

Abstract

 Infants explore the world around them based on their intrinsically motivated curiosity. However, the cognitive mechanisms underlying such curiosity-driven exploratory behaviour remain largely unknown. Here, infants could freely explore two novel categories, triggering a new exemplar from a category by fixating on either of the two associated areas on a computer screen. This gaze-contingent design enabled us to distinguish between exploration – switching from one category to another – and exploitation – consecutively triggering exemplars from the same category. Data from 10-12-month-old infants (*N*=68) indicated that moment-to-moment sampling choices were non-random but guided by the infants' exploration history. Self- generated sequences grouped into three clusters of brief yet explorative, longer exploitative, and overall more balanced sampling patterns. Bayesian hierarchical binomial regression models indicated that across sequence patterns, infants' longer trigger time, shorter looking time, and more gaze-shifting were associated with trial-by-trial decisions to disengage from exploiting one category and making an exploratory switch, especially after consecutively viewed stimuli of high similarity. These findings offer novel insights into infants' curiosity- driven exploration and pave the way for future investigations, also regarding individual differences.

 Keywords: infant curiosity, information sampling, exploration-exploitation, gaze-contingent eye-tracking

Curious Choices: Infants' moment-to-moment information sampling is driven by their

exploration history

 Curiosity is considered the driving force behind exploration, discovery, and learning, motivating us to seek out new experiences, knowledge, and skills. It is, therefore, a crucial developmental factor from infancy onward, which has also been linked to positive outcomes later in life. Although there are various theoretical approaches to defining curiosity, they mostly agree that it reflects an intrinsic motivation to acquire information to enhance our understanding of the world (see reviews Bazhydai et al., 2021; Begus & Southgate, 2018; Kidd & Hayden, 2015; Reio Jr. et al., 2006; but see also Dubey & Griffiths, 2020). It manifests itself in exploratory behaviours; however, little is known about what drives moment-to-moment choices of such curiosity-based exploration in infants. In this study, we aimed to capture infants' active exploration within a controlled environment employing state-of-the-art gaze-contingent eye-tracking methodology.

1.1 Infants explore actively

 Infants are active explorers who help shape their own learning experiences (e.g., Piaget, 1970; Smith et al., 2018). These behaviours manifest themselves in, for example, visual and tactile exploration, but also in requesting information from others by pointing and later through verbal communication. Such exploration opportunities dramatically evolve throughout the first two years of life with infants developing a variety of new skills – gross-motor, fine-motor, and communicative – supporting ever more sophisticated exploratory behaviours and offering new perspectives on their immediately accessible physical (Adolph & Hoch, 2019) and social (Karasik et al., 2014) environments. In fact, infants autonomously adapt their exploration strategies to characteristics of their environment, such as employing different actions on objects based on their properties (e.g., Bourgeois et al., 2005; Fontenelle et al., 2007), selectively preferring an action that previously provided new information, travelling farther in a room with

 toys than without (Hoch et al., 2019), and selectively referring to the more informative adult when seeking an answer in a situation of referential uncertainty (Bazhydai et al., 2020). Infants also showed increased focus, longer-lasting exploration, and better learning when the course of play or interactive exploration followed their attention (C. Chen et al., 2021; Schatz et al., 2022; Suarez-Rivera et al., 2019; Tamis-LeMonda et al., 2013) rather than the caregiver's redirection (Bono & Stifter, 2003; Mendive et al., 2013; Pridham et al., 2000). Similarly, there seems to be a learning advantage for novel labels when these are presented in response to the infant's pointing gesture (Begus et al., 2014; Lucca & Wilbourn, 2019) and object-directed vocalisations (Goldstein et al., 2010) which are interpreted as communicative indices of information-seeking. Together, these studies highlight how infants use their available skills to explore the world on their own terms and benefit from doing so (see also Mani & Ackermann, 2018). An important question within developmental research which has only recently started to gain much-needed attention is to understand the mechanisms underlying infants' dynamic exploration as well as why it leads to these advantages (Begus & Southgate, 2018; Kidd & Hayden, 2015).

1.2 Exploration as a function of environment knowledge and learning mechanism

 To better understand infant exploration, we need to consider which factors may guide infants' exploratory choices dynamically. This includes both previous experience with the environment as well as the mechanism by which that knowledge affects subsequent behaviour. Findings from looking-time studies suggest both novelty (e.g., Fantz, 1964; Siqueland & 90 DeLucia, 1969; Stahl & Feigenson, 2015) and familiarity (e.g., Bushnell, 2001; DeCasper & Spence, 1986; Gaither et al., 2012) to be key characteristics to predict infants' engagement. Studies investigating infants' preferences for complexity found that infants were most likely to stay engaged at intermediate complexity levels ("Goldilocks effect", e.g., Berlyne, 1960; Kidd et al., 2012, 2014; Kidd & Hayden, 2015) whereas infants disengaged from sequences which were too predictable (Addyman & Mareschal, 2013) or unlearnable (Gerken et al., 2011).

 A mechanism proposed to explain these findings is learning progress maximisation (e.g., Altmann et al., 2021; Oudeyer et al., 2007; Twomey & Westermann, 2018) where exploration is driven by making intrinsically rewarding learning progress. Findings from adult populations where higher levels of curiosity have been linked to stronger activation in the dopaminergic brain circuits (Gruber et al., 2014; Kang et al., 2009) support the notion of its intrinsically rewarding nature. Computational models have shown that learning progress can predict infants' looking and looking away above and beyond predictability or surprise alone (Poli et al., 2020). They have also highlighted the importance of a moment-to-moment perspective because what maximises learning progress is dependent on the learner's current knowledge and changes dynamically with every learning experience and knowledge update (Twomey & Westermann, 2018). It is to be noted that learning progress thereby offers a 107 comparatively lean approach to interpreting curiosity as a psychological construct (Goupil & Proust, 2023; Poli et al., 2024). Furthermore, how much learning progress is being made by engaging with something is not only based on the available information in the environment but also on the degree to which it is being encoded. This is in line with previous research that found infants' looking preferences to be best explained by the degree of exposure and encoding rather 112 than the distinction between novelty or familiarity alone (e.g., Hunter & Ames, 1988; Oakes et al., 1991; Rose et al., 1982). Thus, to understand infants' dynamic, curiosity-driven exploration we need to consider the interplay between what information the environment offers but also how the infant engages with that information in order to predict and understand their successive sampling choices.

1.3 Need for a new paradigm

 Studies on infant exploration have thus far followed one of two main methodological approaches: either employing largely unstructured designs such as free play sessions, using observation and video recordings or head-mounted cameras and eye-tracking (e.g., Hoch et al., 2019; Rodriguez & Tamis-LeMonda, 2011; Slone et al., 2019; Yu & Smith, 2012), or controlled laboratory settings to capture visual exploration and engagement across predefined groups of stimuli and sequences (Addyman & Mareschal, 2013; X. Chen et al., 2022; Kidd et al., 2012; Poli et al., 2020). While both allow for invaluable insights into infant exploration, they do represent two ends of a continuum. Free play studies provide rich data on more descriptive characteristics of infants' curiosity-driven exploration, but the emerging variability poses difficulties in deriving precise mechanistic accounts. On the other hand, structured studies allow for precise manipulation of the provided information to disentangle underlying factors explaining exploration behaviour, such as predictability or stimulus similarities, but do not capture the active choices infants would make in more natural settings. Here we propose a paradigm which combines these approaches by using gaze-contingent eye-tracking – where the visual display changes in response to the infant's fixation. This approach enables infants to determine the sequence and timing of their exploration within an otherwise controlled environment.

 Previous studies employing gaze-contingent eye-tracking have shown that infants quickly learn the association between looking towards a specific area on the screen and certain types of information or stimuli being presented (Bazhydai et al., 2022; Keemink et al., 2019; Miyazaki et al., 2015; Sučević et al., 2021; Tummeltshammer et al., 2014; Wang et al., 2012; Zettersten, 2020). It is therefore a powerful method to implement an active component into a structured study design. In fact, similar to our conceptualisation, recent studies (Bazhydai et

 al., 2022; Zettersten, 2020) also employed gaze-contingent eye-tracking as a way to investigate infants' active sampling and exploratory behaviours.

 In our new 'Curious Choices' paradigm, infants can discover interactive information sources in the environment and thereby freely explore two novel categories by fixating on an associated area on the screen, triggering the presentation of a novel exemplar from the respective category. This way, infants can self-generate exploratory sequences which provide data for more general characteristics of the emerging exploration patterns, but also allow for mechanistic investigations regarding infants' dynamic sampling choices based on the information sources they discovered and how they engaged with the encountered, varying visual information.

1.4 Exploration-exploitation framework

 The 'Curious Choices' paradigm allows infants to create sequences for receiving information about two novel categories, where every trigger can be conceptualised as a decision to either continue viewing exemplars from one category or to switch over to the other. A useful framework to explain and predict such dynamic choices of 'staying' versus 'switching' is the exploration-exploitation trade-off (Charnov, 1976). Applied to curiosity- driven exploration, this trade-off would predict the agent to exploit an intrinsically rewarding learning opportunity (in other words the focused exploration of a known information source), but to disengage when learning progress subsides. Instead, the agent would then turn to explore 160 the environment more broadly in pursuit of other options worth exploiting (e.g., Oudeyer & Smith, 2016). Making such an exploratory switch requires cognitive effort to redirect one's attention (Pelz et al., 2015) leading to a baseline tendency to exploit (Hayden et al., 2011). Accordingly, the new paradigm allows us to evaluate these assumptions by linking the exploration-exploitation trade-off to the mechanism of learning progress maximisation. While the exploration-exploitation framework has been applied to investigate information seeking in

 adults often employing a k-armed bandit paradigm where the participant can sample from k- amount of reward sources (Averbeck, 2015), these studies were mainly focused on maximising external rewards (e.g., Daw et al., 2006; Somerville et al., 2017). Furthermore, only recently work has started to study children who had long been assumed to explore un-systematically (Blanco & Sloutsky, 2020; Schulz et al., 2019). For instance, in a computerised task, Meder et al. (2021) found that 4- to 9-year-old children explored the environment in an uncertainty- directed manner to maximise their rewards, with random exploration decreasing with age. Regarding earlier emerging, manual exploration in the absence of external rewards, Karmazyn- Raz & Smith (2023) found a systematic toy selection where 21-month-oldsshowed exploitative engagement with a selection of objects but only rarely engaged with all others. In summary, the exploration-exploitation trade-off lends itself to predicting dynamic exploration choices and, together with the novel paradigm, offers new insights into the systematicity even of infants' active information sampling.

