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Little Scientists & Social Apprentices: Active Word Learning in Dynamic Social Contexts Using a Transparent Dyadic Interaction Platform

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ABSTRACT

Research characterises the child as an active learner who attends more to and selectively retains information they actively elicit better than information they passively receive. At the same time, children learn best from knowledgeable others who tailor information to children's learning progress. Bringing these disparate findings together requires examining children's active learning in social interactions. The current study examines whether the active learning advantage persists in social interactions with others and is influenced by the pedagogical status of their social partner (mother, father or friend). We tested 4- to 5-year-old children with their social partners ($N_{\text{friend}} = 47$, $N_{\text{mother}} = 44$, $N_{\text{father}} = 53$) during a word learning task using a novel setup where two participants can interact with visual objects on a transparent touchscreen while observing each other. Participants could either actively choose objects to hear their labels or passively observe their partner's choices. Early in the task, there was an overall active benefit, although this pattern appeared to be predominantly driven by interactions between peers. Later in the task, learning appeared to be dynamic and more influenced by the social partner with whom the child was interacting, especially when considering interactions with their peers and their fathers. Together, these findings underscore the temporal and social dynamics of an active learning benefit in children's social interactions.

1 | Introduction

Children learn language from their interaction partners in social contexts where they can, nevertheless, choose whom and what they will attend to and learn from. Recent studies highlight an "active boost" in learning, where children show better retention of information they actively elicit relative to information with which they are passively presented (De Simone and Ruggeri 2022). At the same time, pedagogical theories of learning suggest that caregivers—although research to date has predominantly focussed on mothers, as opposed to caregivers in general—play a special role in early development, by providing children with optimal input to steer learning (Csibra and Gergely 2009). Thus, learning passively from such optimal input carefully selected by knowledgeable social partners may be a better, more 'natural', strategy(than active learning)raespecially in social interactions with more knowledgeable partners, like caregivers. The current study targets this dichotomy between the role of the environment and the active child in early development, and examines children's active learning in social interactions with partners varying in pedagogical status, that is, their mothers, fathers and same-aged peers.

Research has long characterised children as "little scientists" who actively shape their learning journey from an early age, curating a developmentally appropriate "curriculum" (Piaget 1957; Smith et al. 2018). Indeed, studies suggest that children selectively elicit and attend to information and sources that target their knowledge gaps, thereby, steering their learning progress (Schütte et al. 2020; Zetterson and Saffran 2021; de Eccher et al. 2023). Studies examining children's learning of information they selectively elicit typically present children with trials where they can elicit information they are interested in, henceforth active trials, and trials where they are passively presented with information chosen for them, that is, passive trials. Admittedly, learning in passive trials also includes an active cognitive component, in terms of attending to and engaging with information presented in such trials, which may be better termed observational learning. However, we retain the active-passive terminology for the sake of consistency with the broad literature on this topic (Ackermann et al. 2020; Kidd et al. 2012; Partridge et al. 2015; Ruggeri et al. 2019; Sim et al. 2015). Importantly, studies examining the influence of active sampling on learning outcomes report inconclusive findings(de Eccher et al. 2023; Liquin and Gopnik 2022; Zettersten and Saffran 2021). Thus, when presented with objects whose labels children were or were not certain about, children who showed more uncertainty-driven sampling did not perform better overall relative to children who showed more random sampling (Zettersten and Saffran 2021; de Eccher et al. 2023). The benefits of active sampling on learning outcomes also vary across development: while young infants exhibit enhanced learning for objects they previously pointed at compared to those they ignored (Begus et al. 2014; Goldin-Meadow et al. 2007; Lucca and Wilbourn 2018), 30-month-olds showed reduced learning in active contexts relative to passive contexts (Ackermann et al. (2020), but see Partridge et al. (2015) for opposing results in 3- to 5-year-olds). Indeed, Foushee et al. (2021) found that the active boost in learning increases across early childhood, matching passive learning only around 4.5- to 6-years of age, and resembling adult-like performance by age 8 (Ruggeri et al. 2019). The influence of active sampling on learning also varies during the course of an experiment, with differences across active and passive sampling conditions decreasing across the experiment (Ackermann et al. 2020). Similarly, manipulating whether children first receive information passively or actively influences the pattern of learning, with active learning being boosted by prior passive exposure (MacDonald and Frank 2016). Taken together, there appears to be considerable dynamicity in children's active role in steering their learning across development.

One reason for such differences in active learning may be that children may not be able to accurately estimate and report their knowledge gaps, thereby requiring more reliable sources to tailor information to their developmental progress. Indeed, learning in early development occurs within rich sociocultural contexts, where children, like 'social apprentices', can benefit from expert models, who shape their input to optimise their child's learning (Csibra and Gergely 2009). Pedagogical accounts suggest that expert models act as optimisation filters, providing children with cues that highlight the relevant aspects of the interaction and bolster early retention of object names (Çetinçelik et al. 2021; Yoon et al. 2008). Given the powerful role of such sociocultural contexts in early development and children's active role in steering their learning progress, here we ask how social contexts shape children's active learning.

There is a burgeoning interest in the extent to which active learning can be influenced by the social context in which information is presented that brings together sociocultural and active theories of learning. For instance, this work examines the social behaviours that elicit and predict an individual's curiosity (Sinha et al. 2017) and finds that the behaviour of a group as a whole can converge to a shared state of curiosity (Paranajape et al. 2018), which can change on a moment-to-moment basis. Similarly, other's interest in new information has been shown to influence the extent to which individuals attend to and selectively sample such information (Berns et al. 2010, Dubey et al. 2021). Thus, information sampling can be socially driven, transcending simplistic classifications of children as "little scientists" or "social apprentices".

Thus far, studies investigating children's sampling behaviour have typically relied on automated computerised paradigms, lacking essential social elements found in real-world interactions (Ackermann et al. 2020; de Eccher et al. 2023; Partridge et al. 2015; Ruggeri et al. 2019; Sim et al. 2015; Zettersten and Saffran 2021). The absence of a responsive social partner in such studies may especially impact performance in passive learning scenarios. Thus, information passively attained may be valued more and retained better when presented by a familiar social partner as opposed to a computer, given the sociality of an interaction with a real person. There is, therefore, a real need to examine children's active learning in social interactions.

Furthermore, these effects are likely to be moderated by the pedagogical status of their social partner, that is, whether the interlocutor is a caregiver or a peer. For instance, children are more likely to follow instructions, elicit or use information provided by an adult relative to a peer (Rakoczy et al. 2008; Kachel et al. 2021). This is typically explained by suggesting that children do not expect to benefit from information provided by their peers (Southgate et al. 2007) and that imitating peer behaviour fulfils more of a social than a pedagogical function (Zmyj et al. 2012). There is, therefore, a similar need to examine the extent to which active learning in social contexts is modulated by the pedagogical status of the social partner in the interaction, that is, whether the social partner is a caregiver or a peer.

