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# How Does Children's Anthropomorphism of a Social Robot Develop Over Time? A Six-Wave Panel Study

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**Abstract**
Research on children's anthropomorphism of social robots is mostly cross-sectional and based on a single measurement. However, because social robots are new type of technology with which children have little experience, children's initial responses to social robots may be biased by a novelty effect. Accordingly, a single measurement of anthropomorphism may not accurately reflect how children anthropomorphize social robots over time. Thus, we used data from a six-wave panel study to investigate longitudinal changes in 8- to 9-year-old children's anthropomorphism of a social robot. Latent class growth analyses revealed that anthropomorphism peaked after the first interaction with the social robot, remained stable for a brief period of time, and then decreased. Moreover, two distinct longitudinal trajectories of anthropomorphism could be identified: one with moderate to high anthropomorphism and one with low to moderate anthropomorphism. Previous media exposure to non-fictional robots increased the probability that children experienced higher levels of anthropomorphism.

**Keywords** Child-robot interaction · Human-robot interaction · Human-machine communication · Robotics · Technology

## 1 Introduction

Social robots are a category of robots made for social interactions and relationships [1]. They come in different shapes and sizes (e.g., robotic animals, human-like androids) and can fulfil a variety of roles (e.g., assistant, tutor, or companion). Anthropomorphism is the attribution of human properties and, in particular, human mental capacities to nonhuman entities [2]. Anthropomorphism is pivotal in interactions between humans and social robots because it facilitates social cognitions, that is, the application of social and psychological criteria to robots [3]. Accordingly, when people anthropomorphize a robot, they are more likely to perceive the interaction with the robots as having a social quality.

As an increasing number of social robots are created for children [4], researchers have begun to investigate anthropomorphism in child-robot interactions (CRI). Findings suggest that children do anthropomorphize social robots, but evidence mainly stems from studies that merely employ one [5] or two measurements of anthropomorphism [6]. The lack of longitudinal research is problematic because children's anthropomorphism of social robots is likely to be highly fluid. Not only are social robots still a novel technology with which children have no or only limited experience, but they are also hybrid entities which combine characteristics of humans and machines [7]. Consequently, most children lack well-developed prior beliefs about the ontological status of social robots and interactions may produce inconsistent and fickle ontological beliefs.

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Two other issues related to longitudinal changes in children's anthropomorphism have also been disregarded. First, almost no research exists on whether children differ in how their anthropomorphism of social robots develops over time. Second, almost no study has addressed how individual differences influence longitudinal changes in children's anthropomorphism of social robots. An exception is the study by van den Berghe et al. [6], which investigated how children's sex and age influenced their development of robot anthropomorphism over time. However, theoretical models of anthropomorphism posit that individual differences are crucial determinants of anthropomorphism [2].

This study addresses these research gaps by investigating 8- to 9-year-old children's anthropomorphism of a social robot in a six-wave panel study. In line with the three aforementioned research gaps, the study focuses on the following research questions: (1) How does children's anthropomorphism of a social robot change over time? (2) How many trajectories of anthropomorphism can be distinguished? (3) Which factors influence children's trajectory of anthropomorphism? In addressing these questions, this study aims at contributing to a better understanding of children's anthropomorphism of social robots by advancing a longitudinal perspective on the concept. By identifying potentially different trajectories of children's anthropomorphism as well as the etiology of these trajectories, the study may help us to better chart and grasp the specificities of the concept in children's interactions with social robots.

### 1.1 Children's Anthropomorphism of Social Robots

Robot anthropomorphism is a psychological response which involves the attribution of human mental capacities to a robot, including the ability to think, feel, perceive, desire, and choose [3]. Social robots have three main characteristics which are likely to facilitate anthropomorphism. First, social robots have the appearance of a social agent, including features such as a head, eyes, a torso, and limbs. Social robots do not necessarily resemble humans, they can also be a caricature of humans or exhibit the morphology of animals or machines [1]. Second, social robots have abilities of social agents, for instance, social intelligence or the ability to communicate verbally and non-verbally [8]. Third, social robots are designed to fulfil social roles and tasks. Notably, children may encounter social robots as tutors at school [9], as robotic toys [4], or in therapy [10].

Most research on children's anthropomorphism of social robots is cross-sectional and consequently based on a single measurement of anthropomorphism. It can roughly be divided into two types of research. In one type of research, children are presented with images or videos of social robots and instructed to evaluate the human-likeness of the robot [5, 11, 12]. In a second type of research, children directly interact with a social robot. Children's anthropomorphism is measured by assessing their verbal and non-verbal behaviors during the interaction or through an interview or survey [13–17]. Many studies include experimental manipulations that are assumed to influence children's anthropomorphism [12, 18].

Cross-sectional research shows that children anthropomorphize social robots to a moderate to moderately high degree: Sample means of measurements of anthropomorphism typically lie around the scale midpoint [5, 11, 13] and, for more advanced social robots, sometimes higher [5, 13]. Similarly, about half or more of children typically attribute human-like mental capacities to social robots [15–17]. In addition, anthropomorphism seems to emerge in response to a broad range of social robots– including anthropomorphic [15], zoomorphic [19], and caricatured social robots [13]– and throughout childhood– that is, in early [16, 18], middle [13, 17], and late childhood [15, 19].

However, scholars of human-robot interaction (HRI) and, more specifically, CRI have recognized that studying robot anthropomorphism with cross-sectional research designs may produce an incomplete picture [6, 20]. The "novelty effect" implies that initial interactions with social robots are likely to elicit psychological responses that are not representative of people's long-term responses [21]. While novelty effects can affect a variety of psychological responses to a variety of new technologies, they are likely to be particularly pronounced in the case of the anthropomorphism of social robots [22, 23]. Social robots constitute a new type of technology because they combine characteristics of humans and machines, which led scholars to refer to social robots as a "new ontological category" [15, 24]. In HRI, humans can not rely on established ontological categorization schemes, which posit a clear-cut distinction between humans and machines [25, 26]. Rather, humans have to assess the level of a social robot's machine- and human-like characteristics to realize an effective interaction [2]. This assessment typically stretches over multiple days and weeks [27]. As a result, anthropomorphism can be expected to fluctuate over time.

Longitudinal changes in robot anthropomorphism may have a second driver: Over time, people may apply different sets of criteria when evaluating the anthropomorphism of social robots. Initially, social robots may be anthropomorphized because they merely have a human-like shape [27] or follow basic principles of interpersonal interactions [8]. At later stages, however, people are likely to expect social robots – similar to other human beings – to perform more complex behaviors (e.g., adaptive behavior, recall of earlier interactions; [28]). As relevant criteria change over time, robot anthropomorphism is also likely to change.