1.5 The current study

 The aim of the current study was to investigate infants' curiosity-driven exploration of two unfamiliar categories within a controlled environment. For this, we developed and employed the Curious Choices paradigm, comparable to a 2-armed bandit task. Here, 10-12- month-old infants were introduced to two Fribble species (TarrLab) which are novel stimuli with animal-like features (Williams, 1998). Two identical "houses" were presented on a computer screen, and at each trial, a new exemplar from one of the categories was revealed if the infant fixated on the corresponding house. This way, we could explore how intrinsic curiosity resulted in specific exploration patterns which, in turn, captured how infants weighed exploration against exploitation. Importantly, it also allowed us to disentangle behavioural and environmental factors explaining their sampling choices. The age group was chosen on the basis that the infants would have relevant skills such as object permanence (e.g., Bremner et

al., 2015) and higher-level representations guiding their looking (Kiat et al., 2022) as the novel

categories would not be visible unless triggered. The research questions were as follows:

1. Do infants explore non-randomly within this new paradigm?

 2. Do group-level patterns emerge from the self-generated sequences based on how exploration was weighed against exploitation?

 3. Can dynamic exploratory choices be predicted by aspects of the infant's behavioural patterns and exploration history?

- 4. Do individual-level predictors differ between the possibly emerging group-level exploration patterns (combining research questions 2 and 3)?
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2. Methods

2.1 Participants

202 The sample consisted of $N = 68$ typically developing infants (age range: 10-12 months, *M* = 11.14, *SD* = 0.52, 50% female) from the northwest of England. Additionally, three infants were excluded due to calibration problems and another infant due to not engaging with the study procedure. Caregivers were reimbursed £5 for their travel and the child received a small gift (book or t-shirt) for participating. Informed consent was obtained before the study 207 commenced. The study was approved by the University Faculty's research ethics committee.

2.2 Materials

 2.2.1 Stimuli. Novel visual stimuli, called Fribbles, were sourced from the open 210 TarrLab repository¹. Fribbles are animal-like figures with four distinct body parts, each of 211 which comes in three variants. Two species (FA2 $&$ FB4, see Figure 1) were chosen under the consideration that none of the four body-parts was dominantly salient (Barry et al., 2014;

TarrLab Stimuli at https://sites.google.com/andrew.cmu.edu/tarrlab/stimuli?pli=1

 Williams, 1998). Thirty out of 81 possible stimuli per species (in the following referred to as categories) were selected to capture the possible variability in stimulus similarities (differences in one to four body-parts). The stimuli were standardised to a size of 400x300 pixels with the exemplar presented on a white background, matched in luminosity using Adobe Photoshop. For both categories, a random stimulus sequence was created determining which stimulus would be presented at any given trial, if triggered, consistent across participants but counterbalanced regarding their associated location. Additionally, 10 exemplars from two 220 animal categories – ducks and tortoises on white background $(532x531$ pixels) – were selected for the warm-up phase. Per phase, two identical houses functioned as 'buttons' triggered by fixations.

 2.2.2 Apparatus & Procedure. Prior to the appointment, caregivers were asked to complete a short infant curiosity questionnaire (Altmann et al., 2024) online which will not be further analysed in the current paper as it was still in the process of validation by the time of submission. At the lab, infants either sat on their caregiver's lap (77%) or in a high-chair (23%), approximately 60 cm away from the screen (24-inch, resolution of 1920x1080 pixels). Fixations were recorded using a TobiiX120 eye tracker positioned below the screen, with a gaze sampling rate of 60 Hz and a five-point calibration. The experimenter ensured adequate calibration quality, paid close attention to the infants' behaviours throughout the testing, and recorded if there were any concerns about a mismatch between looks and triggers. Consequently, each identified case was checked leading to the three excluded infants reported in the participant section. Caregivers were explicitly instructed not to interrupt or influence their child's behaviour.

 The experiment was structured into two parts, warm-up and exploration, each following a similar procedure: an introduction phase and a gaze-contingent phase. In the warm-up introduction, a female voice said in child-directed speech 'There are two *houses*. *Look* who

 lives in the houses!' while in the exploration introduction, the same voice said "Here are two *new* houses. Look who lives in *these* houses!", intended to direct the infants' attention towards the screen. This was followed by a video clip showing all exemplars (animals in the warm-up, Fribbles in the exploration phase) surrounding their respective house for one second, before synchronously moving into those houses over the duration of five seconds, accompanied by some 'squeaky' noises. Which categories were associated with which side in either part was counterbalanced across participants.

 In the gaze-contingent phases, infants could then trigger new exemplars from either category by fixating on the respective house for 700ms. This threshold was based on previous gaze-contingent designs choosing between 500 and 700ms with infants aged between 6 and 23 months (Bazhydai et al., 2022; Sučević et al., 2021; Wang et al., 2012; Zettersten, 2020), choosing a more conservative threshold to ensure more robust (less incidental) triggering. Furthermore, the algorithm was specified to ignore sample-losses of less than 100ms to ensure that triggering was not obstructed by the generally less stable eye tracking data infants generate. When a house was triggered, the next exemplar from this category was presented for four seconds: increasing in size for one second as if it emerged from its respective house, followed by static presentation for three seconds, while the other house was still visible (Fig. 1). Disappearance of the exemplar was followed by a gaze-contingent central attention getter which required being fixated for 250ms to start the next trial. If the infant did not fixate on either house within ten seconds, the trial was automatically terminated, registered as an empty trial, and an attention getter was presented again (following Wang et al., 2012). While the warm-up phase was constrained to 30 seconds (median number of warm-up triggers = 4, *M* = 3.5 , *SD* = 1.57), the exploration phase was constrained to 30 trials (thus, a maximum of 30 Fribble exemplars could be triggered; median number of exploration triggers = 21.5, *M* = 19.8, *SD* = 9.77).

 The experiment ended either after 30 trials (*n* = 27) if the infant had three consecutive 264 empty trials $(n = 12)$, or if they became fussy so that the experimenter terminated the experiment during the following attention-getter phase (*n* = 29). However, this termination did not lead to the participant's exclusion but captured differences in how long infants wanted to engage with the study. Overall, the experiment lasted no longer than six minutes, and the overall visit lasted up to half an hour including time to arrive, getting accustomed to the room, as well as playtime and debriefing afterwards.

- 270
- 271 **Figure 1**
- 272 *Study Design*

273 *Note*. **Left**: An example sequence of two trials: when a house is triggered, an exemplar from this house 274 is shown (coloured AOI here for illustration purposes, not visible in practice). Cursive values indicate 275 looking time necessary to make a trigger. **Right**: Example stimuli from both novel categories: Fribble 276 families A and B as indicated by their main body.

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278 **2.3 Data Processing**

279 Data was processed and analysed using R (Version 4.1.2). Triggers were recoded as 280 either a *stay-event* (triggering the same category as in the previous trial, e.g., A**A**) or a *switch-*

 event (e.g., A**B**), whereas all first triggers were coded as *start-events* from where a decision could be made to stay or switch. Then, *runs* of consecutive triggers towards each category were computed. For instance, a sequence of AABBBBA is made up of three runs: the first and third in category A (lengths of 2 and 1 respectively) and the second of length 4 in category B. Empty trials were coded to end a run as the infant disengaged for at least 10 seconds; thus, returning to exploration, even to the same category, implies renewed engagement, so the first trigger was then again coded as a *start-event*.

 The eye-tracking raw data was initially pre-processed through two rounds of interpolation (e.g., Hessels et al., 2017). The first round identified blinks and smaller technical glitches by interpolating over missing samples of less than 100 ms to connect the preceding and subsequent looking coordinates (R package 'eyetools', Version 0.4.6). The second round connected fixations on certain areas of interest (AOI) if they were interrupted by fixations to another area shorter than 50ms, most likely to reflect technical glitches rather than short looks away (e.g., Hessels et al., 2017). AOIs were defined per screen phase: attention getter in the *centre*, house and stimulus *left*, as well as house and stimulus *right*, whereas fixations to non- relevant areas were coded as *screen,* and *NA* if off-screen. Continuous looks towards each AOI were computed, where looks shorter than 100 ms were excluded as the minimal window-size (e.g., Chen et al., 2022). The remaining continuous looks were then added for total looking time per AOI and trial-phase.

2.4 Measures

 2.4.1 Overall engagement. Overall engagement was defined as the number of triggers the infant made over the course of the exploration phase (min. 1, max. 30).

 2.4.2 Switch-proportion. Switch-proportion was defined as the proportion of valid triggers which were decisions to switch from the current category to the other one (e.g., a sequence of AAA**BAB**B would have a switch-proportion of 3/6 or 0.5 as the decisions to switch or stay begin at the second trigger). Higher values indicate more switching, thus, stronger explorative tendencies.

 2.4.3 Category entropy. Shannon entropy (*H*) is an information theoretical uncertainty index which can quantify the amount of information contained in a random variable based on observed event counts (Shannon, 1948). Here, it was computed as the negative logarithm of the observed probability to trigger either category, characterising the overall systematicity of the sequence. Entropy becomes maximal (*H*=1) for sequences where, based on previous observations, either choice is equally likely (i.e., random) and thus, maximally informative. It becomes minimal (*H*=0) for perfectly predictable sequences, where each choice is minimally informative as it is expected.

 Both switch-proportion and category entropy provide unique information about the participant's exploration. For example, the switch-proportion captures structural dynamics neglected within category entropy (e.g., same *H* for AAABB and ABABA), whereas category entropy factors in the number of observations (e.g., larger *H* for AABBBB than ABB).