Thus far, however, research on caregiver-child interactions has predominantly focussed on mother–child interactions (Yu et al. 2020), with a relative paucity of work on father–child interactions. To some extent, this reflects the status as the mother as the primary caregiver in many societies. However, this pattern is rapidly changing, with fathers becoming more involved in childcare, necessitating research on how father–child interactions compare to mother–child interactions and the extent to which assumptions of pedagogy apply to fathers and mothers equally. To date, research reports differences in the kind of play that fathers and mothers engage in with their children. Thus, father–child interactions are characterised by higher levels of activity and tumble play relative to mother–child interactions (Steenhoff et al. 2019). Mother–child interactions, in contrast, tend to be characterised by more affectionate parenting behaviours, such as nurturing contact and motherese (Gordon et al. 2010), and mothers being more sensitive to their child's cues and signals (Gee and Cohodes 2021). This has implications on a hormonal level as well, with increased oxytocin levels in fathers during rough tumble play and stimulatory parenting behaviours, such as object presentation (Gordon et al. 2010). In contrast, mothers' oxytocin rises occur predominantly during affectionate contact with their children. This pattern of father–child and mother–child interactions appears to also influence child behaviour, with children initiating more conversations with their fathers as opposed to their mothers, and mothers, in turn, initiating more conversations with their child relative to fathers (VanDam et al. 2022). Individual differences in caregiver behaviour also impact child behaviour, with children of fathers who engage in greater autonomy and lower levels of protection, showing less introvertive tendencies (Olofson and Schoppe-Sullivan 2022). Taken together, the research thus far highlights differences in the patterns of father–child and mother–child interactions that may have implications on how active the child is in interactions with their caregiver and their learning from such interactions.

2 | The Current Study

Against this background, the current study examines children's sampling behaviour and active learning during social interactions with same-aged peers or with 'benevolent experts', that is, their mothers and their fathers. Specifically, we examine whether children exhibit differences in learning and retaining information they actively elicit compared to information elicited by their partner in a social interaction.

To this end, we developed the Dyadic Interaction Platform for children (DIPc), building upon previous prototypes tested with non-human primates and adults (Moeller et al. 2023). The DIPc allows for real-time face-to-face interactions, where two participants on opposite sides of a dual transparent touchscreen can view and interact with objects presented on the touchscreen while seeing one another throughout the interaction. Across active and passive learning trials, participants could either choose an object to hear its label (active) or hear the label of an object they saw their partner elicit (passive). Subsequent test trials evaluated participants' recognition of object associations for actively elicited and passively presented labels. Thus, a passive label-object association, in contrast to previous tasks, is not merely presented by a computerised program; rather children see their social partner elicit the label for this object during the interaction. We anticipate that this increased interaction will support learning even in passive trials in the current paradigm. Nevertheless, we predict improved learning of objects whose labels were elicited by their caregivers as opposed to their same-aged peers, especially in interactions with their mothers as opposed to fathers. In other words, we expect an increased active benefit—in terms of improved learning of objects whose labels were elicited by the children themselves (relative to objects whose labels their partner elicited)—in interactions with their peers relative to caregivers, as well as a similarly increased active benefit in interactions with their fathers relative to their mothers.

Note that the DIPc automatically records children's tapping responses, while dual head-mounted eye trackers capture participants' gaze during the task (Franchak and Yu 2022). Thus, we were also able to measure children's eye-movements during learning interactions with different partners. In particular, we were able to examine the extent to which children attended to objects whose labels they elicited, relative to objects whose labels their partner elicited, across interactions with different social partners and active and passive trials. We predict that children will show differences in their attention to passively sampled objects based on who they are interacting with, with increased attention to such objects in interactions with their caregiver as opposed to their peer.

3 | Methods

3.1 | Participants

Data from 144 children aged 48–71 months ($N_{\text{female}} = 72$, $M_{\text{age}} = 57.02$; $SD_{\text{age}} = 5.1$) were analysed in three different social partner conditions ($N_{\text{friend}} = 47$, $N_{\text{mother}} = 44$, $N_{\text{father}} = 53$). Children were recruited from the lab database and were predominantly of White ethnicity. Children either participated with their mother, father or a close friend of the same age ($N_{\text{friend.same.sex}} = 28$ children, 16 female, $N_{\text{friend.different.sex}} = 14$ children, 7 female). Caregivers provided informed consent for their child (and themselves if participating). Caregivers of same-age peers provided online consent. The present study was conducted according to guidelines laid down in the Declaration of Helsinki. The study was approved by the Ethics board of the Institute. All participants were typically developing children with no language deficits and had at least 80% German language exposure. Data from 28 additional children (16.2% of the final dataset) were excluded due to developmental delays, technical issues, interference of a parent, sibling or friend at test, incomplete data or fussiness of the child.

3.2 | Stimuli

The study employed 24 cartoon images of animals and aliens, half of which were familiar animals like cats and turtles, while the other half consisted of aliens created using Canva (Canva 2023). Each object was paired with a two-syllable pseudoword, following German phonotactic rules. Labels were incorporated into sentences during the learning phase (e.g., "Look! This is a Nangi!"). During the test phase, participants heard prompts like "Can you find the Nangi?" The labels were spoken in child-directed speech by a female native German speaker.

3.3 | Apparatus

We made adaptations and modifications to the dyadic interaction platform (DIP) originally developed by Moeller et al. (2023), resulting in a smaller, child-friendly version, see Figure 1. In particular, we used a custom screen with a highly transparent display film (ClearBright, LuxLabs) sandwiched between two sheets of anti-reflective acrylic glass (Optium Museum Acrylic, Tru Vue). The resolution of the visual display (42") was 1120 × 630 pixels. Two ultra-short throw projectors (EB-735F, Epson) were used to present the stimuli on the screen, thereby minimising shadows and ensuring equal brightness on both sides. A single graphics card (AMD Radeon 550) drove both projectors at 60 Hz. Touch frames (G5 42", PQLabs) on both sides allowed participants