Longitudinal research on children's anthropomorphism of social robots is scarce. Michaelis and Mutlu [20] investigated whether a Minnie robot– a small anthropomorphic social robot– can improve children's reading activity. Twelve 10- to 12-year-olds were given a social robot for two weeks (in addition, 12 children functioned as a control group). Children's perceptions of the robot were assessed in two qualitative interviews, one after the initial introduction to the robot and one at the end of the study. The results show that, after the first introduction, seven children felt a strong social companionship with the robot and two children attributed emotions and personality to the robot. After two weeks, ten children referred to the robot as a companion and nine children attributed emotions and personality to the robot. These results imply that robot anthropomorphism increased over time. However, other measurements showed a reverse pattern: After two weeks, fewer children described the robot in human terms (six versus eleven children) or as aware or alive (eight versus twelve children). These findings suggest that children anthropomorphized the social robot to a moderate degree during the two weeks of interaction and that anthropomorphism did not uniformly increase or decrease. However, the findings are preliminary because the study was based on a small sample size and employed only descriptive analyses of anthropomorphism.

Van den Berghe et al. [6] studied whether tutoring sessions with a social robot improve 5-year-olds' second-language vocabulary. One hundred and four children participated in a series of seven language tutoring sessions with a NAO robot over the course of three weeks (see [29]). The study included an experimental manipulation of the robot's gestures, which did not affect the results. Children were familiarized with the robot in a group introduction. Robot anthropomorphism was assessed once before and once after the tutoring sessions with a questionnaire that included indicators referring to the robot's biological, cognitive, and emotional properties. The results show that children's anthropomorphism was initially relatively high: Children attributed more human- than machine-like properties to the social robot. Moreover, there were no significant changes in anthropomorphism after three weeks.

In sum, CRI research on the anthropomorphism of social robots reveals two patterns. Cross-sectional studies show that a single interaction with a social robot leads to moderate and sometimes high levels of anthropomorphism [5, 15]. This finding is corroborated by two longitudinal studies [6, 20]. For the measurement of changes in anthropomorphism, it is important to assess the extent to which children anthropomorphize a social robot before they meet it the first time. Thus, our first hypothesis posited:

**H1** Children's anthropomorphism of a social robot increases from the pre-interaction phase ($T_0$) to after the first interaction ($T_1$).

The two longitudinal studies also suggest that children's anthropomorphism does not substantially change within the first two to three weeks of interacting with a social robot [6, 20]. However, no studies have investigated how anthropomorphism develops after the first few weeks. A theoretical model which addresses longer time frames stems from Lemaignan et al. [27]. The model posits that the anthropomorphism of social robots involves three stages: Anthropomorphism peaks in the initialization phase, starts decreasing in the familiarization phase, and eventually stabilizes on a comparatively low level in the stabilization phase. The model is somewhat ambiguous about the length of the single phases, describing the three phases as lasting "from a couple of second to a couple of hours," (Initialization section, para. 1) "up to several days," (Familiarization section, para. 1) and "over a longer period of time" (Stabilization section, para. 1). Nevertheless, the model suggests that the anthropomorphism of social robots eventually decreases as people acquire a better understanding of the robot and can better predict its behavior.

Together, empirical and theoretical evidence suggests that, after the first interaction with a social robot, children's anthropomorphism remains stable for a brief period of time and then declines. Lemaignan et al.'s model [27] does not specify for how long children's anthropomorphism remains stable, but it implies that the phase probably lasts only a few days. The study by van den Berghe et al. [6], in contrast, points to a period of three weeks. The present study investigated time intervals of two weeks and may thus present a compromise between Lemaignan et al.'s [27] model and van den Berghe et al.'s [6] findings. We hypothesized:

**H2** After the first interaction with a social robot ($T_1$), children's anthropomorphism of a social robot remains stable for two weeks ($T_2$), before steadily declining ($T_3$ to $T_5$).

Hypotheses 1 and 2 suggest one general pattern of change in children's anthropomorphism of a social robot. However, it is unlikely that all children follow the same longitudinal trajectory of anthropomorphism. Van den Berghe et al. [6] found that anthropomorphism developed differently in specific subsamples of children: A descriptive analysis revealed that robot anthropomorphism remained stable for almost half of the children, decreased for 35 children, and increased for 25 children. In line with this finding, CRI scholars have posited that individual differences affect how children perceive, and interact with, social robots [30]. Similarly, communication scholars have posited that individual differences influence the use of, and psychological responses to, media and communication technologies [31, 32]. Thus, research suggests that multiple trajectories of children's anthropomorphism can be distinguished. However, because there is insufficient evidence to formulate hypotheses about the specific number and shape of these trajectories, we propose the following research question:

**RQ1** How many classes of children can be identified that are characterized by distinct longitudinal trajectories of anthropomorphism?

### 1.2 Predictors of Children's Anthropomorphism

A variety of user, robot, and interaction characteristics can influence whether a robot is anthropomorphized [33]. These characteristics may also affect how children's anthropomorphism of a social robot develops over time. In this section, we identify predictors that may influence which longitudinal trajectory a child's anthropomorphism follows (i.e., to which class a child belongs). Because the number and shape of the trajectories are not known yet, we formulate broad hypotheses about how predictors influence whether children are likely to experience high or low levels of anthropomorphism over time.

A psychological model of the predictors of anthropomorphism stems from Epley et al. [2]. The model has been highly influential in HRI research [3]. Epley et al. [2] argue that elicited agent knowledge, effectance motivation, and sociality motivation constitute the three main categories of predictors of anthropomorphism. First, a nonhuman entity is assumed to be anthropomorphized when agent knowledge (i.e., knowledge about humans and their characteristics) is activated; when correction processes do not lead to a discounting of activated agent knowledge; and when activated agent knowledge is applicable to an entity. Second, anthropomorphism is likely to be elicited when an individual is motivated to effectively interact with the environment. By anthropomorphizing an entity, uncertainty associated with the entity is reduced and confidence in being able to predict the entity's behavior is increased. Third, anthropomorphism is likely to be elicited when an individual desires to connect with other humans. By anthropomorphizing nonhuman entities, humans can satisfy their social needs when other humans are not available.