 2.4.4 Behavioural Engagement. **Trigger time** was the time from the moment the two houses appeared on screen (after the offset of the central attention getter) to the moment one of the houses was triggered. **Looking time** was the absolute duration the infant looked at the triggered stimulus. **Gaze-shifts** was defined as how many times during the presentation of an individual stimulus in a trial the infant shifted their gaze away from the currently displayed Fribble to the other side, that is, the untriggered house.

 2.4.5 Stimulus Similarity. This was defined as the subjective similarity between the 327 current stimulus and directly preceding stimulus from the same category² indicating the additional amount of information about the category the current stimulus offered (more similar pairs offering less new information). All variables were standardised within each participant so that trial-by-trial predictions were based on differences in the individual's behaviour.

2.5 Analysis Plan

 While these analyses and hypotheses were not pre-registered due to the novelty of this paradigm and the generally exploratory nature of the study, the variables and general analyses were specified and decided upon before inspecting the data. The report of the behavioural switch-prediction (2.6.3.1) in addition to their interaction with the stimulus similarities (2.6.3.2), however, was made ad hoc due to realising the consequently extensive reduction of observations (detailed below).

 2.5.1 Did infants explore non-randomly? We hypothesised that infants would explore systematically, which means that their trigger choices were different from chance. To analyse randomness in switching behaviour at each trial as well as their category sampling, 1000 draws from a binomial distribution with a likelihood of .50 were simulated for each infant based on their number of triggers. Switch proportions and category entropy were computed for each draw. The simulated distributions consisted of 68000 draws for each variable, and Kolmogorov-Smirnov tests were performed to determine if simulated and observed data came from the same chance distribution or not.

² These scores are based on a supplementary online study with an adult sample ($N = 45$, $M_{age} = 27.41$, range = 18 to 54 years, 52.4% female) in which we obtained subjective similarity scores between all possible combinations of stimuli for each category on a scale from 1 ("not similar at all") to 7 ("extremely similar") which were significantly correlated with the number of objective differences $(r = -0.54, p < 0.001)$; see supplementary materials S2 for more details.

 2.5.2. Did patterns of exploration emerge? We hypothesised that there would be variance regarding how infants structured their self-generated exploration sequences. To identify emerging patterns, a cluster analysis was computed based on overall engagement, switch-proportion, and category entropy, capturing quantitative and qualitative aspects of how infants weighted exploration against exploitation. These variables were checked for clustering 351 using the Hopkins statistic (Hopkins, 1954) where the value of 0.89 (\geq 0.7) indicated clustering 352 in the data³. As the clustering method, we chose Partitioning Around Medoids (PAM; Kaufman & Rousseeuw, 2009) which groups the data permutationally around central data-points (medoids) minimising the pairwise dissimilarities between observations within clusters⁴. The optimal number of clusters was determined using the R package 'NbClust' (Version 3.0.1), the cluster analysis was conducted using the package 'cluster' (Version 2.1.2) and data visualisation was achieved using 'plotly' (Version 4.10.1).

2.5.3. Could trial-by-trial trigger decisions be predicted?

 The novel paradigm allows us to investigate both, infants' engagement with information sources in their environment, and the encountered stimuli's effect on conjointly guiding their dynamic sampling choices.

 2.5.3.1 Behavioural switch-prediction. We hypothesised that behavioural indicators – trigger time, looking time, and gaze shifts – would predict the decision to switch from exploiting the current category to exploring the other. We expected that a decrease in looking time, and an increase in number of shifts during the previous trial's stimulus presentation, as

 It should be noted that a suggested, minimal sample of 100 observations for this statistic was not met and should therefore only be taken as an indication rather than a statistical test (Cross & Jain, 1982).

 Compared to k-means clustering, this method is more robust against outliers and allows better interpretation of the emerging clusters (Kaufman & Rousseeuw, 2009). However, we ran another analysis using k-means with a comparable pattern of results.

 well as increased trigger time for the current trial (as an indication of a switch-cost; Daw et al., 2006; Hayden et al., 2011) would predict an exploratory switch. A Bayesian hierarchical binomial regression model was fitted using the 'brms' package (Bürkner, 2017), with the three 369 predictors as population-level ("fixed") effects and trial-by-trial trigger decisions (stay = , switch = 1) as the outcome variable. Furthermore, we included random intercepts at the individual level to reflect the structure of the data.

 2.5.3.2 Stimulus-dependent switch-prediction. We hypothesised that characteristics of the presented stimuli would affect the likelihood to switch. For instance, experiencing two highly similar stimuli right after one another offers little new information about the category and could lead to disengagement in favour of another information source. Consequently, we would expect greater similarities (as judged by participants in the online rating study) between successive stimuli to predict a subsequent switch. Furthermore, this effect may moderate the behavioural indicators above, so that the same model was used, to which the stimulus similarities interactions were added to capture the full complexity of the task. As this measure required runs of minimum length 2, any single-trial runs and first trials of each run were excluded from this analysis. Thus, we kept these two models separate as they capture the exploration choices to different degrees.

 2.5.3.3 Differences between clusters. If our data showed evidence of clustering with regard to how infants engaged with the paradigm, we would further explore whether the predictors above differed between the emerging clusters. Thus, we would include clusters as interaction effects in both models.

3. Results

 Where possible, both frequentist p-values and Bayes factors (via JASP 0.16.2.0) will be reported. However, we chose to fit Bayesian models for the switch-predictions as they provide effect distributions rather than point estimates which were considered more appropriate

- for the inherently exploratory nature of a study employing a novel paradigm. Additional graphs
- for model fit comparisons can be found in the supplementary materials (S1.1). Data and analysis code are available on the OSF at:
- https://osf.io/ayjv7/?view_only=0574096344c041b4a8d0fa493a1d94d2
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3.1 Infants explored non-randomly

 First, we investigated whether infants' exploration patterns showed any systematicity different from chance. Kolmogorov-Smirnoff tests for two samples indicated for both 399 variables, switch-proportion ($D = 0.63$, $p < .001$) and category entropy ($D = 0.58$, $p < .001$), that the simulated (random) and observed data did not come from the same distribution (supplementary materials Figure S1). More specifically, infants showed a general exploitative 402 tendency as the average switch-proportion was significantly lower than 50% ($M = .28$, $SD =$.28, Wilcoxon signed-rank test against 0.5: *W* = 362.00, *p* < .001; *rc* = -0.67; BF10 = 279.35). 404 There was no systematic bias for triggering either a specific category ($W = 850.00$, $p = .205$, r_c 405 = -0.18, $BF_{10} = 0.32$) or side ($W = 1214.00$, $p = .245$, $r_c = 0.16$, $BF_{10} = 0.20$).

3.2 Three exploration patterns

 Number of triggers, switch-proportion, and category entropy were chosen prior to inspecting the data as a means to characterise different aspects of the infant-generated exploration sequences. We explored their relations via Kendall rank correlations due to non- normality and ties in the data. Across the whole sample, number of triggers moderately 411 negatively correlated with switch-proportion (r_{τ} = -.27*, p* = .002) and category entropy (r_{τ} = - .18*, p* = .044), whereas switch-proportion and category entropy were strongly positively 413 correlated ($r_{\tau} = .56$, $p < .001$). However, examining the distribution of exploration triggers (Figure 2)showed that a group of 10 participants engaged in the study only very briefly, making both switch-proportion and category entropy less informative. When removing this sub-

416 sample, the number of triggers were no longer related to either switch-proportion (r_{τ} = -.13, p 417 = .166) nor category entropy (r_{τ} = -.14, $p = .150$), while the relation between these latter two 418 variables increased even further ($r_{\tau} = .63$, $p < .001$). Thus, these variables appear to largely overlap in the variance they explain, possibly due to having only two triggerable information sources.

 Visualisation of the average silhouette (that is, minimising within-cluster dissimilarities while maximising between-cluster dissimilarities; Rousseeuw, 1987) and within-cluster sums of squares statistics suggested the optimal number of clusters to be three. The three emerging clusters (Figure 2) describe very brief, medium long, and very long sequences with additional variations in switch-proportion and category entropy (Table 1). Especially the sequences of more than 10 triggers could be differentiated by the extent to which the infant switched between and sampled from both categories. As, however, the very short sequences did often sample both categories, we decided to characterise the clusters as *brief explorative* (n = 9), *long exploitative* (n = 22), and *more balanced* (n = 37) sampling sequences (from here on referred to more accessibly as *brief/explorers*, *exploiters,* and *balanced samplers*, however, not implying stable individual differences).

 While balanced samplers tended to explore and exploit both available information sources by sampling from both categories, the other two clusters captured behavioural patterns towards the opposite ends of the explore-exploit spectrum: *brief*/*explorers* engaged only very briefly, often discovered both information sources but lacked exploitation, whereas *exploiters* recorded on average the longest overall engagement, switched the least and focused most of their triggers towards one category, thereby lacking exploration.

Figure 2

Exploratory Clusters based on behavioural characteristics

 Note. Emerging exploration clusters based on overall engagement (number of triggers), exploitative tendencies (switch-proportion) and sampling systematicity (category entropy, reflected in point size with larger shapes indicating larger entropy values and thus, less predictable structures).

 While a sub-sample of participants (*n* = 8) triggered only one side throughout the 447 experiment, the remaining $n = 60$ did record triggers towards both sides. Interestingly, $n = 2$ of the *exploiters* triggered only one side during warm-up but then only the respective other side during the exploration phase, lending support to the notion that repeated triggering was not necessarily due to a persistent side preference established during the warm-up phase. Furthermore, we found that on average, explorers took the longest to make a trigger and exploiters the shortest (Table 1), supported by a negative Spearman correlation between mean

453 trigger time and overall engagement (*r* = -.38, *p* = .001). While infants in all three clusters

 looked similarly long at the triggered stimuli (which did not correlate with any of the exploration variables), higher rates of gaze-shifting were positively related to higher rates of switching (*r* = .38, *p* = .001) and category entropy meaning triggers towards both categories (*r* 457 = .27, $p = .024$). It should be noted, however, that gaze-shifting did not occur during most stimulus presentations and thus, does not imply overall random or erratic looking behaviour (full correlation matrix of exploration and looking variables in supplementary materials).

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461 **Table 1.** Descriptive statistics per cluster. Means (standard deviations) for each of the 462 characterising variables.