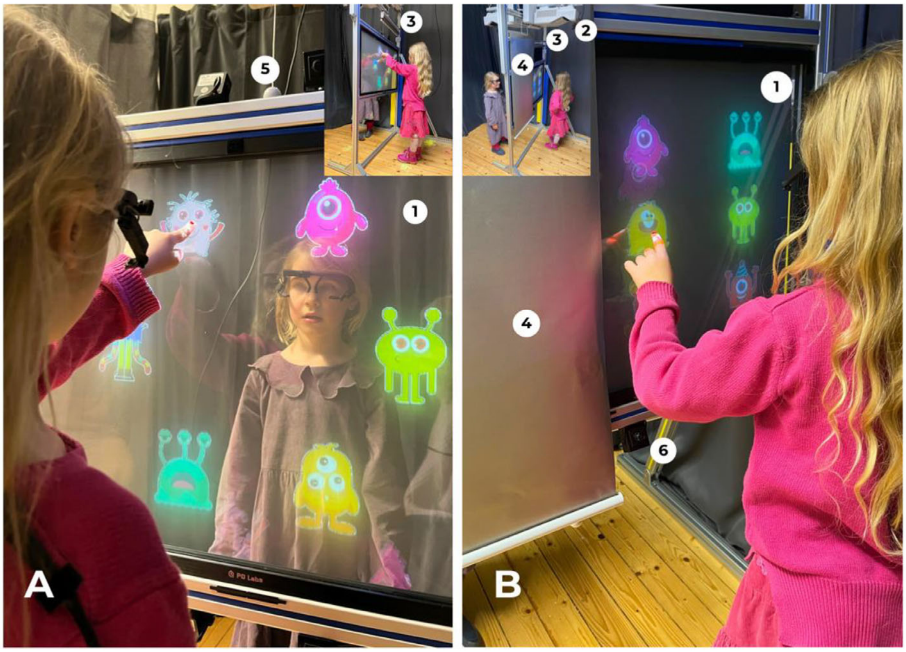

FIGURE 1 | DIPc setup and word-object learning task. (A) Sampling phase. Children stand on either side of the DIPc in front of each other and can see each other through the transparent screen (1) and the objects that are projected onto the screen by the overhead projectors (2). Touching an object on the screen elicited the name for the object through the loudspeakers (3). (B) Test phase. Half of each side of the transparent screen is shielded (4) so that children cannot see each other but see images of six objects. Three cameras on each side (upper edge of the screens (5), lower edge of the screens, overhead attached to the projector) allow for observation of children. Caregiver-child dyads had the exact same setup with the caregiver sitting on a low lounge chair to match the height of their standing child.

to interact with one another as well as stimuli displayed on screen. Touch signals were processed via the SDK of the manufacturer and timestamped in the PsychoPy study at a target frame rate of 60 fps.

The transparent screen embedded in the DIPc provides children with a rich array of cues, including but not limited to their partner's gaze direction, facial expressions and shared visual attention, that are not similarly easily available in side-by-side settings. Indeed, prior research suggests that the transparent setting also allows children to infer which object their partner will tap on prior to the physical tap due to their following their hand movements in real time (Isbaner et al. 2025), thereby reinforcing children's knowledge that an object was chosen by their partner while also being provided with such information earlier.

3.4 | Design

The study consisted of a familiarisation phase, followed by two experimental blocks, each comprising of a yoked learning and test phase. Prior to starting the task, participants were introduced to the setup, and children were told that they could see their partner at any time through the transparent screen, and could still see their partner's feet when the blinds were down during the test phase. The study was presented as a game for the child, where they participated in a mission to explore different planets. Participants were told that they would encounter animals from these planets that were distinct from those found on Earth. The children were encouraged to learn more about these animals by tapping on them on the screen and hearing their names. Participants were told they were either in the blue side or the yellow side, for example, if the child was in the blue side, the panelling to their right was blue, and the panelling on their partner's side was yellow. Participants practised which side they were in by tapping on a submarine to make it move, followed by a sound in turns. We counterbalanced which side was first allowed to tap on the submarine to make it move across dyads. If the side that was cued did not respond, they were reminded that it was their turn to tap on the screen. If the side that was not cued tapped on the screen, they were reminded that it was not their turn to tap on the screen.

3.4.1 | Familiarisation Phase

The familiarisation phase consisted of two blocks, with four familiarisation trials in each block, resulting in a total of eight familiarisation trials per dyad. In each trial, participants could choose one object out of six familiar objects to hear its label, that is, within a block, participants could together choose four of the six objects whose label they wanted to hear. A different array of objects was presented in the second block. Each block included two trials where the child could choose the objects whose label they heard, and two trials where their partner could choose the objects. Thus, across the two familiarisation blocks, the child could tap on an object four times, while their partner could tap on an object four times. Participants were informed that they could choose any of the objects displayed onscreen, even if their partner had previously selected the same object.

Object locations were randomised across blocks and participants. Upon selection, the chosen object's label was presented audibly,

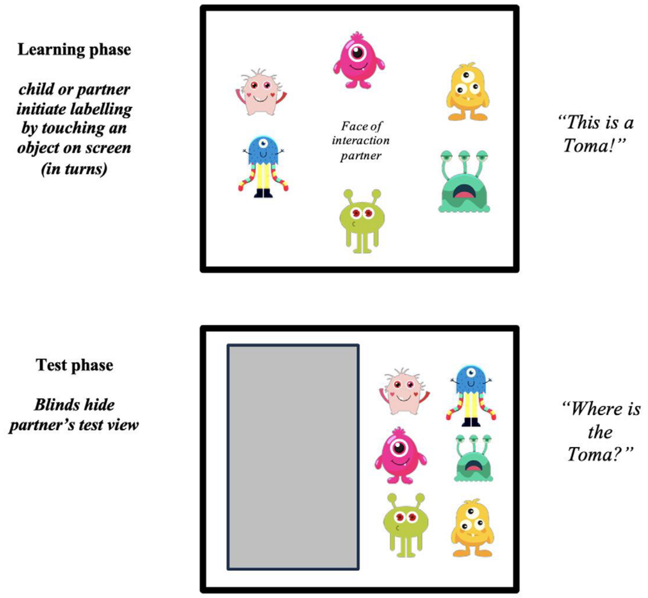

FIGURE 2 | Schematic of the study depicting differences between learning and test phases.

accompanied by a brief animation (object expanding in size and shrinking back). Participants were reminded to take turns choosing objects, with instructions tailored to the current side's turn ('Blue team, you can now press on any animal to hear its name!'). The order of trials, specifying which side was allowed to choose an object, was counterbalanced across blocks. The tapping function on the other side of the screen was deactivated when it was not their turn. In addition, auditory instructions reminded the dyad that it was now the other side's turn ('It's the yellow team's turn'). If participants did not tap an object after 10 s, they were reminded that it was their turn to choose an object. A second reminder was given at 15 s. The trial concluded automatically at 20 s.

3.4.2 | Experimental Phase

The experimental phase comprised two blocks, each with a learning and test phase, see Figure 2. In the learning phase, participants chose from an array of six objects to hear their labels. After tapping an object, its label was presented twice in carrier sentences. Participants took turns choosing objects (as described above), with each participant able to choose two objects (across two trials). Children and their partners were allowed to choose objects chosen in previous trials. Thus, children heard the label of a minimum of one object (chosen either by themselves or their partner) and a maximum of four objects (two of which were chosen by the child and two chosen by their partner) in each block. Reminders were given at ten and 15 s to prompt participants to choose an object if they had not done so. The trial concluded automatically at 20 s.

