Injunctive and descriptive norms

According to Social Cognitive Theory, modeling not only influences the learning of a given behavior but, in the form of abstract modeling, also the learning of rules that underlie the behavior (Bandura, 2001). When observing a model perform a behavior, "observers extract the rule governing the specific judgments or actions exhibited by others" (Bandura, 2001, p. 275). This pattern may also apply to learning the norms of prosocial behavior (Rushton, 1980). Norms are typically divided into injunctive norms, which "specify what ought to be done" (Cialdini, Reno, & Kallgren, 1990, p. 1015), and descriptive norms, which describe "what is typical or normal" (Cialdini et al., 1990, p. 1015). Children tend to pick up injunctive norms from competent others in their environment, such as their parents (Rakoczy & Schmidt, 2013), whereas peers tend to shape descriptive norms, notably in late childhood and adolescence (Brown & Larson, 2009; McAuliffe et al., 2017). If children learn from a highly prosocial robot as hypothesized above, then they are more likely to consider this robot a competent other than a peer. Consequently, we expected that a highly prosocial robot would influence children's injunctive norms of prosocial behavior rather than their descriptive norms of prosocial behavior. Specifically, we hypothesized:

H3. Children who observe a strongly prosocial robot will hold stronger injunctive norms about the prosocial behavior than children who observe a weakly prosocial robot.

3. Method

3.1. Participants

61 children (47% girls, 53% boys) aged eight to ten years ($M = 8.70$, $SD = 0.50$) were recruited from two Dutch elementary schools, both located in the Western part of the Netherlands. Before the start of the study, the investigation had been approved by the Ethical Board of the Faculty of Social and Behavioral Sciences of the University of Amsterdam. In addition, the two schools had consented to participate. Active parental consent was obtained before children were allowed to participate.

We chose children aged eight to ten years (i.e., children in middle childhood) for a number of reasons. First, much research on the social learning of prosocial behavior from human modes has dealt with children in this age group (for a review, see Rushton, 1976) and we wanted to ensure some comparability. Second, children in that age group are able to answer to questionnaires meaningfully (Borgers, De Leeuw, & Hox, 2000). Third, from the roughly the age of seven, children enter what Piaget called the concrete operational stage, in which logical structures and perspective-taking develop and thinking becomes more flexible and abstract, albeit tied to concrete events and things in their environment (Miller, 2011). They may consequently be able to have more abstract notions of robots that go beyond merely seeing them uncritically as another toy. Finally, the time between eight and ten years of age represents a period in which children consider moral behavior such as helping 'right,' but within the context of an instrumental, tit-for-tat reciprocity (Nucci & Gingo, 2011), similarly to what Kohlberg and Hersh (1977) called an instrumental-relativist orientation. Against this background, it is particularly interesting to see whether pro-social behavior with its inherent orientation toward the needs of others and no immediate, instrumental outcomes may be influenced in this age group.

3.2. Materials and procedure

We used the social robot Nao (Softbank), a 57 cm tall humanoid robot. We chose Nao because it is often used in research with children (e.g., Martin et al., 2020; Vogt, de Haas, de Jong, Baxter, & Krahmer, 2017) and relatively stable in research outside the lab. We opted for a humanoid robot to maximize comparability with other research on the persuasive effects of social robots (e.g., Chidambaram et al., 2012; Ghazali et al., 2019; Martin et al., 2020; Siegel et al., 2009). The robot's behavior; the visualization of the game on the computer screen; how each game proceeded; and when child and robots lost or won had been preprogrammed for the study. The robot was fully tele-operated.

The study was conducted in the two participating schools, which had been informed about the details of the study and the procedure before. Similar to earlier research (Vogt et al., 2017), a female research assistant briefly introduced the procedure of the study to all participating children together, along with a photo of the Nao robot. She also told the children that, individually, they and the robot would alternately play a game against a computer. Children were explained, in child-appropriate language, that their participation was voluntary; that they could stop participating at any point without any consequences and that the presentation of the study's results would safeguard their anonymity. After all questions of the children were answered, children who had active parental consent were tested separately in a separate room where the robot already stood on a table next to the laptop on which the children and the robot would play the game against the computer.

