

# How to Make a Proceedings Paper Submission

## Anonymous CogSci submission

### Abstract

Include no author information in the initial submission, to facilitate blind review. The abstract should be one paragraph, indented 1/8 inch on both sides, in 9-point font with single spacing. The heading 'Abstract' should be 10-point, bold, centered, with one line of space below it. This one-paragraph abstract section is required only for standard six page proceedings papers. Following the abstract should be a blank line, followed by the header 'Keywords' and a list of descriptive keywords separated by semicolons, all in 9-point font, as shown below.

**Keywords:** Add your choice of indexing terms or keywords; kindly use a semi-colon; between each term.

Habituation and dishabituation are fundamental processes in learning and cognition. Habituation refers to the decrease in response to a repeated stimulus, while dishabituation describes the renewed increase in response following the introduction of a novel stimulus. These processes are essential for learning from experience and have been widely documented across a broad range of species (Rankin et al., 2009; Thompson, 2009). From single-cell organisms (e.g., Boisseau, Vogel, & Dussutour, 2016; Dussutour, 2021; Ginsburg & Jablonka, 2009) to humans [e.g. Colombo & Mitchell (2009); Jeffrey & Cohen (1971); Sokolov (1990);], habituation and dishabituation enable individuals to filter out repetitive, non-informative stimuli while remaining sensitive to novel or meaningful changes. These mechanisms have become a cornerstone of research methods in cognitive development (Aslin, 2007; Cohen, 2004; Kucharsky, Zaharieva, Raijmakers, & Visser, 2024; Oakes, 2010).

A typical infant study utilizing the habituation paradigm involves repeatedly presenting an infant with the same stimulus until they exhibit a decline in interest, often measured by a progressive decrease in looking time. Once habituation is established (e.g., looking time in the final trials must drop to 50% of initial looking), the infant is presented with two stimuli: one familiar (previously shown) and one novel. A dishabituation response—indicated by significantly longer looking time at the novel stimulus—suggests that the infant can discriminate between the two. Dishabituation magnitude serves as a crucial index of attentional recovery and sensitivity to novel stimuli. As a result, this method – inducing habituation response and testing dishabituation – has been extensively used to investigate infants' perceptual and cognitive development, providing valuable insights into early learning mechanisms.

How do individual differences in habituation and dishabituation reflect underlying cognitive mechanisms and developmental change? Extensive research has explored their variability and predictive value for later cognitive development. In general, findings suggest that the rate of habituation—how quickly an infant's attention declines in response to repeated exposure to a stimulus—is associated with foundational cognitive processes such as information processing speed (Hunter & Ames, 1988; Poli et al., 2024). Infants who habituate more quickly tend to show higher IQ scores, better language acquisition, and stronger executive function abilities in later childhood (Colombo, Shaddy, Richman, Maikranz, & Blaga, 2004; Kavšek, 2004; Slater, 1997). Similarly, individual differences in dishabituation—the extent to which an infant's attention recovers when presented with a novel stimulus—are often interpreted as indicators of memory strength. Greater dishabituation responses have been associated with stronger recognition memory (Fagan III, 1984; Fagan & Singer, 1983). These results highlight the importance of individual variability in early attentional processes. Measures of habituation and dishabituation can serve as early cognitive markers with long-term implications.

Prior work also underscores how factors such as age and stimulus complexity shape habituation and dishabituation (Colombo et al., 2004; Hunter & Ames, 1988). According to the influential Hunter & Ames (1988) model, the more an infant has been exposed to a stimulus, the less novel information remains to be processed, leading to a decline in attention. However, the more complex a stimulus is, the greater the amount of information available to be learned, leading to prolonged engagement. Additionally, older infants are assumed to process information more efficiently than younger infants, allowing them to habituate more quickly. This framework provides a valuable qualitative account of how developmental and stimulus-related factors interact to shape attentional dynamics. Nevertheless, its predictions remain largely qualitative rather than quantitative and have not been systematically tested (cf. Bergmann & Cristia, 2016; Hunter, Ames, & Koopman, 1983; Kosie et al., 2024).