A yoked test phase followed the learning phase in each block. Here, participants were shown the six objects again and asked to tap on the object corresponding to a given label. Participants were only tested on labels they had heard during the learning phase. Opaque screens that came down during the test phase prevented participants from observing each other's responses. Labels were embedded in carrier phrases such as 'Where is the nangi?', where *nangi* was the label for the target object in that trial. Auditory stimuli were timed so that the images were presented in silence for 1 s followed by the onset of the sentence containing the target label. Each object labelled during the learning phase served as the target object in two trials within each test block, resulting in a total of up to eight test trials per block when both sides chose two different objects during the learning phase. This number varied based on the number of objects dyads had tapped on during the learning phase. Object locations were randomised in each test trial. Participants had 5 s in which to respond by tapping on the object whose label they had just been presented with. The trial concluded if no response was given within 5 s. Trial presentation was synchronised across both participants, that is, began and ended at exactly the same time, allowing both to view the objects for 5 s after the label onset. The trial concluded either 1 s after both participants tapped an object or after the maximum duration of 5 s after the label onset. Once the first block was completed, participants were presented with an identical second block, which included a different array of six objects and labels.

Upon arrival, participants were familiarised with the laboratory setting. Participants were fitted with dual head-mounted eye-trackers. Next, they were told that, initially, they would see animals from our planet (familiarisation phase) and subsequently, animals they had never seen before from a different planet (learning phase). Additionally, they were informed that they could touch the images to hear the name for each animal. The experimenter also conveyed that they would engage in a brief game after they had seen all the animals (test phase). Participants received a book as a token of appreciation for their participation at the end of the session.

4 | Analysis

The project's OSF page hosts shared data, analysis code, as well as detailed information on individual models (https://osf.io/6dven/?view_only=ee20746779b643a6a63f91a8e02d3475).

4.1 | Response Accuracy Data

We examined children's accuracy of object-label recognition during the test phase for objects actively or passively sampled, separately for interactions with their mothers, fathers and peers. We ran a binomial Generalised Linear Mixed Model (GLMM) where the dependent variable was a binary variable coding correct and incorrect responses (1 = correct, 0 = incorrect) each child provided in each trial. We also included predictor variables for who had sampled the object during the learning phase (active or passive *sampling*), the status of the social *partner* (mother, father, friend) and *block* (block 1, block 2) and their interactions with each other and *sampling* as additional predictor variables in the model. We included *block* as a predictor variable based on previous findings highlighting the transient and dynamic nature of active learning outcomes (Ackermann et al. 2020, MacDonald and Frank 2016). We z-transformed the child's age in months and included it as a fixed effect to account for *age* variations within the sample. Trials with no response and objects that were sampled more than once during the learning phase were excluded from analyses.

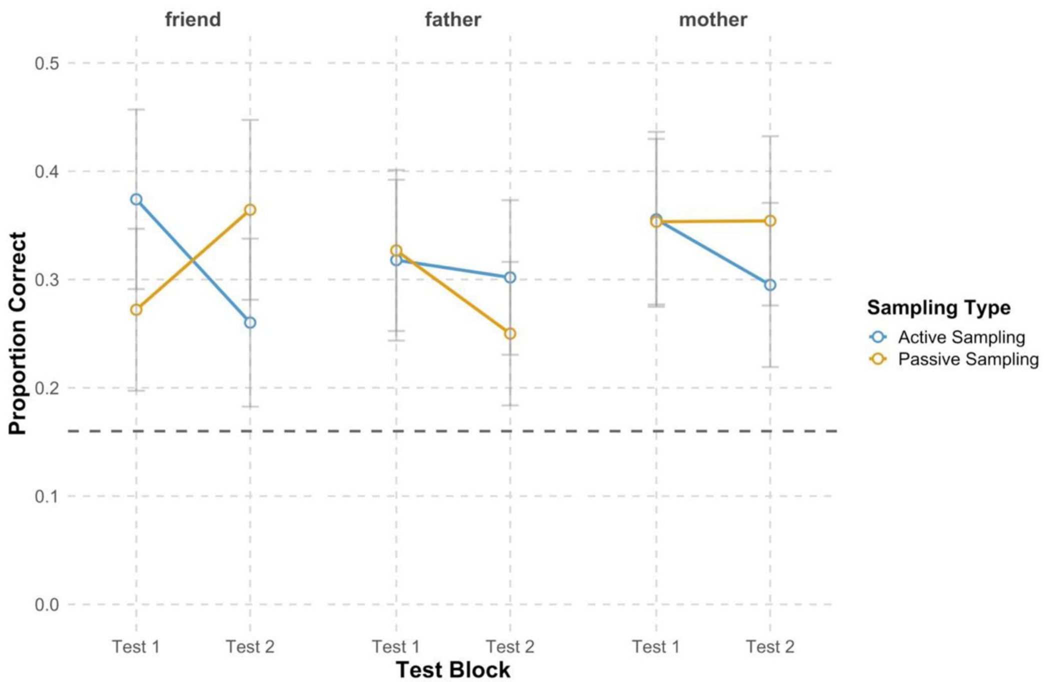

FIGURE 3 | Children's accuracy of object recognition separated by interaction partners, sampling type and test block. The dotted line indicates chance-level performance (1/6 objects). Error bars represent 95% confidence intervals (CIs) for the mean, which are calculated using the SE of the proportion.

Following recommendations in the literature, we accounted for both subject- and item-level variability in mixed-effects models (Baayen et al. 2009; Barr et al. 2013). Thus, we included *target image* (i.e., the image whose label was presented), *child ID* and *dyad ID* (child and their partner) as random intercepts in the random effect structure, as well as all theoretically identifiable random slopes. For the caregiver-child condition, only the child's responses are analysed, whereas in the child–child condition, both children contribute data. For this reason, we included a random term for *dyad* in order to account for the non-independence of the two children's data within the same interaction. In contrast, in the caregiver-child condition, the dyad and the individual effectively coincide. Since this could lead to the variance components for both random terms being difficult to separate, we compared models with and without dyad-level random terms. The model including dyad-level terms fit slightly better in terms of log likelihood, but the likelihood-ration test was only marginally significant ($\chi^2(10) = 17.8$, $p = 0.059$). Since the pattern of results did not change across models including and excluding dyad-level random terms, we report the results of the model including this term to account for the non-independence of children's data within a dyad. Model syntax and a detailed model description can be found on the OSF page. The analyses were conducted in R (version 4.1.2 or higher; R Core Team 2022) using the function glmer from the lme4 package (v1. 1-26; Bates et al. 2015).