The design and procedure of the study was inspired by early psychological research on the social learning of prosocial behavior (e.g., Bryan & Walbek, 1970a; Presbie & Coiteux, 1971; for a review, see Rushton, 1976). Children were randomly assigned to one of two experimental conditions: either the strongly prosocial robot model or the weakly prosocial robot model. Participation was voluntary and, individually, children were once more notified that they could stop anytime. The research assistant asked them whether they understood this and whether they still wanted to participate in the study. Only children who explicitly gave their assent participated. After assessing the child's sex and age, the research assistant explained to the children a five-item Likert-type response scale, which was visualized with a bar chart and had been successfully used in earlier research of ours (see van Straten, Kühne, Peter, de Jong, & Barco, 2020; also for information on origin of response scale). Children practiced the response scale with questions unrelated to the study. Once children understood the response scale, they answered the pre-questionnaire, in which we assessed four dimensions of the Big-5 personality traits as well as children's empathy and anthropomorphism. These measures had been intended to be used as moderators, but overall their psychometric properties did not meet our expectations.

After that, the research assistant announced that both the child and robot would play a computer game called Snakes and Ladders and suggested that the child get to know Nao. The robot introduced itself and said that it would play the game Snakes and Ladders against the computer, just like the child. For the purposes of our study, we had, with permission by the developer (Dhawani, 2017), modified a Snakes and Ladders version available on GitHub. Specifically, we had adjusted the code such that the game was connected with the NAO robot and had four rounds. The research assistant probed the child whether it knew Snakes and Ladders. If a child did not know the game, the research assistant explained it in detail using the Snakes and Ladders board on the computer screen. If a child knew the game, she only repeated the basic rules. All children were told that they would receive five digital stickers each time they win against the computer and one digital sticker each time they lose. It was also emphasized that they could decide each time for themselves whether they wanted to keep the stickers for themselves or give them to other children. Children were notified that they would receive the real stickers after the whole study was done and that we would collect the shared stickers and give them to other children in the school.

Subsequently, the children played two trial rounds of the game on the computer, winning once, and losing once. Similar to other research (Samek et al., 2020), these two rounds were used as a baseline assessment of children's tendency to perform social behavior in the form of sharing with others. After the two rounds, the children were told that they and the robot would now alternately play the game against the computer. They were notified that the robot would also choose how many stickers it would give away, which was shown on the computer screen, and that they should pay attention to this. The children and the robot then each played alternately four games against the computer. The robot started each round and the child followed.

Children activated a "roll the dice" button on the computer screen after which the sound of a rolling dice was audible. The piece of the child moved accordingly on the Snakes-and-Ladders board on the screen. When the robot rolled the dice, one of its hand moved accordingly. When it was the computer's turn, only the sound of rolling a dice was audible, followed by the movement of the computer's piece on the screen. We had preprogrammed each number the dice showed after the robot and the child rolled it. The numbers the computer rolled were also identical for all games that the computer played against the robot and the children, but the sequence of preprogrammed numbers varied across rounds to reduce the possibility of children realizing that everything was preprogrammed. In that way, the rounds were identical in both conditions and across all children.

We had also preprogrammed when robot and child would win or lose. The robot lost the first and third round and won the second and fourth round. Children won the first and fourth round and lost the second and third round. We chose this order for the robot's and children winning and losing to make it less predictable for the children to predict when they would win and lose. Moreover, we also tried to reduce the chance that children would guess that the robot's sharing behavior and its influence on their sharing behavior was the focus of the study. We opted for uneven numbers of stickers, both for winning and losing, so children had to make a decision that was either advantageous or disadvantageous for them.

The strongly prosocial robot shared, each time it lost, the one sticker it got and, each time it won, gave away four of the five stickers it got. In total, the strongly prosocial robot thus gave away ten of the twelve stickers it received. The weakly prosocial robot shared no stickers when it lost and, when it won, gave one sticker away. In total, the weakly prosocial robot thus gave away two of the twelve stickers it received. The ratio of stickers shared/kept in the two conditions was similar to earlier research (Presbie & Coiteux, 1971). The robot always said explicitly how many stickers of the available stickers per round it wished to give away (e.g., "I want to give away [NUMBER] of the [NUMBER] stickers") or keep (e.g., "I would like to keep the sticker that I got"). Children decided how many stickers to give away by clicking on a number of either zero or one, when losing, and on a number between zero to five, when winning. Their decision was also printed on the screen. Children could also see on the screen how many stickers they and the robot had given away in earlier rounds.