Understanding how individual differences in habituation and dishabituation interact with these factors is crucial for developing a comprehensive model of early learning. Individuals who habituate more quickly may process information more efficiently, allowing them to detect and respond to novel

stimuli more effectively, resulting in greater dishabituation. Alternatively, faster habituation could reflect a general tendency to disengage from visual stimuli more rapidly, leading to weaker attentional recovery when a new stimulus appears. Another important factor that may influence dishabituation is volatility—the degree of variability in looking time across habituation trials. Behavioral variability has often been interpreted as random noise (Faisal, Selen, & Wolpert, 2008; Renart & Machens, 2014) or a lack of control (Todorov, 2004). However, variability can also be adaptive, reflecting sensitivity to environmental contingencies and dynamic attention regulation (Aston-Jones & Cohen, 2005; Wu, Miyamoto, Castro, Ölveczky, & Smith, 2014). In the context of habituation and dishabituation, higher volatility in looking time may indicate greater flexibility in attention allocation, potentially enhancing dishabituation by allowing infants to remain more responsive to novel stimuli.

Systematically studying these relationships—especially across different age groups and stimulus contexts—remains challenging. Recruiting and testing large infant samples can be highly resource-intensive (DeBolt, Rhemtulla, & Oakes, 2020; Oakes, 2017), making it difficult to capture sufficient variability. Additionally, habituation outcomes can be influenced by measurement noise and fixed threshold criteria (Dannemiller, 1984; Kucharskỳ et al., 2024; Thomas & Gilmore, 2004), which risk misclassifying infants' true levels of attention. As a result, genuine variability in cognitive processing may be obscured by methodological artifacts. To overcome these limitations and capture more reliable estimates of individual differences, researchers have increasingly adopted large-scale data approaches such as meta-analysis and mega-analysis (Bergmann et al., 2018; Koile & Cristia, 2021), as well as online studies, which facilitate the recruitment of large and diverse participant samples (Chuey et al., 2021; Chuey, Boyce, Cao, & Frank, 2024; Sheskin et al., 2020).

In this study, we use large-scale datasets from online studies and mega-analysis to explore how individual differences in habituation rate predict dishabituation magnitude. Unlike previous work focused solely on infancy (Gilmore & Thomas, 2002; Šimkovic & Träuble, 2021; cf Cao, Raz, Saxe, & Frank, 2023; Raz, Cao, Saxe, & Frank, 2025), here we take a lifespan approach, examining habituation and dishabituation from infancy to adulthood. In addition, we also explored how dishabituation was shaped by factors like habituation volatility (e.g., fluctuations in looking time), age, and stimulus complexity shape dishabituation. By comparing across three age groups, we provide new insights into developmental continuity and discontinuity. To preview our findings, we found (1) Individuals who habituate faster show a stronger rebound in attention to novel stimuli; (2) In adults, but not younger participants, greater variability in looking time during habituation is associated with stronger dishabituation, and (3) Different operationalizations of dishabituation yield somewhat divergent results.

## Methods

### Datasets

We used three datasets, each measuring habituation and dishabituation in adults (Cao et al., 2023), preschoolers (Raz, Cao, Bui, Frank, & Saxe, 2023), and infants (Kunin, Piccolo, Saxe, & Liu, 2024).

**Adults** The adult dataset was collected using a web-based, self-paced looking time paradigm. In this experiment, participants were presented with a sequence of animated creatures and could advance to the next trial at their own pace by pressing the down arrow key. Each block consisted of six trials, with one repeating stimulus and one deviant stimulus. The deviant stimulus appeared at either the second, fourth, or sixth trial of the block. Since the current analysis focuses on habituation trajectories, we preprocessed the data to ensure that the deviant stimulus only appeared in the fourth or sixth trial and included only the first block for each participant to prevent across-block habituation effects. The final dataset consists of 186 habituation-dishabituation sequences from 186 English-speaking participants recruited through Prolific (Age:  $M = 28.98$  Years,  $SD = 9.32$  Years; 111 F; 72 M; 2 NA).

**Preschoolers** The design of the preschooler study was similar to the adult study, with the key difference that it was administered in person at a university-affiliated preschool in the United States using a laptop. We applied the same preprocessing steps as in the adult dataset to maintain consistency. The final dataset includes 33 habituation-dishabituation sequences from 33 participants (Age:  $M = 54.5$  Months,  $SD = 8.35$  Months). We note that this dataset is substantially smaller than the two others, and thus will interpret the results with caution.

**Infants** The infant dataset was compiled through a systematic literature review and meta-analytic approach, drawing from studies that examined infants' habituation and dishabituation responses in violation-of-expectation (VOE) paradigms. The dataset includes infant-level data from studies published after 1985 that tested typically developing infants between 3 and 12 months of age on expectations about physical objects or agents engaging in intentional actions. A typical paradigm involves two phases: in the habituation phase, infants are presented with a sequence of repeating stimulus. In the test phase, infants are presented with a stimulus that is either perceptually novel but conceptually similar to the repeating stimulus, or conceptually novel but perceptually similar. The current analysis focuses on perceptual dishabituation – that is, comparing test trials with perceptually novel stimuli to the last dishabituation trial. To ensure data quality, we excluded participants with fewer than three habituation trials. The final dataset includes 1986 habituation-dishabituation sequences from 1986 participants (Age:  $M = 224.9$  Days,  $SD = 96.45$  Days; F; M; NA).