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 Multinomial regressions revealed that cluster membership was independent of age and sex, as neither predictor reached significance (all *ps* > .05), although there seemed to be a slight tendency for the *brief*/*explorers* to be males and *exploiters* to be females.

3.3 Trial-by-trial trigger decisions were associated with behavioural and stimulus-dependent predictors

 We fitted Bayesian hierarchical binomial regression models to investigate the associations between behavioural and stimulus-dependent indicators of learning progress and the likelihood of making an exploratory switch. The behavioural models included 1176 observations, whereas the stimulus-dependent models included 862 observations. In both cases, we specified a Bernoulli family likelihood (as we focus on each trial instead of an 476 individual's distribution of switch events) and a weakly informative prior $[normal(0,2)]$ across beta parameters. This allowed for possibility effect sizes between -4 and 4. All models fitted successfully with sufficient numbers of samples, stationary, well-mixing chains, all rhats at 1.00, and credible posterior predictive checks. Model fit comparisons (see supplementary materials for more details) found that both behavioural (3.1) and stimulus-dependent (3.2) models improved fit compared to their respective intercept models. Adding the cluster interactions (3.3) explained additional variance but did not greatly improve model fit.

 Figures 3 to 5 illustrate the estimated effect sizes as probability distributions, with values further away from zero indicating stronger associations between predictors and outcome variable. If the distribution's mass is below zero the effect of the predictor on the outcome is negative, and if its mass is above zero the effect is positive. A distribution centred on zero indicates that predictor and outcome are not associated.

 3.3.1 Switches were predicted by behavioural measures. The first model investigated the associations between behavioural predictors and the trial-by-trial likelihood to switch to the

 other category. It showed that the effects were in line with our expectations (Fig. 3): there was a positive association between *trigger time* and the likelihood to switch as the variable's 492 distribution's mass was above zero (estimated mean effect $\Delta b = 0.17$, 95%-Credible Interval(CI)[0.02; 0.32]). Thus, longer times to trigger one of the houses indicated that this trigger would likely be a switch to the other category. Furthermore, there was a marginally negative association between *looking time* and the likelihood to switch (^b = -0.04, 95%-CI[- 0.20; 0.13]), indicating a trend for an association between decreased looking time at the presented stimulus and an increased likelihood of switching to the other category on the following trial. Lastly, there was a positive association between *gaze-shifts* and the likelihood 499 to switch, as most of its distribution's mass was above zero (δ = 0.16, 95%-CI[0.00; 0.31]). This suggests that increased gaze-shifting towards the other, not currently triggered side predicted switching towards that side on the next trial.

503 **Figure 3**

504 *Behavioural Predictors for Switching*

505 *Note.* **Left:** probability distributions of effects for each of the behavioural predictors (mean, 506 50% probability interval, and 95%CI). **Right:** Conditional effects of each predictor on the 507 likelihood to make an exploratory switch.

508

 3.3.2 Stimulus similarities interacted with behavioural predictors. This model investigated whether infants' exploratory decisions were sensitive to environmental measures of learning progress as indicated by the similarities between consecutively observed stimuli (Fig. 4).

Figure 4

Interactions between Stimulus Properties and Behavioural Markers

Stimulus Similarity Model

Note. Main effects (A) and interactions (B) of the predictors on the likelihood to switch.

 A: Probability distributions for each main effect of the predictors on the outcome variable, including stimulus similarities. B: Probability distributions for each interaction effect between the stimulus similarities and each predictor. The dark, vertical line indicates the estimate's mean, the shaded area surrounding the mean represents the 50% probability interval, and the distributions' tails cover the 99% probability interval.

 Both effects for *trigger time* (positive) and *looking time* (negative) were consistent with 523 the previous model's findings (trigger time: $\Delta b = 0.24$, 95%-CI[0.04; 0.44]; looking time: $\Delta b =$ -0.16, 95%-CI[-0.39; 0.07]), albeit strengthened, as their mean estimates were now further away from zero. However, the *gaze-shift* effect was now marginally negative (compared to positive at 3.1), meaning that, after reduction of observations and controlling for stimulus 527 similarities, fewer gaze shifts were associated with a higher likelihood to switch $(2b = -0.10,$ 95%-CI[-0.37; 0.15]). *Stimulus similarities* as a main effect had the smallest direct, negative, association with the likelihood to switch, where the probability distribution is almost centred 530 on zero ($b = -0.01$, 95%-CI[-0.26; 0.23]).

 With regards to interactions (Fig. 4B), all three effects were found to be negative and of similar strength. As the interaction effect for *trigger time* was of opposite polarity to its main effect, this indicated a weakening of the main effect for higher similarity (slopes became less steep). In contrast, interactions were of the same polarity (negative) as the main effects for *looking time* and *gaze-shift*, indicating a strengthening of those effects for higher stimulus similarities (slopes became steeper). In practice, this can be interpreted, that after seeing two 537 very similar stimuli, it took comparatively less time to make a switch $(^{\circ}b = -0.09, 95\%$ -CI[- 0.30; 0.13]), possibly suggesting a reduction in switch cost (compare Daw et al., 2006; Hayden 539 et al., 2011). Then, even smaller decreases in looking time ($\&b = -0.17, 95\%$ -CI[-0.43; 0.08]) 540 and fewer gaze-shifts ($\&b = -0.15$, 95%-CI[-0.45; 0.14]) were associated with a higher likelihood to switch. Overall, these findings indicate that infants showed some sensitivity towards similarities between consecutively presented stimuli, in the sense that they interacted with their engagement behaviour.

 3.3.3 Cluster interactions: pulling effects apart. As the cluster analysis found three clusters of exploratory patterns – capturing brief explorative, long exploitative, and more balanced sampling – we wanted to investigate whether the previously found associations between behavioural and stimulus-dependent indicators would differ between the clusters. Thus, we included interaction effects in both models and also looked at the balanced samplers in isolation (see supplementary materials S.12 and S.13).

 We found that *behaviourally*, adding cluster interactions could explain additional 551 variance making the looking time effect more pronounced (δ = -0.10, 95%-CI[-0.28; 0.09]) which seemed to be mainly driven by the balanced samplers as the interaction indicated weaker 553 effects for exploiters (opposite polarity: $\&b = 0.48, 95\%$ -CI[0.02; 0.25]; Figure S3 in

554 supplementary materials). Contrastingly, the positive effects of trigger time (δ = 0.13, 95%-555 CI[-0.04; 0.09]) and gaze-shifts ($\&b = 0.05$, 95%-CI[-0.13; 0.09]) were stronger for the 556 exploiters than balanced samplers (same polarity for trigger time: $\Delta b = 0.14$, 95%-CI[-0.23; 557 0.19] and gaze-shifting: $\delta b = 0.43$, 95%-CI[0.06; 0.19]). Effects were overall weaker for the 558 group of explorers due to low numbers of observations.

559 Further analyses showed that stimulus-similarity interactions were also mainly driven 560 by balanced samplers where we found very similar patterns of the predictors (looking time: δ b 561 = -0.18, 95%-CI[-0.43; 0.06]); trigger-time: ^b = 0.18, 95%-CI[-0.05; 0.12]; gaze-shifts: ^b = 562 -0.10, 95%-CI[-0.37; 0.14]; similarity: $\&b = -0.05$, 95%-CI[-0.31; 0.13]), with stimulus 563 interactions strengthening the looking time effect for balanced samplers ($\delta b = -0.18$, 95%-CI[-564 0.47; 0.15]) but marginally weakening it for exploiters (δ = 0.02, 95%-CI[-0.63; 0.34]). 565 Conversely, stimulus interactions weakened the trigger time effect for balanced samplers (^b 566 = -0.14, 95%-CII-0.39; 0.13]) but strengthened it for exploiters (δ = 0.19, 95%-CII-0.31; 567 0.26]) but with larger margins (see supplementary materials S1.2 & S1.3 for more details and 568 additional figures).

569

570 **4. Discussion**

 We present a powerful new paradigm enabling infants' active exploration within an otherwise controlled environment. Infants triggered the presentation of exemplars from two novel categories via their fixations on screen, allowing them to generate their own sampling sequences. We found a general exploitative tendency with most infants more likely to make consecutive triggers towards the currently sampled information source, representing a category, than to switch to the other. Furthermore, self-generated sequences clustered into three sampling patterns, characterised by length of engagement and balance between exploration and exploitation of either category. The largest emerging group of infants sampled information

 from both categories in a more balanced way than the other two, who respectively presented shorter, more explorative tendencies (lacking exploitation of either category and with little engagement with the study overall), and longer, more exploitative tendencies (lacking exploration of the alternative category). Importantly, infants' pre-switch engagement behaviour (longer trigger time, less looking, and more gaze-shifting) was associated with infants' increased likelihood to make an exploratory switch at the next trial and interacted with experienced stimulus similarities.

 The overall exploitative tendency to consecutively sample from one information source is crucial for knowledge acquisition especially early in development (e.g., Smith et al., 2018) and can be compared to a familiarity preference leading to full encoding of the encountered information (e.g., Rose et al., 1982). Indeed, more naturalistic studies have found similar exploitative tendencies in the way infants engage with objects in their daily lives (Bambach et al., 2018; Smith et al., 2018) and how they structure their engagement with novel toys during free play (Karmazyn-Raz & Smith, 2023). Due to their developing memory capacities, infants may be especially prone to exploiting information, while its reduction across development could be attributed to exploration becoming more flexible and efficient (Meder et al., 2021; Pelz & Kidd, 2020; Ruggeri et al., 2016).

 Furthermore, we observed that infant-generated sequences grouped into three clusters capturing brief explorative, long exploitative, and more balanced sampling, the latter being characterised by exploration and exploitation of both categories. Note that the labels were chosen with the explicit aim to describe the clusters on one key dimension - between exploration and exploitation. Although some of the sequences were very short, it was notable that in these short sequences infants often switched between categories instead of repeatedly sampling the same category, so that these brief sequences are better described as explorative than exploitative. However, more conservative approaches may have excluded infants with few triggers, in which case the more *balanced* sequences would have been called explorative, instead.