The game playing took place in the presence of the research assistant in order to maximize control of the research situation and help with potential technical problems. Moreover, surveillance has not been found to interact with the modeling of prosocial behavior in research with human models (Poulos & Liebert, 1972). The research assistant was instructed not to evaluate the children's behavior, but could decide to make neutral, descriptive comments to keep the game vivid (e.g., "That's a five, it's going fast now," "Now you're going up the ladder"). Most important, the research assistant was not to comment verbally or non-verbally on children's sharing behavior.

After both the robot and the children had completed their four games against the computer, the research assistant asked them the questions about injunctive and descriptive norms, followed by the last question use to assess whether the treatment worked. Subsequently, the research assistant thanked the children for their participation and explained that the children would receive their stickers after the study had been completed when they would also be told more about the study. They were asked not to tell other children about what the study entailed. Finally, children were led back to their classroom.

Children were debriefed together in one group to facilitate discussion among the children and exchange experiences. The research assistant explained that robots are advanced machines and outlined, in child-appropriated manner, how they function. She emphasized that it was preprogrammed when the robot would lose and win, how many stickers it would give away, and that the robot did not take autonomous decisions. Children were also informed that the number each a time a dice was rolled had been preprogrammed, along with when children would win and lose. Children were explained that all of this was identical to be able to better compare what children did. The research assistant also mentioned explicitly that one group of children had encountered a robot that had shared a lot of stickers and another had seen a robot that had shared only a few stickers. She explained that this was done to see whether the robot's behavior affected how many stickers the children would give away. To have all children encounter the strongly prosocial robot, this robot was also demonstrated to all children, emphasizing that the robot gave away a lot of stickers. All children received eventually twelve stickers, including those children who had been unable to participate due to lacking parental consent. The remaining shared stickers were given to other children. Children could ask any other questions they had to maximize their learning from the experience and were thanked and bid farewell.

3.3. Measures

Injunctive norms. The operationalization of this measure was inspired by earlier research (Baumgartner, Valkenburg, & Peter, 2011;

Paek, 2009). We asked children how important their parents find it that they share things with other children. Response categories ranged from 1 (*Very important*) to 5 (*Not important at all*) and were reversely coded ($M = 3.84$, $SD = 0.78$).

Descriptive norms. Based on an earlier operationalization of descriptive norms (Baumgartner et al., 2011; Paek, 2009), we asked children to assess how many stickers their friends would give to the robot if they played the game. We chose the robot, rather than other children, as the recipient of stickers to reduce the chance that they children would adjust their answer to this question to their own giving behavior. Response categories were 1 (*All stickers*), 2 (*More than half of the stickers*), 3 (*Half of the stickers*), 4 (*Less than half of the stickers*) and 5 (*No stickers at all*) and were reversely coded ($M = 2.41$, $SD = 0.56$).

Treatment check. Children were asked whether they could remember how many stickers the robot approximately gave away. The number that the children mentioned was recorded.

3.4. Data analysis

When the dependent variable was dichotomous (e.g., occurrence of prosocial behavior in H1a and H2a), we ran binary logistic regressions. When the dependent variable was metric (e.g., extent of prosocial behavior in H1b and H2b) or could be interpreted as such (injunctive and descriptive norms in H3), we ran analyses of covariance. As the strong influence of children's baseline tendency to engage of prosocial behavior on prosocial behavior in experiments has been documented (Samek et al., 2020), we controlled for how many stickers children had given away before they were exposed to the experimental manipulation. The present study was conducted at two schools and by two female research assistants. However, controlling for these two potentially influential variables did not affect any significance test (with one exception, see below). We, therefore, present below the analyses without controlling for school and research assistant.