## Analytic approach

All analyses were conducted in R using the nlme package (Pinheiro et al., 2017). All data and analysis scripts can be accessed from XXX. These analyses were exploratory, but we provided a robustness check in section Robustness Check

**Selecting exponential decay parameters for each age group.** We follow the conventions of a vast prior literature (Ashmead & Davis, 1996; Dannemiller, 1984; Sirois & Mareschal, 2002; Thompson & Spencer, 1966) and model habituation with an exponential decay. Here, we fit a nonlinear mixed-effects (NLME) model with an exponential decay function on each dataset. The function takes the general form of:  $LT \sim a * \exp(b * trial\_number)$ . The parameter  $a$  is the intercept, representing initial looking time, and  $b$  is the decay rate, reflecting the speed of habituation (See FIGURE 1 for schematic illustration of how  $a$  and  $b$  shapes the habituation trajectory).

First, we used a data-driven approach to ask, for each age group, which parameters explain variability in habituation across individuals (and thus, which parameters are worth studying as predictors of dishabituation). We selected the model with the lowest Akaike Information Criterion (AIC), with a  $\Delta AIC > 4$  suggesting substantial support for the model with lower AIC (Burnham & Anderson, 2004), among the models with the following random effects:

1. Random effects on  $a$  only – allows individual variation in initial looking time but assumes a shared decay rate across participants.
2. Random effects on  $b$  only – allows individual variation in decay rate while assuming a common initial looking time across participants.
3. Random effects on both  $a$  and  $b$  – allows individual variation in both parameters (Note: In the model, we explicitly assumed  $a$  and  $b$  are uncorrelated because they are conceptually independent. Moreover, this constraint improves statistical parsimony by reducing model complexity.)

**Additional predictors.** In addition to parameters related to exponential decay, we examined three additional predictors: volatility (how much looking behavior varied over the course of habituation), stimulus complexity (whether the stimuli participants saw were relatively simple or complex), and participant age. Volatility was defined as the standard deviation of the model residuals across habituation trials for each age group, capturing the extent to which looking behavior fluctuates over time (Li, Liu, Hartman, & Belsky, 2018; Li, Sturge-Apple, Platts, & Davies, 2023). In the adult datasets, complexity was explicitly manipulated (throughout the experiment, participants saw creatures that had more body parts, or fewer). In the infant dataset, complexity was defined by the domain of the stimuli (studies involving agents acting on objects were deemed more complex than studies involving only

inanimate objects). The preschooler dataset did not include complexity information. Participant age was available for all datasets, and we converted the original units in each dataset to months to facilitate better comparison. Finally, since the infant dataset has sufficient variation to estimate initial looking time for each individual, we include it as a predictor as well.

**Selecting measures of dishabituation.** Our main behavior of interest – recovering attention to a novel stimulus, after seeing a series of repeated stimuli – is best captured as a contrast between looking at the novel stimulus and looking at the prior (familiar) stimulus, right before the novel stimulus is shown. But one challenge in selecting a measure of dishabituation is to ensure that it is de-confounded from individual differences in participants' overall tendency to look at stimuli. Thus, we took two approaches to measure this contrast.

The first was a residual-based approach. Residual is the difference between an observed value and the predicted value from a model. We calculated the dishabituation magnitude as the following:

$$Dishabituation = r_{dishab} - r_{lasthab}$$

$r_{dishab}$  was extracted from fitting an intercept-only linear model on all dishabituation trials:  $LT \sim lme(trial\_looking\_time \sim 1, random = \sim 1 | subject, data = dishabituation.data)$

$r_{lasthab}$  was extracted from the best-fitting nlme model, representing how much an individual's looking time on the last habituation trial deviated from what would be expected given the overall pattern of decline in attention across trials for all participants.

Taking the difference between the two model residuals ensures that dishabituation magnitude is measured relative to each individual's habituation trajectory. In other words, this residual-based approach can effectively control for baseline differences in overall looking time and isolate true attentional recovery from unrelated variability.