 While the *brief*/*explorers* may not have been curious enough about revealing the exemplars in the two houses, or possibly found the setting too unfamiliar and thus only engaged shortly, they nevertheless tended to discover both categories but did not exploit their information potential by creating longer within-category runs. In contrast, *exploiters* engaged the longest but mainly focused on one category and thus missed the opportunity to explore and exploit the second category's information potential. While 36% of *exploiters* did stick to one side throughout the experiment, the remaining 64% also discovered the other side as an information source but did not exploit its potential. This could either indicate a prevailing familiarity preference with which the discovery of the other, unfamiliar category could not compete, or a preferential engagement with the same, repeated motor behaviour.

 However, in studies with toddlers (14-30 months of age) on manual exploration of objects from different categories, Mandler and colleagues (1987, 1991) found similar patterns, characterised as either exhaustive categorisers who, similar to our *balanced samplers*, generated runs of touching exemplars from one or the other category in turn, single categorisers who focused on one category, similar to our *exploiters*, or non-categorisers who did not systematically engage with either category, similar to our *brief/explorers*. Thus, our results present converging evidence with these findings, indicating that similar exploratory patterns can be found across age groups and exploration modalities. Although group membership in our study was not significantly related to age or sex, these exploration patterns may be associated with aspects of cognitive development such as processing speed (manifesting in habituation paradigms: Cao et al., 2023; Feldman & Mayes, 1999), cognitive control (Munakata et al., 2012; Pelz et al., 2015), or personality traits such as temperament (Rothbart, 2007; van den Boom, 1994). Yet, the current paper makes no assumptions of these patterns directly reflecting

 stable individual differences as no test-retest reliability or comparative behaviour was assessed. Future work will address these questions.

 Lastly, we found that infants' engagement behaviour in interaction with stimulus similarities (but not smaller or larger similarities directly; compare Twomey & Westermann, 2018) was associated with their likelihood to re-engage or make an exploratory switch. This indicates that it is not only the information the environment offers that predicts disengagement (Kidd et al., 2012; Poli et al., 2020) but also to what degree the agent engages with said information. For instance, longer looking was predictive of re-engagement with the current information source as would be expected from habituation paradigms and familiarity preferences, indicating that the infant still has more information to encode (e.g., Rose et al., 1982). Conversely, infants were more likely to make a switch on the following trial after looking less at the presented stimulus, and especially so if it was visually highly similar to the previously encountered exemplar, thus, not offering additional information about the category. This looking time effect was most pronounced for the cluster of *balanced samplers*, which may indicate that their behaviour was most in line with the mentioned habituation paradigms and theoretical assumptions made by the explore-exploit framework if the engagement is mainly driven by the sampled and encoded information.

 In contrast, the other clusters may have been more affected by dynamics such as the cognitive switch cost attributed to inhibiting repeated sampling behaviour and redirecting one's attention (Daw et al., 2006; Hayden et al., 2011; Pelz et al., 2015). This cost was observed here as the trigger time effect with longer durations predicting a switch and was most pronounced in the cluster of *exploiters,* suggesting that if they did manage to inhibit their exploitative tendency, they were very likely to make a switch. Lastly, we observed that, before making a switch at the next trial, infants shifted their gaze more towards the non-triggered side during stimulus presentation. This effect, however, disappeared when including the stimulus

 similarities. Due to the nature of consequently excluded observations (e.g., switch trials), this may indicate that infants were especially likely to shift their gaze in a comparative manner after making a switch (Kovack-Lesh et al., 2008; Oakes et al., 2009) and then returned to the previously triggered category.

 Together these findings are also in line with assumptions of the learning progress hypothesis (Altmann et al., 2021; Oudeyer et al., 2007; Poli et al., 2024; Twomey & Westermann, 2018) while offering exciting new insights into the systematicity of infants' exploration history guiding their active sampling behaviour previously only shown for engagement in fully structured infant studies (e.g., Poli et al., 2020).

4.1 Methodological Considerations

 The three variables characterising different aspects of the exploration sequences were chosen prior to inspecting the data. We found, however, that in this paradigm with only two options, switch proportion and category entropy were highly correlated and thus explained very similar variance in the data. Future studies with two options might consider only including switch proportion whereas all three might be more informative for paradigms with multiple sampling options.

 Twenty-nine per cent of infants in this study fell into the cluster of *exploiters*, who triggered mostly or even exclusively one of the two novel categories. As suggested, this behaviour may either be indicative of a prevailing familiarity preference or a lack of cognitive control to overcome the cost of disengaging from a repeated behaviour and could be a remnant of the developmental phenomenon of low-level, visual stickiness (Colombo, 2001; Kulke et al., 2015; Wass & Smith, 2014). Such stickiness itself should, however, disappear by about nine months of age (e.g., Wass & Smith, 2014) and would, by definition, be interrupted here by the central, gaze-contingent attention-getter. Thus, rather than continued staring,

 exploitation of a category required active re-engagement at each trial, making the other explanations more likely.

 While we aimed to keep the warm-up phase as unstructured as possible to truly gauge infants' self-guided exploration, future studies may want to include controls ensuring at least three warm-up triggers to realise the mechanism (Wang et al., 2012), as well as at least one trigger towards all gaze-contingent areas on the screen. This could avoid the possibility that some infants remain ignorant of other potential information sources they could engage with. Nevertheless, by enhancing ecological validity but also accepting the thereby increased variance in the data, our study provides important insights into infants' active sampling behaviours reflecting that exploration is also a skill and might require initial guidance (Matas et al., 1978; McQuillan et al., 2020; Vygotsky & Cole, 1978).

 The stimuli being complex visual categories did not allow us to compute trial-based learning progress in a more straightforward way as was possible in previous studies investigating improvements in anticipation of a target's location (Poli et al., 2020, 2022). Nevertheless, we were able to show convergent evidence for the association between infants' engagement behaviour and information sampling behaviour in interaction with the experienced stimulus characteristics as proximal indicators of learning progress. Future studies could seek to gather differentiating insights into predominantly environmental exploration (e.g., number of/cost associated with interactive information sources; Wang et al., 2012; Bazhydai et al., 2022) compared to predominantly information-based exploration (e.g., manipulating stimulus similarities or reward value; Tummeltshammer et al., 2014).

4.2 Conclusion

 In this study, 10-12-month-old infants self-generated exploration sequences within the novel Curious Choices paradigm. This allowed us to gather new insights into both, general patterns of curiosity-driven exploration in infants, e.g., exploitative tendencies, but also the

 mechanisms underlying such dynamic behaviour. Importantly, for the first time, we showed that moment-to-moment sampling choices were not spontaneous but associated with the infant's preceding engagement behaviour modulated by the information offered from the presented stimuli. However, we also observed a large variance within infants' curiosity-based information sampling which may be constrained by their developing exploration skills. A remaining question is whether the observed exploration tendencies are stable and related to other aspects of development, which we are currently investigating. Together, we offer new methodological avenues for future research into infants' active exploration and present novel insights converging with and expanding the current literature regarding this crucial aspect of human development.

Author contributions

 Elena Altmann: Conceptualisation; Data curation; Formal analysis; Investigation; Methodology; Project administration; Software; Visualisation; Writing - original draft; and Writing - review & editing. **Marina Bazhydai:** Conceptualisation; Methodology; Supervision; Writing - review & editing. **Gert Westermann:** Conceptualisation; Funding acquisition; Methodology; Supervision; Writing - review & editing.

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- Bazhydai, M., Westermann, G., & Parise, E. (2020). "I don't know but I know who to ask": 12-month-olds actively seek information from knowledgeable adults. *Developmental Science*, *23*(5), e12938. https://doi.org/10.1111/desc.12938
- Begus, K., Gliga, T., & Southgate, V. (2014). Infants Learn What They Want to Learn: Responding to Infant Pointing Leads to Superior Learning. *PLoS ONE*, *9*(10), e108817. https://doi.org/10.1371/journal.pone.0108817
- Begus, K., & Southgate, V. (2018). Curious Learners: How Infants' Motivation to Learn Shapes and Is Shaped by Infants' Interactions with the Social World. In M. M. Saylor
- & P. A. Ganea (Eds.), *Active Learning from Infancy to Childhood: Social Motivation,*
- *Cognition, and Linguistic Mechanisms* (pp. 13–37). Springer International Publishing.
- https://doi.org/10.1007/978-3-319-77182-3_2
- Berlyne, D. E. (1960). *Conflict, arousal, and curiosity* (pp. xii, 350). McGraw-Hill Book Company. https://doi.org/10.1037/11164-000
- Blanco, N. J., & Sloutsky, V. M. (2020). Attentional mechanisms drive systematic exploration in young children. *Cognition*, *202*, 104327. https://doi.org/10.1016/j.cognition.2020.104327
- Bono, M. A., & Stifter, C. A. (2003). Maternal Attention-Directing Strategies and Infant Focused Attention During Problem Solving. *Infancy*, *4*(2), 235–250. 772 https://doi.org/10.1207/S15327078IN0402_05
- Bourgeois, K. S., Khawar, A. W., Neal, S. A., & Lockman, J. J. (2005). Infant Manual Exploration of Objects, Surfaces, and Their Interrelations. *Infancy*, *8*(3), 233–252. https://doi.org/10.1207/s15327078in0803_3
- Bremner, J. G., Slater, A. M., & Johnson, S. P. (2015). Perception of Object Persistence: The Origins of Object Permanence in Infancy. *Child Development Perspectives*, *9*(1), 7–13.
- https://doi.org/10.1111/cdep.12098

- Bürkner, P.-C. (2017). brms: An R package for Bayesian multilevel models using Stan. *Journal of Statistical Software*, *80*, 1–28.
- Bushnell, I. w. r. (2001). Mother's face recognition in newborn infants: Learning and memory. *Infant and Child Development*, *10*(1–2), 67–74. https://doi.org/10.1002/icd.248
- Cao, A., Raz, G., Saxe, R., & Frank, M. C. (2023). Habituation Reflects Optimal Exploration Over Noisy Perceptual Samples. *Topics in Cognitive Science*, *15*(2), 290–302. https://doi.org/10.1111/tops.12631
- Charnov, E. L. (1976). Optimal foraging, the marginal value theorem. *Theoretical Population Biology*, *9*(2), 129–136. https://doi.org/10.1016/0040-5809(76)90040-X
- Chen, C., Houston, D. M., & Yu, C. (2021). Parent–Child Joint Behaviors in Novel Object Play Create High-Quality Data for Word Learning. *Child Development*, *92*(5), 1889–1905.