4.2 | Eye tracking Data

Next, we examined children's visual attention to the chosen objects during the learning phase across interactions with different social partners, that is, their mother, their father and their peer. Details of the preprocessing of children's and partner's gaze during the task are provided in the Supporting Information. Here, we focus mainly on the description of the analysis. We ran a GLMM with a beta distribution to analyse children's looking times towards the object that they either *actively* chose during the learning phase or *passively* observed their partner choose. The response variable was the *proportion of looking to the target (PTL)*, which ranged between 0 (no looks to target) and 1 (only looks to target). Since the data included exact values of 0 and 1, we transformed the response to normalise it for further analysis. The fixed effects included the three main predictors: *sampling*, *partner* and *block*. A preliminary model revealed no significant interaction between the three predictors on PTL. We, therefore, excluded this interaction in the final model that we report. The random effects structure consisted of the intercept for *child ID*, *dyad ID* and *target image*, with all identifiable random slopes added to the model (see model details in the repository). The analyses were again conducted in R (version 4.1.2 or higher; R Core Team 2022) using the function glmmTMB, the equally named package (v1. 1-10; Brooks et al. 2017).

5 | Results

The 144 children included in the final analysis contributed data for 2099 test trials. We excluded 137 trials (6.526%) where both the child and their partner touched the screen simultaneously at test, 84 trials (4.002%) where they chose the same object in the learning phase, and 301 trials (14.938 %) with no response.

Overall, children recognised object names reliably above chance at test, see Figure 3 (chance = 0.16, represented by the dashed line in Figure 3). Table 1 presents the average accuracy of responses across the two *blocks* of testing in *active* and *passive* trials in

TABLE 1 | Mean values of correct object label identification at test based on block, sampling and partner.

Test block	Sampling type	Interaction partner		
		Friend	Father	Mother
Test block 1	active	0.374	0.318	0.356
	passive	0.272	0.327	0.353
Test block 2	active	0.260	0.302	0.295
	passive	0.364	0.250	0.354

TABLE 2 | GLMM estimating children's accuracy of object recognition based on partner, sampling condition and block. The model was referenced to active trials in block 1 and to interactions with a friend.

Response accuracy					
Predictors	**Estimates**	**SE**	**CI**	**Statistic**	***p***
(Intercept)	−0.581	0.229	−1.029 to −0.133	−2.541	0.011
Sampling [passive]	−0.729	0.349	−1.414 to −0.044	−2.087	0.037
condition [father]	−0.252	0.304	−0.848 to 0.345	−0.827	0.408
condition [mother]	−0.038	0.310	−0.646 to 0.571	−0.121	0.904
block [second test]	−0.653	0.369	−1.376 to 0.071	−1.767	0.077
child age	0.115	0.078	−0.039 to 0.268	1.466	0.143
Sampling [passive]* condition [father]	0.664	0.461	−0.239 to 1.566	1.441	0.150
Sampling [passive]* condition [mother]	0.531	0.466	−0.382 to 1.444	1.140	0.254
Sampling [passive]* block [second test]	1.254	0.465	0.343 to 2.165	2.697	0.007
Condition [father]* block [second test]	0.536	0.470	−0.385 to 1.458	1.141	0.254
Condition [mother]* block [second test]	0.267	0.481	−0.677 to 1.210	0.554	0.580
(sampling [passive]* condition [father])* block [second test]	−1.549	0.608	−2.741 to −0.358	−2.548	0.011
(sampling [passive]* Condition [mother])* block [second test]	−0.752	0.615	−1.958 to 0.454	−1.222	0.222

TABLE 3 | GLMM estimating children's accuracy of object recognition based on interaction partner and sampling type in each individual test block.

	Response accuracy									
	Test block 1					Test block 2				
Predictors	**Estimates**	**SE**	**CI**	**Statistic**	***p***	**Estimates**	**SE**	**CI**	**Statistic**	***p***
(Intercept)	−0.590	0.233	−1.048 to −0.133	−2.530	0.011	−1.288	0.283	−1.842 to −0.733	−4.553	0.001
sampling [passive]	−0.742	0.358	−1.444 to −0.039	−2.069	0.039	0.571	0.322	0.060 to 1.202	1.772	0.076
condition [father]	−0.216	0.311	0.824 to 0.393	−0.694	0.488	0.326	0.352	0.363 to 1.016	0.928	0.353
condition [mother]	−0.033	0.317	0.654 to 0.588	−0.104	0.917	0.290	0.364	−0.423 to 1.004	0.797	0.425
child age	0.051	0.106	0.157 to 0.260	0.483	0.629	0.170	0.115	−0.055 to 0.395	1.481	0.139
sampling [passive]* condition [father]	0.651	0.468	0.266 to 1.568	1.391	0.164	−0.869	0.413	−1.678 to −0.060	−2.105	0.035
sampling [passive]* condition [mother]	0.534	0.473	0.393 to 1.461	1.129	0.259	−0.227	0.420	−1.051 to 0.597	−0.540	0.589

interactions with *mothers, fathers* or *friends*. Table 1 suggests an *active* learning boost only in interactions with *friends* and only in the first *block* of testing, that is, children showed improved recognition of objects whose labels they had *actively* elicited relative to objects whose labels they *passively* observed their *friend* eliciting (see Table 1). There does not appear to be an *active* or *passive* learning boost in interactions with their *mother* and *father* in the first *block* of testing. In the second *block*, during interactions with *friends* or *mothers*, children appeared to show a passive learning boost, showing improved recognition of objects that their social partner elicited the label for relative to objects whose label the child *actively* elicited. In contrast, there appears to be an active learning boost in interactions with their *fathers* in the second block of testing.

The model revealed a significant *active* learning benefit in interactions with their *friends* in the first *block* of testing ($\beta = -0.729$, 95% CI [−1.414 to −0.044], $p = 0.037$; model referenced to the *active* sampling condition in the first *block* of testing in interactions with their *friends*). Furthermore, there was a significant interaction between *sampling* and *block* ($\beta = 1.254$, 95% CI 0.343–2.165], $p = 0.007$) in interactions with *friends*. As suggested by Table 2, there was more of an *active* benefit in the first *block* of testing in interactions with their *friends*, which changed to a *passive* benefit in the second *block* of testing. Finally, there was an interaction between *sampling, block* and *partner* when comparing interactions with *friends* to interactions with their *fathers* ($\beta = -1.549$, 95% CI [−2.741 to −0.358], $p = 0.011$), but not comparing interactions with *friends* and *mothers*. Given the significant interactions detailed above, post hoc analyses were conducted to examine the influence of *sampling* within each *block* separately.

5.1 | Sampling Behaviour Per Block

The binomial GLMM used here was similar to the model above with regards to the fixed and random effect structure and was applied to two individual subsets, one containing the data from test *block* 1 and the other from test *block* 2. The fixed effect structure hence, excluded the factor *block*. In *block* 1, *sampling* significantly impacted children's accuracy in selecting object names; children were more likely to correctly identify the target object when they *actively* sampled it during the learning phase, compared to when they *passively* observed their partner *sampling* it ($\beta = -0.742$, 95% CI [−1.444, −0.039], $p = 0.039$), see Table 3. In *block* 2, however, children's accuracy in selecting object names at test varied depending on their *sampling* strategy during learning and whether their interaction partner was a *friend* or their *father*. Specifically, during the second test phase, children interacting with *friends* were more likely to correctly choose the target label for objects sampled by their *friend*. In contrast, children interacting with their *fathers* were more likely to accurately identify the target label for objects they had *actively* sampled ($\beta = 0.869$, 95% CI [−1.678, −0.060], $p = 0.035$).