4. Results

Randomization to the two experimental groups was successful. No significant differences emerged between the two groups in terms of age, $F(1, 59) = 1.24$, $p = .27$, $\eta^2 = 0.02$, and sex, $\chi 2$ $(1, N = 61) = 0.18$, $p = .89$. The treatment check indicated that children observed the manipulation correctly, $F(1, 59) = 138.80$, $p < .001$, $\eta^2 = 0.70$. Children who saw the strongly prosocial robot ($n = 30$) estimated on average that it gave away 9.33 stickers ($SD = 3.08$) and children who saw the weakly prosocial robot ($n = 31$) estimated on average that it gave away 2.55 stickers ($SD = 0.89$).

4.1. Occurrence and extent of children's prosocial behavior

H1a stated that children who observed a strongly prosocial robot would more frequently behave prosocially than children who observed a weakly prosocial robot. Across the four rounds of playing, 55 (90%) children showed prosocial behavior in the sense that they shared a sticker at least once. Eighty-seven percent of the children did so in the weakly-prosocial-robot condition, as compared to 93% of the children in the strongly-prosocial-robot condition. A logistic regression with children's baseline tendency to share at least one sticker as a control variable confirmed the absence of a significant difference between the two conditions. H1a was not supported.

H1b made a similar prediction as H1a, but focused on the extent to which children behaved prosocially (i.e., the total number of stickers a child gave away across the four rounds of playing). An ANCOVA with the number of stickers shared in the trials as a covariate showed that children shared significantly more stickers when they saw a strongly prosocial robot ($M = 4.70$, $SD = 2.72$) than when they saw a weakly prosocial robot ($M = 3.00$, $SD = 2.45$), $F(1, 58) = 15.31$, $p < .001$, $\eta_p^2 = 0.21$. Similar to earlier research (Samek et al., 2020), we found a strong effect of children's baseline tendency to share stickers on how many stickers they share in the experiment, $F(1, 58) = 66.60$, $p < .001$, $\eta_p^2 = 0.54$. Because the Breusch-Pagan test indicated heteroscedasticity, we reran the analysis with a heteroscedasticity-consistent standard error (HC3), which confirmed the results. H2a was thus supported.

4.2. Repetition and sharing

The second set of hypotheses predicted that the more often children observed a strongly prosocial robot and the more they had the chance to enact the prosocial behavior, (a) the more frequently they would behave prosocially and (b) the stronger the extent would be to which they would behave prosocially, compared to children who observe a weakly prosocial robot. To test these hypotheses, we analyzed the four rounds separately. We controlled not only for children's baseline tendency to engage in prosocial behavior at all (H2a) or the number of stickers shared before the experimental manipulation (H2b), but also for whether any stickers where shared in the previous round(s) (H2a) or how many where shared in the previous round(s) (H2b). For example, when analyzing the fourth round in testing H2b, we controlled, next to the baseline measure, for how many stickers children had given away in rounds 1, 2, and 3.

As to H2a, in the first round, children were significantly more likely to behave prosocially after seeing a strongly prosocial robot than after seeing a weakly prosocial robot, $e^{1.851} = 6.37$, $p = .02$, Nagelkerke $R^2 = 0.31$, with 77% of the cases overall correctly classified. That is, when children saw a strongly prosocial robot, the odds of behaving prosocially increased by a factor of 6.37, compared to children who observed a weakly prosocial robot. However, in none of the remaining rounds did a significant difference between the two experimental conditions emerge, with one exception. When we controlled for experimenter and school, the effect of a strongly prosocial robot on the occurrence of prosocial behavior in round 4, which had just failed to reach conventional levels of significance before, became significant, $e^{1.961} = 7.10$, $p = .04$, Nagelkerke $R^2 = 0.54$, with 90% of the cases overall correctly classified. Overall, however, there was no evidence that prosocial behavior occurred more frequently, as a result of observing a strongly prosocial robot, at the end than at the beginning of the four rounds. H2a was thus not supported.