https://doi.org/10.1111/cdev.13620

- Chen, X., Twomey, K. E., & Westermann, G. (2022). Curiosity enhances incidental object encoding in 8-month-old infants. *Journal of Experimental Child Psychology*, *223*, 105508. https://doi.org/10.1016/j.jecp.2022.105508
- Colombo, J. (2001). The Development of Visual Attention in Infancy. *Annual Review of Psychology*, *52*(1), 337–367. https://doi.org/10.1146/annurev.psych.52.1.337
- Cross, G. R., & Jain, A. K. (1982). MEASUREMENT OF CLUSTERING TENDENCY**Research supported in part by NSF Grant ECS-8007106. In A. K. Mahalanabis (Ed.), *Theory and Application of Digital Control* (pp. 315–320).
- Pergamon. https://doi.org/10.1016/B978-0-08-027618-2.50054-1
- Daw, N. D., O'Doherty, J. P., Dayan, P., Seymour, B., & Dolan, R. J. (2006). Cortical substrates for exploratory decisions in humans. *Nature*, *441*(7095), Article 7095. https://doi.org/10.1038/nature04766
- DeCasper, A. J., & Spence, M. J. (1986). Prenatal maternal speech influences newborns' perception of speech sounds. *Infant Behavior and Development*, *9*(2), 133–150. https://doi.org/10.1016/0163-6383(86)90025-1
- Dubey, R., & Griffiths, T. L. (2020). Reconciling novelty and complexity through a rational analysis of curiosity. *Psychological Review*, *127*(3), 455–476. https://doi.org/10.1037/rev0000175
- Fantz, R. L. (1964). Visual Experience in Infants: Decreased Attention to Familiar Patterns Relative to Novel Ones. *Science*, *146*(3644), 668–670. https://doi.org/10.1126/science.146.3644.668
- Feldman, R., & Mayes, L. C. (1999). *THE CYCLIC ORGANIZATION OF AITENTION DURING HABITUATION IS RELATED TO INFANTS" INFORMATION PROCESSING*. *22*(1).
- Fontenelle, S. A., Alexander Kahrs, B., Ashley Neal, S., Taylor Newton, A., & Lockman, J. J.
- (2007). Infant manual exploration of composite substrates. *Journal of Experimental Child Psychology*, *98*(3), 153–167. https://doi.org/10.1016/j.jecp.2007.07.001
- Gaither, S. E., Pauker, K., & Johnson, S. P. (2012). Biracial and monoracial infant own-race
- face perception: An eye tracking study. *Developmental Science*, *15*(6), 775–782. https://doi.org/10.1111/j.1467-7687.2012.01170.x
- Gerken, L., Balcomb, F. K., & Minton, J. L. (2011). Infants avoid 'labouring in vain' by attending more to learnable than unlearnable linguistic patterns. *Developmental Science*, *14*(5), 972–979. https://doi.org/10.1111/j.1467-7687.2011.01046.x
- Goldstein, M. H., Schwade, J., Briesch, J., & Syal, S. (2010). Learning While Babbling: Prelinguistic Object-Directed Vocalizations Indicate a Readiness to Learn. *Infancy*,
- *15*(4), 362–391. https://doi.org/10.1111/j.1532-7078.2009.00020.x

- Goupil, L., & Proust, J. (2023). Curiosity as a metacognitive feeling. *Cognition*, *231*, 105325. https://doi.org/10.1016/j.cognition.2022.105325
- Gruber, M. J., Gelman, B. D., & Ranganath, C. (2014). States of Curiosity Modulate Hippocampus-Dependent Learning via the Dopaminergic Circuit. *Neuron*, *84*(2), 486– 496. https://doi.org/10.1016/j.neuron.2014.08.060
- Hayden, B. Y., Pearson, J. M., & Platt, M. L. (2011). Neuronal basis of sequential foraging decisions in a patchy environment. *Nature Neuroscience*, *14*(7), Article 7. https://doi.org/10.1038/nn.2856
- Hessels, R. S., Niehorster, D. C., Kemner, C., & Hooge, I. T. C. (2017). Noise-robust fixation
- detection in eye movement data: Identification by two-means clustering (I2MC). *Behavior Research Methods*, *49*(5), 1802–1823. https://doi.org/10.3758/s13428-016- 0822-1
- Hoch, J. E., O'Grady, S. M., & Adolph, K. E. (2019). It's the journey, not the destination: Locomotor exploration in infants. *Developmental Science*, *22*(2), e12740. https://doi.org/10.1111/desc.12740
- 842 Hunter, M. A., & Ames, E. W. (1988). A multifactor model of infant preferences for novel and familiar stimuli. *Advances in Infancy Research*, *5*, 69–95.
- Kang, M. J., Hsu, M., Krajbich, I. M., Loewenstein, G., McClure, S. M., Wang, J. T., & Camerer, C. F. (2009). The Wick in the Candle of Learning: Epistemic Curiosity Activates Reward Circuitry and Enhances Memory. *Psychological Science*, *20*(8), 963–
- 973. https://doi.org/10.1111/j.1467-9280.2009.02402.x
- Karasik, L. B., Tamis-LeMonda, C. S., & Adolph, K. E. (2014). Crawling and walking infants elicit different verbal responses from mothers. *Developmental Science*, *17*(3), 388–395. https://doi.org/10.1111/desc.12129

- Karmazyn-Raz, H., & Smith, L. B. (2023). Sampling statistics are like story creation: A network analysis of parent–toddler exploratory play. *Philosophical Transactions of the*
- *Royal Society B: Biological Sciences*, *378*(1870), 20210358. https://doi.org/10.1098/rstb.2021.0358
- Kaufman, L., & Rousseeuw, P. J. (2009). *Finding Groups in Data: An Introduction to Cluster Analysis*. John Wiley & Sons.
- Keemink, J. R., Keshavarzi-Pour, M. J., & Kelly, D. J. (2019). Infants' responses to interactive gaze-contingent faces in a novel and naturalistic eye-tracking paradigm. *Developmental Psychology*, *55*(7), 1362–1371. https://doi.org/10.1037/dev0000736
- Kiat, J. E., Luck, S. J., Beckner, A. G., Hayes, T. R., Pomaranski, K. I., Henderson, J. M., & Oakes, L. M. (2022). Linking patterns of infant eye movements to a neural network model of the ventral stream using representational similarity analysis. *Developmental*

Science, *25*(1), e13155. https://doi.org/10.1111/desc.13155

- Kidd, C., & Hayden, B. Y. (2015). The Psychology and Neuroscience of Curiosity. *Neuron*, *88*(3), 449–460. https://doi.org/10.1016/j.neuron.2015.09.010
- Kidd, C., Piantadosi, S. T., & Aslin, R. N. (2012). The Goldilocks Effect: Human Infants Allocate Attention to Visual Sequences That Are Neither Too Simple Nor Too Complex. *PLoS ONE*, *7*(5), e36399. https://doi.org/10.1371/journal.pone.0036399
- Kidd, C., Piantadosi, S. T., & Aslin, R. N. (2014). The Goldilocks Effect in Infant Auditory Attention. *Child Development*, n/a-n/a. https://doi.org/10.1111/cdev.12263
- Kovack-Lesh, K. A., Horst, J. S., & Oakes, L. M. (2008). The Cat is out of the Bag: The Joint
- Influence of Previous Experience and Looking Behavior on Infant Categorization.
- *Infancy*, *13*(4), 285–307. https://doi.org/10.1080/15250000802189428
- Kulke, L., Atkinson, J., & Braddick, O. (2015). Automatic Detection of Attention Shifts in Infancy: Eye Tracking in the Fixation Shift Paradigm. *PLOS ONE*, *10*(12), e0142505. https://doi.org/10.1371/journal.pone.0142505
- Lucca, K., & Wilbourn, M. P. (2019). The what and the how: Information-seeking pointing gestures facilitate learning labels and functions. *Journal of Experimental Child Psychology*, *178*, 417–436. https://doi.org/10.1016/j.jecp.2018.08.003
- 880 Mandler, J. M., Bauer, P. J., & McDonough, L. (1991). Separating the sheep from the goats: Differentiating global categories. *Cognitive Psychology*, *23*(2), 263–298. https://doi.org/10.1016/0010-0285(91)90011-C
- Mandler, J. M., Fivush, R., & Reznick, J. S. (1987). The development of contextual categories. *Cognitive Development*, *2*(4), 339–354. https://doi.org/10.1016/S0885- 2014(87)80012-6
- Mani, N., & Ackermann, L. (2018). Why Do Children Learn the Words They Do? *Child Development Perspectives*, *12*(4), 253–257. https://doi.org/10.1111/cdep.12295
- Matas, L., Arend, R., & Sroufe, L. A. (1978). Continuity of Adaptation in the Second Year: The Relationship between Quality of Attachment and Later Competence. *Child Development - CHILD DEVELOP*, *49*, 547–556. https://doi.org/10.1111/j.1467- 8624.1978.tb02354.x
- McQuillan, M. E., Smith, L. B., Yu, C., & Bates, J. E. (2020). Parents Influence the Visual Learning Environment Through Children's Manual Actions. *Child Development*, *91*(3), e701–e720. https://doi.org/10.1111/cdev.13274
- Meder, B., Wu, C. M., Schulz, E., & Ruggeri, A. (2021). Development of directed and random exploration in children. *Developmental Science*, *24*(4), e13095. https://doi.org/10.1111/desc.13095