In the present study, we investigated the effects of one predictor from each category of Epley et al.'s [2] model. Media exposure is likely to affect children's anthropomorphism of robots by eliciting agent knowledge. Media are an important source of people's beliefs about robots [33, 34], notably because many people have limited firsthand experience with robots [35]. Science fiction books, magazines, and movies typically depict robots with highly advanced abilities that approach or even surpass the abilities of humans [33, 36, 37]. Similarly, news reports often focus on how advanced real robots are. Righetti and Carradore [38] investigated how robots are covered in Italian online newspapers between 2014 and 2018. They found that the most frequent topic was robot's ability to perform jobs as well as or even better as humans. Preliminary evidence suggests that such media depictions may affect how people perceive robots. Horstmann and Krämer [34] studied the influence of experience with robots on expectations about robots' skills. Experience with robots was a composite concept comprising the contact with real robots, the reception of robot reports, and knowledge of fictional robots. Expectations about robots' skills included the two facets "human skills" and "robot skills" and was, thus, closely related to anthropomorphism. They found that higher levels of experience with robots were related to increased expectations about robots' abilities. Although the presented research focused on adults, we expect similar effects to emerge among children. That is, as a proxy of Epley et al.'s [2] elicited agent knowledge, the exposure to media reports about robots should increase children's anthropomorphism:

**H3** Exposure to media reports about non-fictional robots increases the probability of a child belonging to a class characterized by higher levels of anthropomorphism.

Children's epistemic curiosity may be an additional predictor of robot anthropomorphism and cover effectance motivation in Epley et al.'s [2] model. Epistemic curiosity is defined as "the desire for knowledge that motivates individuals to learn new ideas, eliminate information-gaps, and solve intellectual problems" [37, p. 1586]. Litman [39] distinguishes two types of epistemic curiosity that differ in their motivation: I-type epistemic curiosity is driven by the pleasure of learning new things, whereas D-type epistemic curiosity is driven by the displeasure of not knowing or understanding a thing.

D-type epistemic curiosity and effectance motivation are closely related because they share a motivational core. Like effectance motivation, D-type epistemic curiosity aims at reducing uncertainty to achieve a good performance [39, 40]. Accordingly, D-type epistemic curiosity is likely to foster anthropomorphism of a social robot because this increases the predictability of the robot and facilitates interactions. Research shows that I- and D-type epistemic curiosity can be identified already among children aged 3 to 8 years [40]. To our knowledge, influences of children's epistemic curiosity on robot anthropomorphism and its development over time have not been studied yet. Given the conceptual similarity between D-type epistemic curiosity and effectance motivation and robust findings about the influence of effectance motivation on anthropomorphism [41], we expected D-type epistemic curiosity to increase children's anthropomorphism of a social robot:

**H4** D-type epistemic curiosity increases the probability of a child belonging to a class characterized by higher levels of anthropomorphism.

Peer problems may increase children's tendency to anthropomorphize a social robot and form a proxy for sociality motivation in Epley et al.'s [2] model. Children's peer problems can manifest in different ways, for instance, being disliked by other children, being bullied at school, or having no friends to play with [42]. In the absence of positive relationships with peers, children may look for other avenues to satisfy their social needs. By anthropomorphizing a social robot, they can construe an other with which they can have social interactions. Evidence that children may interact with social robots to fulfill social needs stems, for example, from de Jong et al. [43] who studied interactions between children aged 7 to 11 and a NAO robot. They found that, before the interaction, children were interested in having a social interaction with the robot (e.g., playing or chatting with the robot), and that these expectations were fulfilled in the interaction. The impact of children's loneliness on anthropomorphizing social robots has to our knowledge not been studied yet. However, there exists evidence that loneliness increases the propensity of adults to anthropomorphize robots [44, 45]. Accordingly, we hypothesized that children with peer problems would be more likely to anthropomorphize a social robot:

**H5** Peer problems increase the probability of a child belonging to a class characterized by higher levels of anthropomorphism.

Finally, we also investigated the influences of age and sex on robot anthropomorphism. Some cross-sectional research shows that younger children are more likely to anthropomorphize robots than older children [5, 14, 46], but the findings are not consistent [11, 12, 18]. Similarly, findings on the effects of sex are inconsistent [5, 6, 46]. The only study that investigated the impact of children's age and sex on longitudinal changes in robot anthropomorphism found that both children's age and sex influenced how their anthropomorphism changed over the course of language tutoring sessions [6]. The younger the children were, the stronger was their decrease in anthropomorphism. Moreover, while girls' anthropomorphism of NAO after the tutoring sessions remained at the same level as before the start of the tutoring session, boys' anthropomorphism significantly decreased.

Overall, evidence about the effects of age and sex on longitudinal changes in robot anthropomorphism is limited. Predictions about the impact of age are particularly difficult: On the one hand, the present study focuses on 8- to 9-year-old children and, thus, on a narrow age range, which may preclude effects of age on anthropomorphism. On the other hand, 8- to 9-year-olds' social cognitions are still developing [47], and small age differences may impact anthropomorphism. Given these limitations, we pose a research question about the effects of age and sex:

**RQ2** Do age and sex influence which longitudinal trajectory a child's anthropomorphism follows?

## 2 Methods

The data stems from a large project on children's acceptance of the social robot Cozmo at home. We focused on 8- to 9-year old children because they are capable of participating in survey research [48] and have a well-developed Theory of Mind – i.e., first- as well as higher-order false-belief understanding and advanced social-cognitive skills – which allows for the attribution and evaluation of mental states [47]. The data has been used in two publications that focus on different research questions and variables [49, 50]. Comprehensive information about the procedure and data collection can be found in de Jong et al. [49] and de Jong et al. [50]. Below, we describe the aspects that are relevant for this study.

Recruitment and data collection were conducted by Kantar Netherlands from July to December 2019. The study employs a longitudinal survey design, which includes a baseline questionnaire ($T_0$) plus five panel waves ($T_1$ to $T_5$). The baseline measurement was conducted between August 21 and September 8. The panel measurements were conducted between September 24 and November 25, with a time interval of about two weeks between each wave. Participating families received a Cozmo robot (see https://www.digitaldreamlabs.com/products/cozmo-robot) briefly before $T_1$. Cozmo is a small bulldozer-like social robot. It possesses a front-facing digital display which depicts facial expressions, such as joy and anger, and it makes speech-like sounds. Cozmo can move independently, but needs to be connected to a smartphone or tablet to function. Cozmo includes a series of pre-programmed games and it can be programmed by the user. The study was approved by the Ethics Review Board of the Faculty of Social and

Behavioural Sciences at the University of Amsterdam (ID: 2019-YME-10,929).