As to H2b, children who observed a strongly prosocial robot did not differ in rounds 1, 2, and 3 in the extent to which they engaged in prosocial behavior from children who had observed a weakly prosocial robot. (Note that, for rounds 2 and 3 in which children lost and could only give away one sticker, the binary logistic regression model only differed in terms of the control variables baseline sharing and sharing in rounds 1 and 2 from the model run for the investigation of rounds 2 and 3 for H2a). However, in the fourth and last round, children showed a greater extent of prosocial behavior when they saw a strongly prosocial robot ($M = 2.13$, $SD = 1.41$) than did children who saw a weakly prosocial robot ($M = 1.06$, $SD = 1.24$), $F(1, 55) = 9.39$, $p = .003$, $\eta_p^2 = 0.15$. Overall, then, the extent to which children engaged in prosocial behavior in response to the type of prosocial robot observed was stronger after children had seen the robot repeatedly and had had the chance to enact the behavior. However, as this behavior was only visible in the last round, H2b was only partly supported.

4.3. Injunctive and descriptive norms

H3 predicted that children who observed a strongly prosocial robot would hold stronger injunctive norms about the prosocial behavior than children who observe a weakly prosocial robot. We did not expect this effect for descriptive norms. Next to the children's baseline tendency to share stickers (i.e., number of stickers), we controlled for the total number of stickers children gave away across the four rounds. In contrast to our expectations, there was no difference between the experimental conditions in terms of children's injunctive norms ($M =$

3.90, $SD = 0.79$ for the weakly prosocial robot and $M = 3.77$, $SD = 0.77$ for the strongly prosocial robot), $F(1, 57) = 0.71$, $p = .40$, $\eta_p^2 = 0.01$. H3 was not supported. Although not formally hypothesized, we tested the effect of the experimental conditions on children's descriptive norms to understand better whether a prosocial robot model can influence norms about prosocial behavior at all. Descriptive norms were affected: Children who observed a strongly prosocial robot thought that more children gave stickers away ($M = 2.60$, $SD = 0.56$) than did children who observed a weakly prosocial robot ($M = 2.23$, $SD = 0.50$), $F(1, 57) = 6.19$, $p = .02$, $\eta_p^2 = 0.10$.

5. Discussion

Against the background of growing interest in the link between social robots and prosocial behavior (Oliveira et al., 2021; Paiva et al., 2018) and children's increasing encounters with robot technology (Mascheroni & Holloway, 2019; Peter et al., 2019), the present study applied insights from earlier research on children's learning of prosocial behavior from human models (for a review, see Rushton, 1976) to social robots. A social robot that modeled strongly prosocial behavior elicited more prosocial behavior than a robot that modeled weakly prosocial behavior. Compared to its weakly prosocial counterpart, the strongly prosocial robots also increased more strongly children's perception of how many other children engage in prosocial behavior. The robot's prosocial modeling behavior only affected the occurrence of prosocial behavior – whether children engaged in prosocial behavior at all – at the initial stages of playing. Across the entire study, there was no effect. However, the effect of the strongly prosocial robot on the extent of prosocial behavior – how much children engaged in prosocial behavior – seemed to be most distinct at the last stage of playing.

5.1. The role of social robots for children's prosocial behavior and norms

Our results on the effect of a robot's modeling of prosocial behavior on the occurrence of children's prosocial behavior suggest that this impact only emerges when children observe the robot model the first time. Four explanations of this unexpected finding are possible. First, in line with earlier research (Benenson et al., 2007; Blake & Rand, 2010), we conceptually and operationally defined the occurrence of prosocial behavior as a single act of prosocial behavior. However, the inherent focus of this definition on a one-time behavior renders it difficult to find an effect of a robot model's prosocial behavior across a study with multiple occasions for performing prosocial behavior; notably when taking into account whether children already engaged in prosocial behavior as we did in our statistical analyses. In this context, it seems logical that the effect of a robot's prosocial behavior only occurred at the first occasion that the children could be influenced by it. Second, it may be that children at some point did engage in prosocial behavior because even the weakly prosocial robot did show, at two occasions, prosocial behavior. Consequently, a comparison of a truly non-prosocial robot with a strongly pro-social robot may have elicited different results.

A third, more developmental explanation of our failure to find an effect of a robot's prosocial behavior other than in the first round may be that our sample – children aged eight to ten – may already be too old to *not* share at all. As Benenson et al. (2007) have shown, children aged nine and older decide significantly less often to not share than do younger children, at least when they have a higher socio-economic standard. Our findings may consequently look different in a study with younger children. Fourth and finally, it is also possible that the number of stickers that children could share is relevant to the occurrence of prosocial behavior. The significant effect when controlling for school and experimenter suggests that, when children had more stickers to share, the occurrence of prosocial behavior may be more likely than when children had fewer stickers to share. But as we can only speculate about the reasons why this particular finding emerged when school and experimenter were controlled for, further research is needed before meaningful interpretations can be made.