- Mendive, S., Bornstein, M. H., & Sebastián, C. (2013). The role of maternal attention-directing strategies in 9-month-old infants attaining joint engagement. *Infant Behavior and Development*, *36*(1), 115–123. https://doi.org/10.1016/j.infbeh.2012.10.002
- Miyazaki, M., Takahashi, H., Rolf, M., Okada, H., & Omori, T. (2015). The image-scratch paradigm: A new paradigm for evaluating infants' motivated gaze control. *Scientific Reports*, *4*(1), 5498. https://doi.org/10.1038/srep05498
- Munakata, Y., Snyder, H. R., & Chatham, C. H. (2012). Developing Cognitive Control: Three Key Transitions. *Current Directions in Psychological Science*, *21*(2), 71–77. https://doi.org/10.1177/0963721412436807
- Oakes, L. M., Kovack-Lesh, K. A., & Horst, J. S. (2009). Two are better than one: Comparison influences infants' visual recognition memory. *Journal of Experimental Child Psychology*, *104*(1), 124–131. https://doi.org/10.1016/j.jecp.2008.09.001
- Oakes, L. M., Madole, K. L., & Cohen, L. B. (1991). Infants' object examining: Habituation and categorization. *Cognitive Development*, *6*(4), 377–392. https://doi.org/10.1016/0885-2014(91)90045-F
- Oudeyer, P.-Y., Kaplan, F., & Hafner, V. V. (2007). Intrinsic Motivation Systems for
- Autonomous Mental Development. *IEEE Transactions on Evolutionary Computation*,
- *11*(2), 265–286. IEEE Transactions on Evolutionary Computation. https://doi.org/10.1109/TEVC.2006.890271
- Oudeyer, P.-Y., & Smith, L. B. (2016). How Evolution May Work Through Curiosity-Driven Developmental Process. *Topics in Cognitive Science*, *8*(2), 492–502. https://doi.org/10.1111/tops.12196
- Pelz, M., & Kidd, C. (2020). The elaboration of exploratory play. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *375*(1803), 20190503. https://doi.org/10.1098/rstb.2019.0503

- Pelz, M., Piantadosi, S. T., & Kidd, C. (2015). The dynamics of idealized attention in complex
- learning environments. *2015 Joint IEEE International Conference on Development and*
- *Learning and Epigenetic Robotics (ICDL-EpiRob)*, 236–241. https://doi.org/10.1109/DEVLRN.2015.7346147
- Piaget, J. (n.d.). *Piaget's theory* (Vol. 1).
- Poli, F., Meyer, M., Mars, R. B., & Hunnius, S. (2022). Contributions of expected learning progress and perceptual novelty to curiosity-driven exploration. *Cognition*, *225*, 105119. https://doi.org/10.1016/j.cognition.2022.105119
- Poli, F., O'Reilly, J. X., Mars, R. B., & Hunnius, S. (2024). Curiosity and the dynamics of optimal exploration. *Trends in Cognitive Sciences*, *0*(0). https://doi.org/10.1016/j.tics.2024.02.001
- Poli, F., Serino, G., Mars, R. B., & Hunnius, S. (2020). Infants tailor their attention to maximize learning. *Science Advances*, *6*(39), eabb5053. https://doi.org/10.1126/sciadv.abb5053
- Pridham, K., Becker, P., & Brown, R. (2000). Effects of infant and caregiving conditions on an infant's focused exploration of toys. *Journal of Advanced Nursing*, *31*(6), 1439–
- 1448. https://doi.org/10.1046/j.1365-2648.2000.01448.x
- Reio Jr., T. G., Petrosko, J., Wiswell, A., & Thongsukmag, J. (2006). The Measurement and Conceptualization of Curiosity. *The Journal of Genetic Psychology*, *167*(2), 117–135. https://doi.org/10.3200/GNTP.167.2.117-135
- Rodriguez, E. T., & Tamis-LeMonda, C. S. (2011). Trajectories of the Home Learning Environment Across the First 5 Years: Associations With Children's Vocabulary and Literacy Skills at Prekindergarten. *Child Development*, *82*(4), 1058–1075.
- https://doi.org/10.1111/j.1467-8624.2011.01614.x
- Rose, S. A., Gottfried, A. W., Melloy-Carminar, P., & Bridger, W. H. (1982). Familiarity and novelty preferences in infant recognition memory: Implications for information

- processing. *Developmental Psychology*, *18*(5), 704–713. https://doi.org/10.1037/0012- 1649.18.5.704
- Rothbart, M. (2007). Temperament, Development, and Personality. *Current Directions in Psychological Science*, *16*, 207–212. https://doi.org/10.1111/j.1467- 8721.2007.00505.x
- Rousseeuw, P. J. (1987). Silhouettes: A graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics*, *20*, 53–65. https://doi.org/10.1016/0377-0427(87)90125-7
- Ruggeri, A., Lombrozo, T., Griffiths, T. L., & Xu, F. (2016). Sources of developmental change
- in the efficiency of information search. *Developmental Psychology*, *52*(12), 2159– 2173. https://doi.org/10.1037/dev0000240
- Schatz, J. L., Suarez-Rivera, C., Kaplan, B. E., & Tamis-LeMonda, C. S. (2022). Infants' object interactions are long and complex during everyday joint engagement. *Developmental Science*, *25*(4), e13239. https://doi.org/10.1111/desc.13239
- Schulz, E., Wu, C. M., Ruggeri, A., & Meder, B. (2019). Searching for Rewards Like a Child
- Means Less Generalization and More Directed Exploration. *Psychological Science*, *30*(11), 1561–1572. https://doi.org/10.1177/0956797619863663
- Shannon, C. E. (1948). A mathematical theory of communication. *The Bell System Technical Journal*, *27*(3), 379–423. The Bell System Technical Journal. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x
- Siqueland, E. R., & DeLucia, C. A. (1969). Visual Reinforcement of Nonnutritive Sucking in Human Infants. *Science*, *165*(3898), 1144–1146. https://doi.org/10.1126/science.165.3898.1144
- Slone, L. K., Smith, L. B., & Yu, C. (2019). Self-generated variability in object images predicts vocabulary growth. *Developmental Science*, *22*(6), e12816. https://doi.org/10.1111/desc.12816
- Smith, L. B., Jayaraman, S., Clerkin, E., & Yu, C. (2018). The Developing Infant Creates a Curriculum for Statistical Learning. *Trends in Cognitive Sciences*, *22*(4), 325–336. https://doi.org/10.1016/j.tics.2018.02.004
- Somerville, L. H., Sasse, S. F., Garrad, M. C., Drysdale, A. T., Abi Akar, N., Insel, C., & Wilson, R. C. (2017). Charting the expansion of strategic exploratory behavior during adolescence. *Journal of Experimental Psychology: General*, *146*(2), 155–164. https://doi.org/10.1037/xge0000250
- Stahl, A. E., & Feigenson, L. (2015). Observing the unexpected enhances infants' learning and exploration. *Science*, *348*(6230), 91–94. https://doi.org/10.1126/science.aaa3799
- Suarez-Rivera, C., Smith, L. B., & Yu, C. (2019). Multimodal parent behaviors within joint attention support sustained attention in infants. *Developmental Psychology*, *55*(1), 96– 109. https://doi.org/10.1037/dev0000628
- Sučević, J., Althaus, N., & Plunkett, K. (2021). The role of labels and motions in infant category learning. *Journal of Experimental Child Psychology*, *205*, 105062. https://doi.org/10.1016/j.jecp.2020.105062
- Tamis-LeMonda, C. S., Kuchirko, Y., & Tafuro, L. (2013). From Action to Interaction: Infant
- Object Exploration and Mothers' Contingent Responsiveness. *IEEE Transactions on Autonomous Mental Development*, *5*(3), 202–209. https://doi.org/10.1109/TAMD.2013.2269905
- Tummeltshammer, K. S., Mareschal, D., & Kirkham, N. Z. (2014). Infants' Selective Attention to Reliable Visual Cues in the Presence of Salient Distractors. *Child Development*, n/a-n/a. https://doi.org/10.1111/cdev.12239
- Twomey, K. E., & Westermann, G. (2018). Curiosity-based learning in infants: A neurocomputational approach. *Developmental Science*, *21*(4), e12629. https://doi.org/10.1111/desc.12629
- van den Boom, D. C. (1994). The Influence of Temperament and Mothering on Attachment
- and Exploration: An Experimental Manipulation of Sensitive Responsiveness among
- Lower-Class Mothers with Irritable Infants. *Child Development*, *65*(5), 1457–1477. https://doi.org/10.2307/1131511
- Vygotsky, L. S., & Cole, M. (1978). *Mind in Society: Development of Higher Psychological Processes*. Harvard University Press.
- Wang, Q., Bolhuis, J., Rothkopf, C. A., Kolling, T., Knopf, M., & Triesch, J. (2012). Infants in Control: Rapid Anticipation of Action Outcomes in a Gaze-Contingent Paradigm. *PLoS ONE*, *7*(2), e30884. https://doi.org/10.1371/journal.pone.0030884
- Wass, S. V., & Smith, T. J. (2014). Individual Differences in Infant Oculomotor Behavior During the Viewing of Complex Naturalistic Scenes. *Infancy*, *19*(4), 352–384. https://doi.org/10.1111/infa.12049
- Williams, P. (1998). *Representational Organization of Multiple Exemplars of Object Categories*. 21.
- Yu, C., & Smith, L. B. (2012). Embodied attention and word learning by toddlers. *Cognition*, *125*(2), 244–262. https://doi.org/10.1016/j.cognition.2012.06.016
- Zettersten, M. (2020). *Seeking New Words: Active Word Learning in Infants and Children* [Ph.D., The University of Wisconsin - Madison]. https://search.proquest.com/docview/2408896456/abstract/E02DABE6983D46B2PQ/ 1
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Figure S1

Distributions of observed and simulated exploration variables

 A: Overall engagement as illustrated by the distribution of triggers across participants **B:** Exploitative tendencies as indicated by majority of switch-proportions being below 50% (vertical line), **C:** Simulated switch-proportions based on a chance mechanism (1000 draws per

 participant based on their number of triggers) **D:** Distribution of longest continuous runs (consecutively triggering the same category) per participant, **E:** Category entropies across participants, where higher values indicate more similar number of triggers towards both categories and the minimum of 0 indicates that all triggers were towards only one category, and **F**: Simulated category entropies based on a chance mechanism.