5.2 | Sampling Behaviour in Peer, Mother–Child and Father–Child Interactions

Given the significant interaction between *sampling, block* and *partner* when comparing *peer* interactions and *father–child* interactions, we analysed the data from interactions with *fathers* and *friends* separately. We also separately analysed the data from interactions with *mothers*, although we state that this analysis is exploratory given the absence of a significant three-way interaction between *partner*, *sampling* and *block* when comparing interactions with *friends* and *mothers*. We applied the binomial GLMM described above, excluding the predictor *partner* in the fixed and random effects structure, that is, applying the GLMM to individual datasets obtained from children's interactions with their *friend, father* or their *mother*, see Table 4.

TABLE 4 | GLMM estimating children's accuracy of object recognition based on interaction partner and sampling type in each individual test block.

	Response accuracy														
	Friend					Father					Mother				
Predictors	**Estimates**	**SE**	**CI**	**Statistic**	***p***	**Estimates**	**SE**	**CI**	**Statistic**	***p***	**Estimates**	**SE**	**CI**	**Statistic**	***p***
(Intercept)	−0.579	0.209	−0.987 to −0.170	−2.776	0.006	−0.798	0.199	−1.187 to −0.409	−4.020	<0.001	−0.588	0.220	−1.019 to −0.157	−2.677	0.007
sampling [passive]	−0.492	0.274	−1.028 to 0.045	−1.796	0.073	0.091	0.255	−0.408 to 0.591	0.358	0.720	−0.017	0.261	−0.529 to 0.496	−0.063	0.949
block [T2]	−0.580	0.286	−1.140 to −0.020	−2.030	0.042	−0.082	0.252	−0.577 to 0.412	−0.326	0.744	−0.271	0.273	−0.805 to 0.263	−0.995	0.320
z age	0.150	0.113	−0.071 to 0.371	1.332	0.183	−0.056	0.102	−0.255 to 0.143	−0.555	0.579	0.296	0.173	−0.043 to 0.635	1.714	0.087
sampling [passive]* block [T2]	0.999	0.396	0.223 to 1.775	2.522	0.012	−0.357	0.359	−1.061 to 0.346	−0.996	0.319	0.333	0.375	−0.401 to 1.067	0.889	0.374

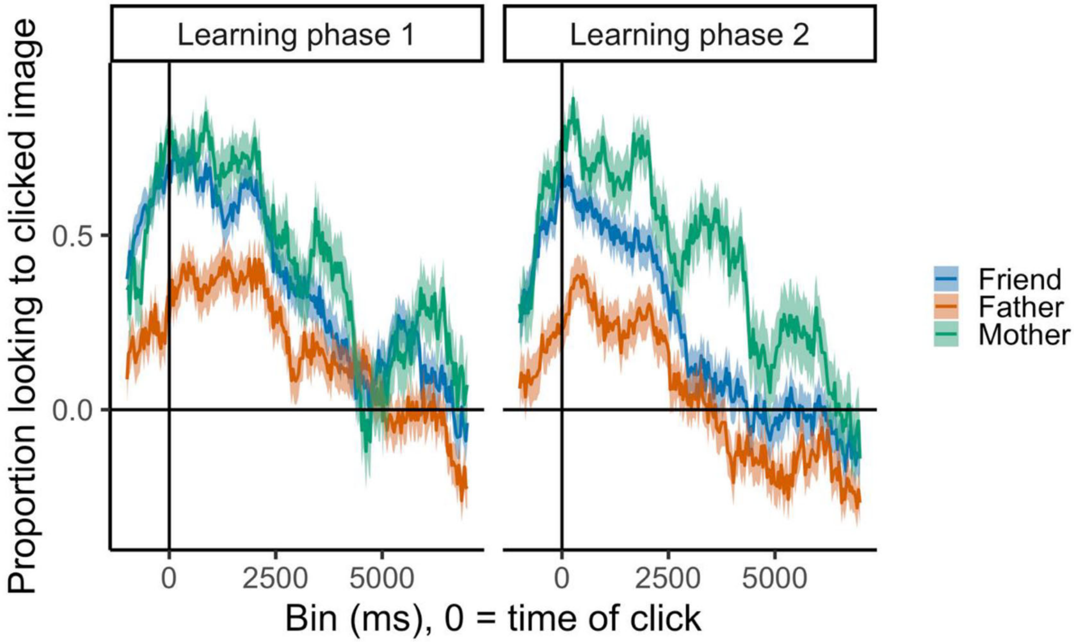

FIGURE 4 | Proportion looking to clicked image during the learning phases by children's partners.

Children's *accuracy* in recognising objects *actively* and *passively* sampled varied across *blocks* in interactions with their *friends*. Specifically, while children were better at identifying objects they had *actively* sampled compared to those they had *passively* observed in *block* 1, this trend reverses in *block* 2, where children were better at identifying objects they had *passively* observed (β = 0.571, 95% CI [0.06–1.202], $p = 0.076$).

When considering the data from children's interactions with their *fathers*, however, the interaction between *sampling* and *block* was not significant (β = 0.357, 95% CI [−1.061 to 0.346], p = 0.319), nor did the overall benefit of *active* versus *passive sampling* across *blocks* reach significance (β = 0.091, 95% CI [−0.408 to 0.591], p = 0.072). The same was true for children's interactions with their mothers, where neither the interaction between sampling and block (β = 0.333, 95% CI −0.401 to 1.067], p = 0.374) nor sampling alone (β = −0.017, 95% CI [−0.529 to 0.496], p = 0.949) was significant, see Table 4.

5.3 | Children's Looking Behaviour During Word-Object Learning

Ninety-one children in the sample (M_{age} = 57.25 months, SD_{age} = 5.44 months, age range = 48–71 months) provided eye-tracking data during the study. The remaining 53 children, for whom we report touchscreen data above, did not agree to wear the eye-tracking glasses. For this reason, only a subset of the full sample is included in the eye-tracking analyses. Of the 91 children wearing the eye trackers, 18 children participated with their *mothers*, 36 participated with a same-aged *friend*, and 37 participated with their *fathers*. Figure 4 plots the proportion of time children spent looking at the chosen object in interactions with their mother, father and friend. Overall, children appeared to look at the object on screen the most in interactions with their mothers, followed by interactions with their friends and then interactions with their fathers. Table 5 presents the proportion of time children spent looking at the chosen object in active and passive trials separately for the two blocks and social partners. Overall, across blocks, children looked more at the objects they *actively* sampled relative to objects they *passively* observed being sampled in interactions with their *friends* and their *mothers*, although this difference appears greater in the first block.

TABLE 5 | Mean (SD) of children's proportion of target looking for active and passive trials, by partner.