## 2.1 Sample

Data were collected from 8- to 9-year-old children and one of their parents. Families were recruited through the panel of Kantar Netherlands, which includes 62,825 Dutch families. The panel is approximately representative of the Dutch population with regard to sex, age groups, geographical distribution, and household size. Families were eligible for participation if they had one child aged 8 or 9. Families with multiple children aged 8 to 9 were excluded to ensure that the same child participated in each wave. Moreover, families could only participate if they did not already have a Cozmo robot at home and if the child had no cognitive, emotional, and/or physical impairments that would prevent it from filling in the questionnaire or interacting with the robot. Of the 1,574 eligible families, 688 families (43.7%) consented to participate in the study, of which 570 child-parent dyads (82.8%) eventually participated at $T_0$. Of the families that agreed to participate, 385 child-parent dyads were randomly selected to take part in the panel study (i.e., $T_1$ to $T_5$). However, 58 child-parent dyads that participated in the panel study had not participated in the $T_0$ survey and they, thus, lacked a series of measurements relevant for this study. To compensate for the incomplete cases, an additional sample of 25 child-parent dyads that had filled in $T_0$ was subsequently selected for participation in the panel study (field phase: October 29 to December 25, 2019). In total, 400 child-parent dyads participated at least once in the panel study ($T_1$ to $T_5$). The 58 child-parent dyads that had not participated in $T_0$ were excluded so that the analyses were based on 342 cases.

## 2.2 Procedure

Before the data collection, parents were informed about the study procedure and about their rights and their children's rights. Parents were also informed that a random subsample would be selected for participation in the panel study, in which the child would be provided with a small social robot and a tablet. Parents were instructed to not tell their child about the robot until he/she had filled in the $T_0$ survey. To participate, parents had to give active consent for themselves and their child to take part in the $T_0$ survey as well as the panel study ($T_1$ to $T_5$).

In each wave ($T_0$ to $T_5$), a questionnaire was administered which included a first part for the parent (about 5 min long) and a second part for the child (about 30 min long). At the start of each questionnaire, parents were reminded of their rights as participants. Parents were instructed that they and their child should fill in their questionnaire independently. They were also informed that they could help their child, but that they should avoid influencing their child. Children were informed at the start of each questionnaire about the procedure and their rights. Children were notified that they could take a break while filling in the questionnaire. To participate, children had to indicate that they understood everything and that they wanted to take part. Since most measures in the questionnaire used 5-point Likert scales, children were instructed on how to fill in such scales [51].

The questionnaire for the children included a general part and a part with questions about Cozmo, including questions about the robot's anthropomorphism. At $T_0$, children were shown a 26-second video of Cozmo before answering the Cozmo-specific questions. In the video, Cozmo moved around, picked up a cube, and put it down again, made an excited sound, and finally faced and approached the camera. We opted for a video instead of pictures because children may struggle to answer questions about a robot if they have only seen a picture [52]. Before $T_1$, the children received a Cozmo and tablet in their homes. Information on how to set up the robot was included. Before filling in the questionnaire at $T_1$, the children were instructed to play with Cozmo for 30 min to get a first impression. After $T_1$, the children were not prompted to interact with Cozmo.

At the end of the study, children were allowed to keep Cozmo. The research company compensated participating parents with reward points. In a debriefing, children and parents were notified about the goals of the study. Children also received information about the workings of robots and about the differences between humans and robots.

## 2.3 Measures

A pilot study was conducted to test whether the measures were intelligible and reliable. The study was conducted in the first half of July 2019 among 42 children and 32 parents at a science museum for children in Amsterdam (ethical approval id: 2019-YME-10,828; 2019-YME-10,830). Generally, the measures proved to be intelligible and reliable, and only minor adjustments were required. Below, we present the English translations of the Dutch measurement instruments that were used in the main study.

Anthropomorphism was measured with a scale adapted from van Straten et al. [53] which itself is an adapted version of Severson and Lemm's [54] Individual Differences in Anthropomorphism Questionnaire-Child Form (IDAQ-CF). The first item used by van Straten et al. [53] was adjusted because an earlier study showed that it negatively impacted the reliability of the scale [13]. Thus, the following four items were administered to the children: "Cozmo does what it itself wants to do," "Cozmo can be happy and angry," "Cozmo knows that Cozmo is a robot," "Cozmo can think for itself." Children responded on a five-point Likert scale, ranging from "does not apply at all" to "applies completely." For each wave, a mean index of anthropomorphism was created. It is important to note that the measurement of anthropomorphism at $T_0$ was conducted before any interaction with Cozmo had taken place (children had only seen a short video of the robot), and that the measurement at $T_1$ was conducted after the first 30-minute interaction. Thus, the measurement points represented pre-interaction anthropomorphism ($T_0$), anthropomorphism during the initialization phase ($T_1$), and anthropomorphism during the familiarization and stabilization phase ($T_2$ to $T_5$) (see [27]). Descriptive statistics and reliabilities are summarized in Table 1. Both alpha and omega indicate that the scale's reliability is sufficient at $T_0$ and from $T_3$ to $T_5$, but reliability is relatively low at $T_1$ and $T_2$. The lower reliability may indicate that children evaluated Cozmo's mental capacities inconsistently in early stages of the interaction. This may be the result of children still making up their mind about the ontological status of Cozmo. Given that reliability was overall acceptable, we used the scale instead of single-item measures in the subsequent analyses.

All predictors of children's change in anthropomorphism over time were measured at $T_0$. Information about the age (165 8-year-olds, 177 9-year-olds) and sex of the children (167 boys, 175 girls) were provided to us by Kantar Netherlands. Children's media exposure to non-fictional robots was assessed through a content-specific self-report measure [55]. Children were shown a set of pictures of non-fictional robots and asked how frequently they had seen this type of robot or similar robots "on TV," "in books," "on the Internet (for example, YouTube)," and "in magazines." Children responded on a five-point Likert scale, ranging from "never" to "very often." A mean index of exposure to non-fictional robots was created ($M = 2.11$, $SD = 0.77$; $\alpha = 0.73$; $\omega = 0.72$).