Our findings on the impact of a robot's prosocial behavior on the extent of children's prosocial behavior merge with predictions from Social Cognitive Theory (Bandura, 2001). Children shared more after seeing a strongly prosocial robot and did so mainly after repetition of sharing. On average, however, children shared less than half of the stickers they could give away, even after repeatedly seeing a strongly prosocial robot, who consistently shared more than half of its stickers. This pattern merges with empirical studies from social psychology (Bryan & Walbek, 1970b; Elliott & Vasta, 1970; cf.; Presbie & Coiteux, 1971) and behavioral economics (Blake et al., 2016, Indian sample; Blake, Piovesan, Montinari, Warneken, & Gino, 2015; McAuliffe et al., 2017; Smith et al., 2013). These studies all showed that young children usually share less than, or only up to, 50% of their resources with others even when the modeled behavior or instructions implied that children give more than 50% of their resources to others, typically to other children (for a review, see Blake, 2018). Our results thus suggest that the majority of children do not engage in prosocial behavior to such an extent that it would be unfavorable to them.

A social robot that modeled strong prosocial behavior affected children's descriptive norms of sharing rather than their injunctive norms. Two explanations are conceivable. First, children may not consider a robot a competent other, who, similar to parents, would be likely to affect children's injunctive norms. Rather children may consider a robot a peer, who, similar to friends, may affect children's descriptive norms. Second, the notion put forward by Social Cognitive Theory (Bandura, 2001) that modeled behavior also affects the learning of rules underlying social behavior, and thus injunctive norms, may not apply to sharing when studied among children in middle-childhood. As outlined above, children in middle childhood tend to be familiar with the norm of sharing (Benenson et al., 2007; Blake, 2018; Smith et al., 2013), which also seems to be reflected in the rather high means of the injunctive-norms measure. Regardless of whether the modeled behavior is weakly or strongly prosocial, a social robot thus only reinforces what children already know but does not change it.

Although the found effect on descriptive norms awaits replication in future research, the idea that social robots affect how children perceive what other children do may be challenging. As we controlled for both children's baseline tendency to share stickers and the number of stickers they actually shared, it is rather unlikely that children adjusted the descriptive norms to their behavior. Rather, children seem to use the robot's behavior as a diagnostic tool for assessing behavior of other children in their environment. If our pattern of results can be corroborated, we may not only have more evidence of humans treating computers or, more specifically, robots as social actors (Nass & Moon, 2000), but also need to face the possibility that something that regulates human behavior – descriptive norms – is influenced by non-human agents. In the same way as interactions with digital agents in an online environment may have real-world consequences outside an online environment (Yee, Bailenson, & Ducheneaut, 2009), we may see that interactions with non-human agents, such as robots, may have real-world consequences outside human-non-human interaction.

5.2. Theoretical and ethical implications

At a theoretical level, our study shows that the insights from social learning also apply to how social robot models influence children's prosocial behavior, confirming that social learning is one of the most appropriate theoretical frameworks to explain children's learning of sharing behavior (Blake, 2018). More generally, our findings, notably the effects of social robots on the extent of children's prosocial behavior, merge with the results of the small, but consistent research line on how human models affect children's prosocial behavior (e.g., Bryan & Walbek, 1970a, 1970b; Elliott & Vasta, 1970; Hartup & Coates, 1967; Presbie & Coiteux, 1971; for a review, see Rushton, 1976) and recent findings from behavioral economics (Blake et al., 2016, Indian sample;

McAuliffe et al., 2017). However, our findings go beyond these research lines in that they suggest that children can learn prosocial behavior also from non-human, embodied models, such as social robots. Our results need to be (conceptually) replicated in different circumstances and research settings, with different (age) samples of children, and with different types of social robots. But if our findings hold, they may call – together with other studies on social robots and prosocial behavior among children (Beran et al., 2011; Chernyak & Gary, 2016; Martin et al., 2020; Zaga et al., 2017) – for a theoretical extension of both social scientific and robotics-oriented approaches to prosocial behavior.