		Block 1		Block 2	
Partner	**Sampling**	**Mean**	**SD**	**Mean**	**SD**
Friend	Active	0.815	0.165	0.701	0.278
	Passive	0.674	0.264	0.644	0.288
Mother	Active	0.800	0.256	0.801	0.150
	Passive	0.693	0.226	0.720	0.232
Father	Active	0.618	0.351	0.496	0.365
	Passive	0.518	0.353	0.502	0.328

As noted above, a preliminary model found no significant interaction between sampling, block and partner ($\chi^2(2) = 1.183$, $p = 0.553$) in predicting the proportion of time children spent looking at the object during the learning phase. We, therefore, report the results of a model excluding this interaction but retaining all three predictors as main effects. We found a significant difference in the proportion of time children spent looking at the object on screen during interactions with their fathers relative to their friends (β = −0.790, 95% CI [−1.244 to −0.33], $p < 0.001$), but not between friends and mothers (β = 0.375, 95% CI [−0.184 to 0.934], $p = 0.189$). Furthermore, children spent more time looking at the image during active trials relative to passive trials overall (β

= −0.317, 95% CI [−0.478 to −0.157], $p < 0.001$), as well as more time in block 1 relative to block 2 ($\beta = -0.267$, 95% CI [−0.501 to −0.033], $p = 0.025$).

6 | Discussion

This study investigated children's learning of novel word-object associations in interactions with different social partners, namely their mothers, fathers and close friends. We examined whether children displayed an active learning boost, that is, showed improved learning and retention of object-label associations they actively sampled as opposed to passively received, in interactions with social partners. Participants performed the task on a shared, transparent dual-touchscreen setup, allowing both participants to mutually engage in the task and elicit labels for chosen objects while observing each other's responses during selected parts of the task. In the first half of the study, we found some evidence for an active boost in learning, with children showing improved recognition of object-label associations they had actively sampled relative to passively observed object-label associations elicited by their social partner. However, we found independent evidence for an active learning benefit only when considering the data obtained from interactions with their friends, while there was no difference between active and passive trials in interactions with their caregivers, when considering this data separately.

Later in the study, the active learning benefit regarding interactions among children changed to a passive learning benefit in interactions with friends. Furthermore, the pattern of responses in the second block of testing differed between interactions with friends and fathers, with more of an active learning benefit in interactions with their fathers relative to friends. Children interacting with their fathers were less likely to retain object labels they observed their father elicit, but reliably identified object labels they had actively elicited. Children's eye movements corroborated this pattern of results, with children spending the least amount of time looking at the screen in interactions with their fathers relative to their mothers or friends, and also spending more time looking at the screen in active trials relative to passive trials. Overall, our findings reveal differences in how children retain object label information learned from social interactions with their friends or caregivers, with distinct dynamics observed in father–child interactions. Social interactions, in particular, appear to influence children's learning by shaping their attention to and retention of visual and linguistic information about novel objects.

We note that our paradigm focuses on short-term retention rather than broader learning processes, and we, therefore, use the term learning to refer specifically to the immediate encoding and recall of label-image associations within the task. The literature on a potential active boost in learning is inconclusive, with some studies reporting a passive learning boost (Ackermann et al. 2020; Foushee et al. 2021) and others reporting an active learning boost (Partridge et al. 2015; Sim et al. 2015). Our findings suggest that these differences may be attributed to the fact that any active learning benefit is dynamic and fleeting and influenced by the social context in which information is presented. Future research could take into account measures such as interaction duration, quality (Madhavan and Mani 2024)and language (Mahlke et al. 2025)used in children's social interactions, which may provide valuable insight into these dynamic learning patterns. In particular, we only found evidence for an active learning boost in the first block of the study, while performance in the second block of the study was influenced by whom the child was interacting with during the task. Similar findings of initial differences between active and passive trials, which diminish during the study, have been noted in the literature to date (Ackermann et al. 2020; Partridge et al. 2015). While Ackermann et al. (2020) attribute such differences to task demands—that is, the cognitive or memory requirements imposed by the structure of the task—Partridge et al. (2015) suggest that differences in task engagement, that is, the child's motivation, interest, or attentional investment in the task, explain their pattern of results. Thus, early in the task, children may engage more with the task, while also attending more to objects whose labels they actively elicited, thereby leading to an active boost in learning. Later in the task, children's attention to the objects appears to be dynamically influenced by the social partner with whom they were interacting, leading to a passive benefit in interactions with their friends and a renewed active benefit in interactions with their fathers, independent of overall engagement.

Such differences in children's attention during interactions with their peers are in keeping with work highlighting the value of close-in-age peers as social partners (Zmyj et al. 2012). In the novel situation of using an unfamiliar device, children likely experienced heightened enthusiasm when exploring objects, motivating them to attend to on-screen objects early on, thus enhancing their involvement in the task. When the novelty of the paradigm fades, and as familiarity with the task grows, children interacting with peers display a more socially curious sampling strategy (Dubey et al. 2021), with increased learning of objects whose labels their partner elicited. This is in keeping with a host of findings showcasing children's learning from their peers (Whiten and Flynn 2010, McGuigan and Graham 2010, Flynn and Whiten 2012; Qiu and Moll 2022; Abramovith and Grusec 1978; VanderBorght and Jaswal 2009), with some research suggesting that peers may be particularly effective teachers due to the similarity of their interests and developmental limitations to the learner (Over and Carpenter 2012; Corsaro and Eder 2025; Lew-Levy et al. 2023). Our findings, similarly, suggest that the effect of social curiosity persists in early development, with learning being influenced by the actions of their peers (Kashdan and Fincham 2004; Parr and Townsend 2002).

Critically, this pattern of responses was specific to children's interactions with their peers and differed from interactions with their fathers, but not their mothers. We found a significant difference in children's responses in the second block of testing depending on whether they were interacting with their friends or their fathers. Thus, fathers appeared to support further active exploration, especially in the second block of testing, while friends, as noted above, appeared to trigger more socially curious strategies. Indeed, children spent the least amount of time fixating on the screen in interactions with their fathers relative to their friends or mothers. In contrast, there was no evidence of a significant difference in children's responses across interactions with friends and their mothers, although we note that we found independent evidence for an active learning benefit in the first block of testing only in interactions with friends.