D-type epistemic curiosity was measured with the corresponding subscale of Piotrowski et al.'s [40] instrument for measuring individual differences in I- and D-type curiosity in young children (I/D-YC). Five items were administered to the parents (e.g., "My child is bothered when he/she does not understand something and tries hard to make sense of

**Table 1** Descriptive statistics and reliability of mean index of anthropomorphism

| Wave | Mean (SD) | Cronbach's Alpha | McDonald's Omega |
|---|---|---|---|
| 0 | 2.88 (0.86) | 0.68 | 0.70 |
| 1 | 3.42 (0.71) | 0.57 | 0.59 |
| 2 | 3.43 (0.72) | 0.56 | 0.62 |
| 3 | 3.28 (0.85) | 0.72 | 0.73 |
| 4 | 3.24 (0.88) | 0.76 | 0.78 |
| 5 | 3.22 (0.88) | 0.75 | 0.77 |

$n_0 = 342$; $n_1 = 326$; $n_2 = 326$; $n_3 = 338$; $n_4 = 336$; $n_5 = 336$

it"). Two items were slightly simplified to increase clarity. Parents responded on a five-point Likert scale, ranging from "does not apply at all" to "applies completely." The items were summarized into a mean index ($M = 3.27$, $SD = 0.67$; $\alpha = 0.82$; $\omega = 0.82$).

Peer problems were measured with the Dutch version [56, see also 57] of a subscale of Goodman's [42] Strength and Difficulties Questionnaire. Five items were administered to the parents (e.g., "My child is rather solitary, tends to play alone"). Children responded on a five-point Likert scale, ranging from "does not apply at all" to "applies completely." Before creating a mean index, two reversed-coded items were recoded so that high item scores were indicative of having peer problems ($M = 2.06$, $SD = 0.59$; $\alpha = 0.74$; $\omega = 0.73$).

## 2.4 Analytical Approach

To investigate changes in children's anthropomorphism over time, we used latent class growth analysis (LCGA; [58, 59]). LCGA identifies latent classes that are characterized by distinct sets of growth parameters or, in short, growth trajectories. Covariates can be included in LCGA to predict class membership via (multinomial) logistic regression [60]. LCGA can be seen as a specific type of growth mixture modeling (GMM) [59]. While GMM allows for intra-class variation in the estimated growth parameters, LCGA assumes that the parameters are the same for each class member. We opted for LCGA because of the lower sample size requirements and better model convergence [59]. It is noteworthy that there do not seem to be clear guidelines for the required sample size of LCGA, but that LCGA and GMM have been used with small samples, for instance, with 34 cases [61], 107 cases [62], and 110 cases [63].

The LCGA was conducted in Mplus 8.7. Our analyses included three steps. First, we estimated a one-class growth model and inspected its findings to test the hypotheses 1 and 2. Second, we estimated models with an increasing number of classes. We stopped estimation at a model with four classes to avoid exceedingly small class sizes. We inspected the best fitting model to answer research question 1. Third, based on the best fitting model, we tested whether the predictors influenced class membership to test the hypotheses 3 to 5 and answer research question 2.

Changes in children's anthropomorphism were modelled by including the $T_0$ to $T_5$ measurements as indicators of a latent intercept and a latent slope. The slope loadings were freely estimated, except the loadings at $T_0$ and $T_1$ which were fixed to 0 and 1 respectively to identify the model. The intercept of each indicator was fixed to 0, and error terms were constrained to equality across time and, in the multi-class models, across classes [61]. In the multi-class models,

**Table 2** Class sizes and fit statistics of one-, two-, three-, and four-class latent class growth models

| Statistics | One-class model | Two-class model | Three-class model | Four-class model |
|---|---|---|---|---|
| Class sizes | | | | |
| Class 1 | 342 | 76 | 142 | 16 |
| Class 2 | – | 266 | 156 | 60 |
| Class 3 | – | – | 44 | 67 |
| Class 4 | – | – | – | 199 |
| Loglikelihood | -2441.28 | -2121.44 | -2030.76 | -1976.69 |
| Replications of loglikelihood | 156 | 116 | 25 | 3 |
| AIC | 4896.55 | 4270.87 | 4103.52 | 4009.38 |
| BIC | 4923.40 | 4324.56 | 4184.05 | 4116.75 |
| ABIC | 4901.19 | 4280.15 | 4117.43 | 4027.93 |
| Entropy | 1.00 | 0.895 | 0.773 | 0.831 |
| VLMR-LRT *p*-value | – | $<0.001$ | 0.627 | 0.016 |
| ALMR-LRT *p*-value | – | $<0.001$ | 0.631 | 0.017 |

$N = 342$

distinct growth parameters (i.e., intercept, slope, and slope loadings) were estimated for each class. Mplus estimates parameters by Maximum Likelihood (ML). More specifically, multiple sets of random starting values for parameters are generated and subjected to a multi-stage optimization procedure [64]. If the best loglikelihood value is reproduced, the global ML solution has been identified. Using more sets of random starting values facilitates the identification of the global ML solution [64]. In the present study, we used 600 and 160 sets of random starting values in the first and second stage of optimization respectively [65]. Moreover, the maximum number of iterations in the first stage and second stage of optimization was increased to 20 and 150 respectively [64].

Age, sex, media exposure to non-fictional robots, D-type epistemic curiosity, and peer problems were entered as predictors of class membership. Following Asparouhov and Muthén [66], the predictors were entered as auxiliary variables using Mplus' R3STEP option. In this approach, the estimation of the latent class model precedes the prediction of class membership and, thus, predictors do not influence the creation of classes.

Following Ram and Grimm [61], five sets of criteria were employed to evaluate model fit. A model was preferred if it had (1) admissible estimates (e.g., no negative variances); (2) reasonable class sizes (notably, no very small groups); (3) a low Akaike (AIC), Bayesian (BIC), and Adjusted Bayesian Information Criterion (ABIC) (i.e., a high comparative model fit); (4) a high entropy value (i.e., a high classification confidence); (5) a significant Vuong-Lo-Mendell-Rubin likelihood-ratio test (VLMR-LRT) and a significant Adjusted Lo-Mendell-Rubin likelihood-ratio test

**Table 3** Parameter estimates of one- and two-class latent class growth model

| Statistics | One-class model | Two-class model | |
|---|---|---|---|
| | | Class 1 | Class 2 |
| Class size | 342 | 76 | 266 |
| Latent means | | | |
| Intercept | $2.88^{***}$ | $2.14^{***}$ | $3.10^{***}$ |
| Slope | $0.54^{***}$ | $0.57^{***}$ | $0.53^{***}$ |
| Slope loadings | | | |
| T0 | $0.00^{a}$ | $0.00^{a}$ | $0.00^{a}$ |
| T1 | $1.00^{a}$ | $1.00^{a}$ | $1.00^{a}$ |
| T2 | $1.03^{***}$ | $0.83^{***}$ | $1.05^{***}$ |
| T3 | $0.73^{***}$ | 0.20 | $0.89^{***}$ |
| T4 | $0.67^{***}$ | -0.03 | $0.89^{***}$ |
| T5 | $0.63^{***}$ | -0.07 | $0.84^{***}$ |
| Errors variances | $0.67^{***}$ | $0.42^{b***}$ | $0.42^{b***}$ |

$N = 342$; [a] Fixed parameters. [b] Parameters constrained to equality. $^{***}p < .001$

(ALMR-LRT) (i.e., a significantly better fit than a model with one class less).