Social scientific approaches to prosocial behavior (for reviews, see, e.g. Eisenberg et al., 2015; Rushton, 1980), as well as underlying theoretical frameworks (Bandura, 2001), have typically focused on the role of humans in children's learning of prosocial behavior. Although not only face-to-face, but also mediated human-human interactions may affect children's prosocial behavior (Mares & Woodard, 2005), research on non-mediated non-human influences in that context is still limited (for notable exceptions, see Beran et al., 2011; Chernyak & Gary, 2016; Martin et al., 2020; Zaga et al., 2017). In line with broader calls in other disciplines for including non-humans in studies of social interactions (e.g., in sociology, Cerulo, 2009) as well as other research on social robots and children's prosocial behavior (Beran et al., 2011; Chernyak & Gary, 2016; Martin et al., 2020; Zaga et al., 2017), our findings tentatively suggest that non-humans, such as social robots, may influence children's prosocial behavior in a similar way as humans do. We, therefore, agree with other researchers (Oliveira et al., 2021; Paiva et al., 2018) that a stronger attention to social robots – or non-humans more generally – may inspire exciting and important questions on children's learning of prosocial behavior, for example, whether the effect of social robots equals that of humans or whether it complements or even overrides human influence on children's prosocial behavior.

Robotics-oriented research lines on prosocial behavior have often centered on social robots as agents that make a request for people's prosocial behavior, for example, donating money (Sarabia et al., 2013; Siegel et al., 2009; Wills, Baxter, Kennedy, Senft, & Belpaeme, 2016; for a review, see Oliveira et al., 2021). Similarly, researchers have focused on whether robot and situational characteristics influence children's pro-social behavior toward social robots (i.e., helping the robot, Beran et al., 2011; Martin et al., 2020; Zaga et al., 2017). All these studies have dealt with children's compliance, which is "a particular kind of response—acquiescence—to a particular kind of communication—a request…[where] the target recognizes that he or she is being urged to respond in a desired way" (Cialdini & Goldstein, 2004, p. 592). Our study, however, dealt with children's conformity, which is "the act of changing one's behavior to match the responses of others" (Cialdini & Goldstein, 2004, p. 606). The conceptual focus on conformity is important because conformity may occur more frequently than compliance in mundane, everyday interactions that people are increasingly likely to have with social robots. Moreover, centering on conformity responses implies that we go beyond intended effects of robots, which are central in request-compliance processes, to unintended effects, which are more likely to occur in conformity processes. For example, a social robot designed to model healthy behavior may also have the unintended effect that it entertains children (or vice versa).

Overall, our study fits in the emerging research line of pro-social computing (Oliveira et al., 2021; Paiva et al., 2018), with its goal of using technology for socially desirable, societally beneficial purposes. A robot that models strong prosocial behavior seems to be able to elicit this behavior among children, at least in the short term. However, the same effects we found for modeling a socially desirable behavior – sharing – may also apply to socially undesirable, inappropriate, or even illicit behavior. For example, a human model acting aggressively can also increase children's aggressive behavior (e.g., Grusec, 1972; Rice & Grusec, 1975). As research on persuasive technology more generally has been criticized for being used to trick technology users into unhealthy and disadvantageous behavior (e.g., Lanier, 2018), the principles underlying the prosocial effects of social robots may be used for manipulating children and adults. It is therefore crucial that research on persuasive robotics (Siegel et al., 2009) more generally and pro-social computing (Paiva et al., 2018) more specifically be accompanied by thorough ethical discussions (e.g., Borenstein & Arkin, 2016). Ultimately, we need to be able to distinguish what social robots can and should do from what social robots can but should not do.

Credit author statement

Jochen Peter: Conceptualization, Methodology, Formal analysis, Writing – original draft, Supervision, Project administration, Funding acquisition, Rinaldo Kühne: Conceptualization, Methodology, Formal analysis, Writing – review & editing, Project administration, Alex Barco: Conceptualization, Software, Investigation, Writing – review & editing, Project administration.

Declaration of competing interest

None.

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Appendix A. Supplementary data

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