Why would the active learning benefit differ across interactions with caregivers and friends? We tentatively suggest that these differences may be attributed to the pedagogical status of the social partner in the interaction (Bonawitz and Shafto 2016; Shafto et al. 2012, 2014; Yang et al. 2019). Thus, children may initially attend less to objects chosen by their peers because they do not expect educational value from these interactions, leading to an initial active learning benefit in peer interactions. Indeed, we found that children spent more time fixating on objects whose labels they actively elicited relative to objects their partners elicited, thus speaking to the mechanisms underlying an active benefit in learning. Furthermore, they appear to attend equally to the screen in interactions with their friends or their mothers. We note that we found no evidence for a difference in the pattern of responses in interactions with friends and interactions with their mothers. However, to better understand potential individual variability that might be obscured at the group level, we conducted supplementary analyses examining individual children's typologies of active versus passive benefits. These analyses suggested that, numerically, more children showed a passive learning benefit (relative to an active learning benefit) in interactions with their mothers, while the opposite pattern was found in interactions with their fathers (see Supporting Information). We tentatively suggest—given the absence of independent evidence for an active benefit in interactions with their mothers—that caregiver interactions, especially interactions with their mothers, may be more tailored to the interests of the child, with parents following in on their child's focus of attention and presenting them with higher quality information when they believe their child to be interested in something (Madhavan et al. 2024; Madhavan and Mani 2024). Thus, children may come to value interactions with their mothers and attend more to these interactions overall, regardless of whether they are active or passive in nature, as also reflected in our eye-tracking results showing that children spent more time looking at the screen in interactions with their mothers than with their friends or fathers. We are currently following up on this issue with a series of studies examining the temporal dynamics of children's interactions with their caregivers, in terms of the extent to which children lead or follow their caregiver's attention in play interactions and the influence of child-led or caregiver-led episodes of joint attention on learning(Madhavan et al. 2024). An important limitation to note here is that, in our paradigm, the labels were provided by a computerised voice rather than by the social partner. This choice enabled us to compare child–child and caregiver–child dyads on equal terms, but it may have reduced the ecological validity of caregiver interactions. Recent work using a similar setup, in which caregivers provided the labels themselves, has shown how dynamics unfold when the caregiver is both the partner and the teacher within the interaction (Bothe et al. 2025), thus complementing the present findings. The pattern of results with the fathers(with a more persistent active benefit that differed from the passive benefit in interactions with friends in the second block of testing)is in keeping with the limited literature on father–child interactions, with fathers supporting more independent, exploratory play.

We highlight, however, that further research is required to make stronger conclusions about children's learning from father–child and mother–child interactions. This is especially true given the fact that we found no evidence of an influence of the social partner (especially comparing friends and mothers) on children's learning of actively elicited or passively observed object-label associations, and no evidence of an active or passive benefit when separately examining data from interactions with mothers or fathers. Our conclusions, therefore, draw support primarily from the significant difference in performance patterns between peer interactions and father–child interactions and the dynamic pattern of results in peer interactions(changing from an initial active benefit to a later passive benefit)that we observed. Furthermore, age was included as a covariate in our models to control for variability across the age range (48–71 months), but it did not explain additional variance in children's learning outcomes. Since this may have been due to the narrow age-range of the participants tested, it would be important to examine these findings from a developmental perspective by testing a wider range of children across early childhood. Finally, we note that participants were presented with the same set of objects across multiple test trials. While we attempted to ensure that children's response on later trials was not influenced by their response on earlier trials by not providing them with feedback on their choices, it remains possible that their response in one trial was contingent on their response in previous trials. Unfortunately, this is a constraint built into studies with young children who can only be taught a limited number of words in a single session. However, we suggest that the fact that we provided children with no feedback on their performance and that children also saw two unfamiliar, name-unknown objects in each test trial allows us to mitigate the influence of prior trials on later performance.

Curiosity-driven theories highlight the role of children in actively seeking out information of interest, and also learning and retaining such information better (Piaget in Papert 1999). Recent pedagogical theories of learning, in contrast, (Csibra and Gergely 2009; Shafto et al. 2012, 2014) emphasise the role of the caregiver as the optimal provider of information, with children displaying increased receptivity to information sampled by more knowledgeable relative to less knowledgeable models. The findings of our study bring together these theories that have, traditionally, been viewed independently. In particular, in keeping with curiosity-driven theories, our findings suggest that children show improved retention of objects whose labels they actively elicit. However, this active learning benefit is fleeting and transient, transitioning to a passive learning benefit later in the study, cautioning against direct application to educational contexts. This was especially so in interactions with their friends, while we found more of an active benefit in interactions with fathers even towards the end of the study. The active benefit observed in interactions with fathers in the second block speaks to potential differences in how caregivers(and fathers in particular)may shape children's exploration over time, especially given the absence of a similar difference between peer interactions and mother–child interactions. We tentatively suggested above that this may be due to the pedagogical boost of mother–child interactions, with children attending equally to information actively and passively received in interactions with mothers, although we noted that strong conclusions in this direction cannot be made due to the pattern of results reported above.

Equally, the passive learning benefit in the latter part of the study is in line with recent discussions of social curiosity and its influence on learning and behaviour. Studies on adult social curiosity mirror our findings, bridging pedagogical and curiosity-driven learning theories. Thus, Dubey et al. (2021) report that socially-driven information sampling is modulated by the extent to which participants were made aware of the content of the question, the perceived utility of the information provided (Dubey et al. 2021) and an individual's perceived similarity and affiliation to those contributing to the popularity ranking (Naylor et al. 2011). The passive benefit reported with peers resonates with the latter result, in particular, showing effects of both similarity and affiliation in socially curious information sampling.

7 | Conclusion

Our findings show that the benefits of active learning extend into social interactions but are shaped by both time and partner identity. An early advantage for active learning emerged most clearly in peer interactions, while later performance reflected increasing influence of the social partner;particularly with peers and fathers. This suggests that children adapt their learning strategies depending on who they are learning with and how the interaction unfolds. By integrating eye-tracking data, we captured how attention patterns support these dynamics, highlighting that children remain highly attuned to their partner's choices. Overall, the study demonstrates that active learning is not just an individual process but one embedded in(and influenced by)social relationships. This view transcends the passive versus active learning dichotomy, characterising children as active agents in a dynamic learning process, specifically with their peers, flexibly adjusting their attention to their environment based on their repertoire and resources.

Author Contributions

Ricarda Bothe: conceptualization, methodology, data curation, validation, investigation, formal analysis, visualization, writing – original draft, writing – review and editing. **Sebastian Isbaner**: conceptualization, methodology, software, data curation, investigation. **Xiaoyun Chen**: conceptualization, methodology, investigation, validation, writing – original draft. **Shreya Venkatesan**: Software, Data curation. Igor Kagan: conceptualization, methodology, validation, funding acquisition, resources, writing – review and editing. **Alexander Gail**: conceptualization, funding acquisition, resources. **Nivedita Mani**: conceptualization, methodology, investigation, validation, formal analysis, supervision, funding acquisition, resources, writing – review and editing.

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Ethics Statement

This study was conducted in accordance with the guidelines outlined in the Declaration of Helsinki and was approved by the Ethics Board of the Institute. Permission to reproduce material from other sources: Permission is hereby granted to reproduce the material from this manuscript, subject to proper acknowledgment of the original source.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data, analysis code, and detailed information on individual models are available on the project's OSF page: https://osf.io/6dven/.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.

Supporting File 1: sode70046-sup-0001-SuppMat.docx