## 3 Results

The best loglikelihood value could be reproduced when the LCGA with one to four classes were estimated. However, the number of replications decreased with increasing model complexity (see Table 2). To evaluate the overall pattern of changes in children's anthropomorphism, we first inspected the one-class model. Parameter estimates are summarized in Table 3 (column 2) and the trajectory is plotted in Fig. 1 (top panel). Hypothesis 1 posits that anthropomorphism increases from the pre-interaction phase ($T_0$) to after the first interaction ($T_1$) with a social robot. Because the slope loadings at $T_0$ and $T_1$ are fixed to 0 and 1 respectively, the latent intercept represents children's anthropomorphism at $T_0$ and the latent slope represents the change in anthropomorphism from $T_0$ to $T_1$. As Table 3 shows, children's anthropomorphism started at a moderate level of 2.88 (on a scale ranging from 1 to 5) and then significantly increased by 0.54 ($p < .001$). Thus, Hypothesis 1 was supported.

Hypothesis 2 posits that children's anthropomorphism of Cozmo remains stable between $T_1$ and $T_2$ and decreases afterwards ($T_3$ to $T_5$). The time-specific loadings revealed a steady decline in anthropomorphism, which set in after $T_2$: The time-specific loading remained at 1.03 at $T_2$, and then dropped to 0.73, 0.67, and 0.63 between $T_3$ and $T_5$. To substantiate this descriptive finding, we tested whether anthropomorphism from $T_2$ to $T_5$ was significantly lower than anthropomorphism at $T_1$. This was done by consecutively constraining time-specific loadings between $T_2$ and $T_5$ to 1 and conducting a Wald test [67]. Results showed that, in comparison to $T_1$, anthropomorphism remained at about

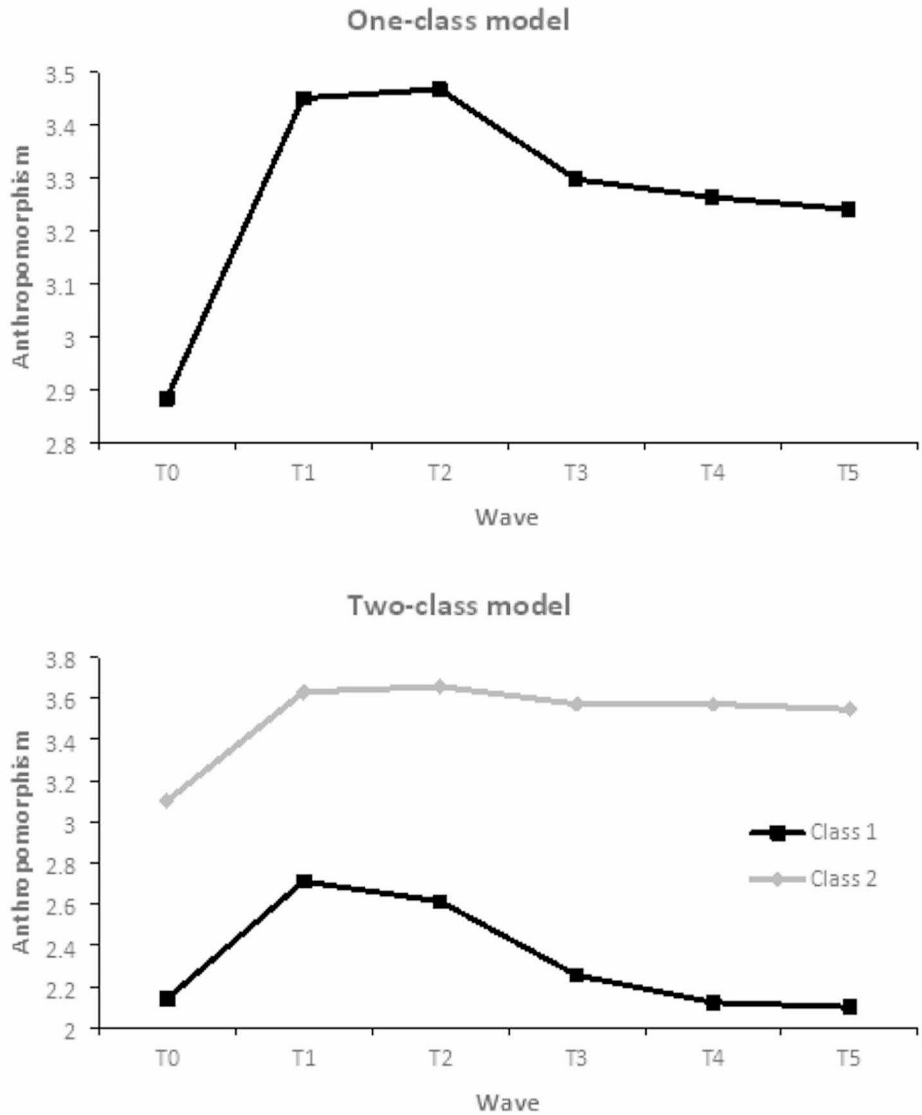


**Fig. 1** Trajectories of anthropomorphism in one- and two-class model

the same level at $T_2$ ($\chi^2(1)=0.18$, $p=.670$), but was significantly lower at $T_3$ ($\chi^2(1)=15.33$, $p<.001$), $T_4$ ($\chi^2(1)=18.39$, $p<.001$), and $T_5$ ($\chi^2(1)=23.42$, $p<.001$). However, the loadings from $T_2$ to $T_5$ were all significant (see Table 3, column 2), which indicates that anthropomorphism remained at a higher level than before the first interaction with Cozmo. These findings supported hypothesis 2.