S1 Trial-by-trial trigger decision predictions

S1.1 Model comparisons

 S1.1.1 Behavioural Models. Model fit comparison based on the leave-one-out cross validation values (looic) measure (Fig. S2, left) showed that the main model greatly improved the fit compared to the intercept model as its looic value is substantially smaller and standard errors are not overlapping. Adding the interaction terms for clusters did improve the fit further, however, the standard errors are widely overlapping suggesting that the added complexity may not be worth the fit improvement.

Figure S2

Model Comparisons

Note. Model comparisons based on the leave-one-out cross validation (looic) values on the x-

axis. Smaller looic values suggest better fit. Standard errors are indicated.

 Left: Behavioural models (with reference to 3.1 and 3.3). Right: Stimulus-dependent models (with reference to 3.2).

 S1.1.2 Stimulus-dependent Models. Model fit comparison based on the looic measure (Fig. S2, right) showed that the main model improved the fit compared to the intercept model as its looic value is substantially smaller and standard errors are not overlapping. Adding the interaction terms for clusters did improve the fit further, however, the standard errors are widely overlapping suggesting that the added complexity may not be worth the fit improvement.

Figure S3

 -0.25

 0.00

Estimate

 0.25

 0.50

1067 *Note.* Probability distributions for each of the behavioural predictors on the outcome variable. 1068 **A**: main effects. **B**: Interaction effects comparing the *balanced samplers* to the *explorers*. **C**: 1069 Interaction effects comparing the *balanced samplers* to the *exploiters*.

 -4

 $\frac{0}{\text{Estimate}}$

 $\overline{4}$

 -0.5

 0.0

 0.5
Estimate

 1.0

 $\overline{1.5}$

 If the interaction effect is of the same polarity as the main effect (e.g., both negative), it indicates a strengthening of that effect in the comparative group (slopes become steeper). If the interaction effect is of opposing polarity, the effect is weaker in the comparative group (slopes become less steep).

1074

1075 **S1.2 Three-way interactions**

 In more detail, the main effects are still the same in polarity and look mostly like the main model (Fig. S4A). The three stimulus similarity interaction effects reported above have strengthened with slightly more negative values (Fig. S4B). The 3-way-interactions then indicate to what degree these interaction effects differ between clusters (Figures S4C, S4D). If the terms have the same polarity, the comparison cluster seems to have a stronger effect, whereas opposite polarities suggest a weaker interaction effect for that cluster. Regarding looking time, interaction terms for both explorers and exploiters are centred around zero indicating that there are no differences between clusters in the way that stimulus similarities affect looking time and in turn the likelihood to switch. In contrast, the interaction effects for

 the other two predictors are positive across clusters indicating that there are differences between the clusters. As noted above, the simple interactions are all negative which means they are of opposing polarity to these 3-way-interactions. This indicates that both, the effect of stimulus similarity on trigger time and on gaze-shifts is weaker for explorers and exploiters compared to the balanced samplers. This suggests that the main effects and interaction effects may be stronger if we had only looked at the balanced samplers.

Figure S4

Effects for 3-way interaction model

 Note. Probability distributions for each of the behavioural predictors on the outcome variable. A: main effects of the behavioural predictors on likelihood to switch. B: Simple interaction effects of stimulus similarities on the behavioural predictors. C: 3-way-interaction comparing how similarity interaction effects differ between *explorers* compared to *balanced samplers*. D: 3-way-interaction comparing how similarity interaction effects differ between *exploiters* compared to *balanced samplers*. Note the scale difference for the *explorer* plot, which is likely due to the limited number of observations in the cluster of explorers.

S1.3 Balanced samplers in isolation

 As the 3-way interactions suggested that the effects were mostly driven by the balanced samplers, we decided to look at this group in isolation. This model included 405 observations

 and fit successfully. Indeed, main effects and interaction effects were comparable to the other two stimulus-dependent models, and therefore in line with the notion that those were mostly 1106 driven by this group. Here, looking time (\textdegree b = -0.18, 95%-CI[-0.43; 0.06]) and trigger time (\textdegree b 1107 = 0.18, 95%-CI[-0.05; 0.42]) had similarly strong effects, whereas both, gaze-shifts (δb = -1108 0.09, 95%-CI[-0.37; 0.18]) and stimulus similarities ($\&b = -0.04$, 95%-CI[-0.31; 0.21]) were only marginally negatively associated with higher likelihood to switch. All three interaction effects are again negative, meaning a strengthening of looking-time and gaze-shift effects and a weakening of the trigger-time effect for higher stimulus similarities.

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- **Figure S5**
- *Effects for Balanced Samplers in isolation*

 Note. Main effects (A) and interactions (B) of the predictors on the likelihood to switch when isolating the cluster of balanced samplers. **A**: Probability distributions for each main effect of the predictors on the outcome variable, including stimulus similarities. **B**: Probability distributions for each interaction effect between the stimulus similarities and each predictor.

S2 Adult Experiment

S2.1 Similarity Ratings

The novel stimuli used in the reported infant study were taken from the open $TarrLab¹$ repository. Two species of *Fribbles* from different families were chosen, under the consideration of not having a dominantly salient, variable body part (Barry et al., 2014). Perceptual differences between two stimuli from the same species, then, are mainly defined by counting the body parts in which they differ (0 to 4) as the variations are nominally different (Williams, 1998). However, it may be that subjective similarity between the stimuli does not perfectly map onto this objective way of categorising the differences (see Barry et al., 2014 with different stimulus sets) but could allow for more nuanced, perceptual measures of similarity. Thus, the aim of this supplementary study was to collect similarity ratings for each possible pair of the 30 stimuli for each category to account for subjective rather than objective measures. We collected the ratings for each possible pair as the presentation of stimuli in the study was randomised without repetition. This led to 465 possible pairs per category. To minimise fatigue effects, each participant was asked to only rate 155 pairs from one category.

S2.2 Methods

S2.2.1 Participants

 Participants were recruited over Prolific [\(www.prolific.co\)](https://prolific.co/) [2021] and the final sample consisted of 45 participants who completed the study (Mean age = 27.41, range = 18 to 54 years, 52.4% female) so that each individual pair would be rated seven times. One additional participant was excluded has they left the experiment after 12 trials. Prolific suggests to shortly inspect the data visually before accepting or rejecting submissions as one shortcoming of these online platforms is that participants sometimes do not submit high quality data. Based on such inspection, three further participants were messaged about their very short rating times suggesting a lack of attention necessary for conscious assessments. They admitted to these worries based on fatigue from earlier experiments and returned their submissions voluntarily.

S2.2.2 Materials

S2.2.2.1 Stimuli. Novel stimuli were taken from the open TarrLab¹ repository. Species FA2 and FB4 were chosen from which 30 stimuli were semi-randomly selected each, in alternating triplets to sample from the full range of body-part variations including objective differences of all four distances (0-4, Williams, 1998; the full list of included stimuli can be found in the appendix and supplementary online materials).

 S2.2.2.2 Design & Measures. The study was created with PsychoPy3 and online conducted via Pavlovia. First, a list of all possible combinations of stimuli per category was created. Each list was randomly ordered and separated into three equal sets of 155 pairs. This was based on the consideration to not ask for too many ratings per participant to ensure high quality data. Each pair then was presented in random order, where the two stimuli were presented next to each other on grey background for 2 seconds to allow only for a subjective impression of the similarities rather than counting the differences (Barry et al., 2014). Each pair was then rated on a scale from 1 (not similar at all) to 7 (extremely similar). After every 52 stimuli (roughly each third), the participant could take a little break which they could terminate by pressing 'space' but which also automatically ended after 20 seconds.

 S2.2.2.3 Exclusion criteria. Besides the ratings for each pair, the reaction times for each rating was recorded. This was used as a rough indication of data quality as reaction times below 200ms are typically viewed as too short to be conscious and even more so if two stimuli had to be compared. Thus, if the reaction times were too often in the area of 0.1-0.4 seconds when roughly inspecting the data visually, we suspected a lack of attention and contacted the anonymous participant for a follow up. This kind of inspection was only conducted if the completion time was suspiciously low or high – in accordance with Prolific's data quality check suggestion. Out of 45 participants, only three were inspected and contacted this way leading to them returning their submissions voluntarily after admitting they had not completed the study giving their full attention. While this was a subjective exclusion criterion, it did allow for economical recruitment where submissions of clearly lacking data quality were not paid for, but the participants were also not reprimanded by having their submission rejected.

S2.2.3 Analysis

 21 ratings with a reaction time of below 200ms were excluded as these could not be assumed to have been made consciously. Each of these ratings belonged to a different stimulus pair leading to 21 out of 930 pairs receiving six instead of seven scores included in their aggregates. We computed the objective difference count for each pair, as well as the mean score, standard deviation, and range. To investigate the relation between objective and subjective scores, a correlation analysis was conducted and plotted.

S2.3 Results

 The Shapiro-Wilk normality tests indicated that the data for both variables – objective 1186 differences and mean rating scores – were not normally distributed ($p < 0.001$). Thus, a parametric Kendall rank correlation test was computed. This analysis estimated the rank-based measure of association between the two variables to be significantly correlated, so that the 1189 mean similarity scores decreased with the number of differing body parts (r_{tau} = -0.54, p < 0.001). In other words, stimuli were perceived as more similar the more body parts they had in common. As the relation, however, was not exactly one to one, we chose to include these subjective mean scores in any further analyses instead of the objective nominal values as they were deemed more indicative of the perceived differences between consecutively presented stimuli.

2.4 Discussion

 We conducted this supplementary study of collecting similarity ratings between every possible pairing amongst the stimuli included in the related exploration studies. We found that the number of objective differences significantly correlated with the subjective similarity ratings so that mean scores decreased with increasing objective differences. This confirms that objective differences were also subjectively perceived. However, as the relation was not perfect – for instance, pairs of identical stimuli received a number of scores different from the maximum score (7) – this also shows that including the subjective scores may better represent

- the subjective perception of consecutively presented stimuli more so than referring to the
- objective measure. The findings of this study are in accordance with Barry et al. (2014) who
- also found a strong relation between the two whilst suggesting that the objective scores cannot
- perfectly indicate subjective perception.
-