Research question 1 asks whether different trajectories of anthropomorphism can be identified. To address the research question, we inspected the fit of the different models (see Table 2). We selected the two-class model because it had a better fit than the one-class model, which is indicated by substantive decreases in AIC, BIC, and ABIC, and significant results of the VLMR-LRT and the ALMR-LRT. Moreover, the two-class model had the highest entropy ($E=0.895$). The three-class model was rejected because it had a lower entropy ($E=0.773$) and because it only marginally increased model fit: AIC, BIC, and ABIC did further decrease, but the VLMR-LRT and the ALMR-LRT were not significant. Finally, the four-class model produced a better model fit than the three-class model (as indicated in Table 2 by reductions in the AIC, BIC, ABIC, and, more importantly, significant results of the VLMR-LRT and the ALMR-LRT). However, the four-class model produced a very small class, which included only 16 children, and it had a lower entropy ($E=0.831$) than the two-class model. The analysis of the model fit suggested that two trajectories were adequate to describe changes in children anthropomorphism over time.

Table 3 (columns 3 and 4) summarizes class-specific parameter estimates of the two-class model. The class-specific trajectories are depicted in Fig. 1 (bottom panel). The model included a smaller class of 76 children and a larger class of 266 children. The latent intercepts indicate that the children in the first class had a relatively low level of anthropomorphism before the first interaction with the social robot ($M=2.14$), whereas the level in the second group was moderate ($M=3.10$). After the first interaction ($T_1$), anthropomorphism increased in both classes, as indicated by the fact that both slopes are positive (i.e., 0.57 and 0.53 respectively). The similar size of the two slopes indicates that the initial difference in anthropomorphism between the two classes persisted up to $T_1$, when anthropomorphism reached a low-to-moderate level in the first class ($M=2.71$), and a moderate-to-high level in the second class ($M=3.63$). After $T_1$, the trajectories developed differently. In the smaller group, anthropomorphism steadily declined, which is reflected in the steady decrease of the time-specific loadings. Notably, only the loading at $T_2$ was significantly different from 0, whereas the loadings from $T_3$ to $T_5$ were not significant. This suggests that children's anthropomorphism of Cozmo fell over time to its pre-interaction level.

In the larger class, in contrast, anthropomorphism only slightly declined after $T_1$ (as indicated by the loadings which never fall below 0.84) and consistently stayed above its pre-interaction level (as indicated by the significance of each loading). With regard to research question 1, we thus concluded that two types of longitudinal trajectories of children's anthropomorphism could be distinguished. One class of children started with a relatively low level of anthropomorphism, which increased after the first interaction with Cozmo and subsequently receded to its pre-interaction level. A second class of children started with a moderate level of anthropomorphism, which increased after the first interaction and then remained at a moderate-to-high level.

Finally, the hypotheses 3 to 5 posited that children's media exposure to non-fictional robots, D-type epistemic curiosity, and peer problems would favor longitudinal trajectories characterized by higher levels of anthropomorphism. Research question 1 asked whether age and sex influenced which longitudinal trajectory a child's anthropomorphism followed. Given that we identified a class with low and a class with moderately high robot anthropomorphism, we expected the three predictors to increase the likelihood of children belonging to the moderate-to-high anthropomorphism class. To investigate research question 2, we studied whether children's age and sex influenced their class membership.

**Table 4** Logistic regression predicting membership in moderate-to-high anthropomorphism class

| Predictors | b | SE | $e^b$ | *p*-value |
|---|---|---|---|---|
| Age (0 = 8 years, 1 = 9 years) | 0.18 | 0.31 | 1.19 | 0.561 |
| Sex (0 = male, 1 = female) | 0.25 | 0.31 | 1.28 | 0.418 |
| Media exposure to non-fictional robots | 0.54 | 0.20 | 1.72 | 0.006 |
| D-type epistemic curiosity | 0.13 | 0.22 | 1.14 | 0.542 |
| Peer problems | -0.15 | 0.25 | 0.86 | 0.554 |

$N=342$

Table 4 summarizes the results of a logistic regression model, which predicted membership in the moderate-to-high anthropomorphism class. Age, sex, D-type epistemic curiosity, and peer problems did not predict class membership. However, media exposure to non-fictional robots positively predicted membership in the moderate-to-high anthropomorphism class. That is, the more frequently children had seen non-fictional robots in the media before the start of the study, the more likely they were to belong to the class with a moderate-to-high level of anthropomorphism that increased after the first interaction and then remained at a relatively high level. With regard to Hypothesis 3, we thus conclude that children's media exposure to non-fictional robots increased the level of anthropomorphism over time. Hypotheses 4 and 5 were not supported. In response to research question 2, age and sex did not influence which longitudinal trajectory a child's anthropomorphism followed.

## 4 Discussion

This paper investigated how children's anthropomorphism of a Cozmo robot changed over time and how individual differences affected this change. Children's anthropomorphism reached its peak level after the first interaction with Cozmo and remained at this level until about two weeks later. Over the course of the next six weeks, anthropomorphism steadily decreased. This trajectory, however, differed between two groups of children. In one large group of children, anthropomorphism decreased slightly after a moderately high peak, but remained above the pre-interaction level. In a second, smaller group, anthropomorphism steadily declined after a moderate peak and eventually fell to its pre-interaction level. Furthermore, we found that the more frequently children had been exposed to non-fictional robots in the media before our study, the higher their levels of anthropomorphism were over time. Other theoretically derived potential predictors of children's longitudinal trajectory of anthropomorphism, such as D-type epistemic curiosity and peer problems, as well as their age and sex did not predict the trajectories.

Our findings are in line with research which showed that single interactions with social robots can produce moderate to moderately high levels of anthropomorphism [5, 13]. The findings also corroborate two longitudinal studies which showed that children's anthropomorphism of a social robot did on average not substantially decrease after two weeks [20] and three weeks respectively [6]. Our study extends previous findings by demonstrating that, overall, children's anthropomorphism decreased over a longer time frame (i.e., from $T_2$ to $T_5$), but consistently remained above the pre-interaction level. Moreover, our study adds to the literature by showing that children differ in their trajectories and that at least two groups can be distinguished.

Our findings have two main implications. First, a relatively simple, toy-like social robot like Cozmo can elicit a moderate-to-high level of anthropomorphism among many children, which persists over the course of about eight weeks. Even in the smaller group of children that anthropomorphized Cozmo to a lower degree, anthropomorphism did not fall below the pre-interaction level. This suggests that children can anthropomorphize social robots over a considerable time period even if the robot is not highly anthropomorphic. Presumably, features that make a robot fun to use or allow for social activities, notably, being able to play games with the robot, may support sustainable levels of anthropomorphism. Second, prior experiences with and knowledge about non-fictional robots (e.g., acquired through media) can affect how children perceive and respond to robots over time. Thus, to foster long-term engagement and preclude disappointments, it may be useful to inform children early on about the abilities and limitations of a social robot.

The findings of this study should be regarded as tentative as it may be difficult to generalize them because children's anthropomorphism is likely to be context-dependent. Notably, our study was done with one type of social robot, Cozmo, and characteristics of social robots may significantly affect how robot anthropomorphism develops over time. Current social robots differ in their characteristics and, accordingly, children anthropomorphize them to different degrees [17]. Moreover, social robots are continuously refined and equipped with more advanced skills. In the future, they may successively acquire human-like skills and be increasingly anthropomorphized, especially by children, who tend to easily anthropomorphize nonhuman entities [2]. Next to robot features, changes in children's knowledge and understanding of social robots may also affect robot anthropomorphism. Similar to children who grew up with the Internet [68], future generations of children may be acquainted with social robots early in their lives, and they may develop novel views on the differences and boundaries between humans and machines.

Our study revealed that the overall pattern of changes in anthropomorphism was produced by two distinct trajectories within subgroups of children. These findings broadly match the results by van den Berghe et al. [6], who showed that children's anthropomorphism of a social robot does not develop uniformly over time. However, a detailed comparison of findings reveals a difference. Next to a stable level of anthropomorphism and decreases in anthropomorphism, van den Berghe et al. found that anthropomorphism increased among about a quarter of children. In contrast, we found that robot anthropomorphism was stable in the larger group and decreased in the smaller group of children after two weeks (i.e., from $T_1$ to $T_2$). It is difficult to exactly pinpoint the causes of these differences because discrepancies in the time interval (two versus three weeks), robot model (Cozmo versus Nao), and/or main activity (play versus learning) may have influenced anthropomorphism. Future research may investigate the discrepancies between our and van den Berghe et al.'s findings by conducting a panel study with smaller time intervals between panels and/or by systematically varying robot characteristics or activities.

In line with our expectations, higher exposure to non-fictional robots in the media increased the probability that children followed the trajectory characterized by moderate-to-high levels of anthropomorphism. Again, this effect is likely to be context-dependent. The current media environment seems to frequently depict robots with advanced abilities [36]. However, as robots increasingly acquire more advanced abilities and invite uncanny-valley type of reactions [69], concerns may rise and media reporting may place a stronger emphasis on risks and the otherness of robots. Longitudinal analyses over an extended period of how media reporting about robots develops may help to understand the public's views and, more specifically, anthropomorphic perceptions of robots and may help to contextualize the findings of our study.

None of the other predictors that we had chosen either based on Epley et al. [2] (i.e., D-type epistemic curiosity, peer problems) or general interest (age, sex) significantly affected anthropomorphism. The non-significant effects of age and sex contradict the findings of van den Berghe et al. [6] who showed that children's age and sex can moderate changes in robot anthropomorphism. However, the findings are in line with cross-sectional research which did not find age [11] and sex [46] to impact robot anthropomorphism. Age may not have affected robot anthropomorphism in the present study because we focused on 8- to 9-year-olds. Accordingly, the age range may have been too small to identify effects on anthropomorphism. Future research could investigate broader age ranges because more substantial differences in children's Theory of Mind are likely to affect longitudinal changes in anthropomorphism.

Robust evidence exists that effectance motivation increases anthropomorphism [41]. However, D-type epistemic curiosity, a type of effectance motivation, did not influence changes in anthropomorphism in the present study. The finding may be the result of D-type epistemic curiosity having opposing effects on anthropomorphism. Smedegaard [21] argues that "if the anthropomorphization was brought on by a need for effectance,… then this should disappear as the individual gradually becomes familiarized with the robot" (p. 416). Accordingly, D-type epistemic curiosity may lead to high levels of initial anthropomorphism, but also to a stronger decline in anthropomorphism over time. If this is true, D-type epistemic curiosity may not have predicted membership in one particular trajectory because a high level of initial anthropomorphism and a strong decline in anthropomorphism were part of different trajectories. To address this issue, future research could investigate in more detail how covariates influence specific growth parameters (e.g., the intercept and slope of a longitudinal trajectory). A post-hoc analysis of our data, however, did not reveal any significant effects of D-type epistemic curiosity or any other covariate on the growth parameters. Alternatively, covariates could be modelled as time-varying predictors. This may be particularly useful for predictors that are likely to substantively vary during long-term interactions with social robots, such as (state) effectance motivation.

Although sociality motivation has been shown to increase anthropomorphism [70], peer problems did not influence children's anthropomorphism of Cozmo either. Potentially, the previously mentioned modeling techniques (i.e., prediction of specific growth parameters and inclusion as time-varying predictor) may provide a more nuanced picture. Alternatively, peer problems may not have affected robot anthropomorphism because they are an imprecise proxy of children's sociality motivation. Put differently, peer problems may increase sociality motivation as children struggle to make friends. However, children may still have fulfilling relationships, for instance, with parents, siblings, and other family members. Including a better proxy or a direct measure of sociality motivation may provide a better test of its effect on robot anthropomorphism.

Finally, robot anthropomorphism is assumed to function as an important predictor of key outcomes of HRI [3], such as the attachment to [71] and trust in robots [72]. However, longitudinal effects of anthropomorphism in HRI have rarely been studied to date. Accordingly, future research should investigate how longitudinal changes in anthropomorphism relate to fluctuations in outcomes of HRI, and how these relationships differ across the main phases of HRI, that is, the initialization, familiarization, and the stabilization phase [27].

This study provided a first insight into how children's anthropomorphism of a social robot develops over a longer time frame, how anthropomorphism develops within subgroups, and how individual differences influence which trajectories children's anthropomorphism follows. In this respect, it advances our knowledge on the development of a key variable in CRI and HRI, anthropomorphism, over time and its predictors. At the same time, our findings likely depend on boundary conditions, such as the robot model and features of the interactions, and additional research into the role of such boundary conditions is required to contextualize our results.

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**Data Availability** The data analyzed in this study is available from the first author on reasonable request.

## Declarations

**Conflict of interest** The authors declare that they have no conflict of interest. Anki® and Cozmo® are registered trademarks of Anki, Inc. (at the time of the data collection; now Digital Dream Labs). This research project is not sponsored by, supported by, or affiliated in any manner with Anki (at the time of the data collection; now Digital Dream Labs).



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