Second, as a robustness check, we also calculated dishabituation magnitude as follow:

$$Dishabituation = \log(LT_{dishab}) - \log(LT_{lasthab})$$

In this supplementary analysis, features of each participant's habituation trajectory (for all age groups, volatility and decay rate; for infants, volatility, decay rate, and  $a$ ) was estimated using only the habituation trials preceding the last trial to avoid any potential spurious dependency between the measures of decay rate estimation and dishabituation.

**Relating predictors to dishabituation.** For each age group, we then ran a linear regression model predicting dishabituation magnitude based on decay rate, age, and volatility (for all age groups), stimulus complexity (infants and adults), and initial looking time (in infants).

In this section, we begin by evaluating whether there is sufficient variability in decay rates to investigate individual

differences. We then examine key predictors of dishabituation magnitude, followed by a robustness check on our operationalization of this measure.

**Exponential decay model selection.** We found sufficient variability in  $a$  and  $b$  in the infant dataset, and sufficient variability in  $b$  in the adult and preschooler dataset. We then used these best-fitting models to extract individual decay rates ( $b$ ; all age groups) and initial looking time ( $a$ ; infants only) for each age group.

**Collinearity between potential predictors of dishabituation** Before studying the effects of our predictors on dishabituation, we measured their first-order correlations to each other and to the dependent measures. Since some of these predictors are conceptually related (i.e. decay rate, volatility, and age), we examined their correlations to assess potential collinearity within each dataset (See Supplementary Information: Figure XX). We found small to moderate relationships between some of these variables in all three datasets: For example, volatility and decay rates were moderately positively correlated in adults and preschoolers (Adults:  $r = 0.51$ ; Preschoolers:  $r = 0.44$ ) and initial looking time and volatility were moderately positively correlated in infants (0.65). Furthermore, our primary and secondary dependent measures were positively correlated for all three age groups (Adults: 0.63; Preschoolers: 0.62; Infants: 0.53), suggesting both that they are converging measures, but also that they might be capturing different processes and noises. For all of the following statistical models, the variance inflation factors (VIFs) were below standard thresholds (Adults:  $VIF_{max} = 1.38$ ; Preschoolers:  $VIF_{max} = 1.35$ ; Infants:  $VIF_{max} = 1.91$ ). This indicates that multicollinearity did not pose a major concern in our models.

### What predicts dishabituation in individual participants?

Since the preschooler dataset includes significantly less data ( $N = XXX$ ), we will mainly focus interpreting the results on the infants and adults dataset. First, we found that looking behavior during habituation predicted dishabituation in both infants and adults. In both infants and adults datasets, individuals who habituated more quickly to repeated stimuli also looked longer when a new stimulus appeared (STATS; STATS). For infants, individuals who looked longer to the first habituated stimulus ( $a$ ) also dishabituated more (STATS).

We also found that higher volatility predicts greater dishabituation magnitude in adults, though there was no relationship in infants (STATS; STATS). However, the role of complexity and volatility differed: in adults, individuals who viewed complex (vs simple) stimuli throughout the study dishabituated more (STATS), while in infants, individuals who viewed simple stimuli (involving just inanimate objects) dishabituated more than those who viewed more complex stimuli (involving agents interacting with objects) (STATS). Last not but least, in infants, younger age was linked to

greater dishabituation (STATS), but there was no significant relationship in neither adult nor the preschooler dataset (STATS; STATS). In the preschooler dataset, only decay rate was a significant predictor, suggesting that preschoolers who habituated slower showed a larger dishabituation magnitude (STATS). See Table 1 for a summary of the results.

**Robustness check.** Next, we repeated our analyses using our alternative measure of dishabituation (the difference between the dishabituation trial and the last habituation trial in log seconds). These two measures were moderately to strongly correlated in our three datasets (adults: STAT; preschoolers, STAT; infants: STATS). We repeated the same model selection procedure, dropping data from the last habituation trial to avoid spurious correlations between the habituation parameters and our dependent measure, and the same models had the lowest AICs across the two analyses.

Despite this consistency of which model was selected as the best fitting model, the specific predictors differed slightly when using the log-transformed measure (See Table 1). In adults, only complexity remained a significant predictor of dishabituation magnitude (STATS). In preschoolers, decay rate was only marginally positively associated with dishabituation (STATS). (Given the small sample size, this result should be interpreted with caution.) For infants, the pattern largely mirrored our main analysis, with decay rate, age, and complexity all negatively associated with dishabituation magnitude (STATS). The initial looking time was negatively associated with the dishabituation magnitude (STATS), whereas in the residual-based method, the estimate was marginally positive (STATS).

Overall, while key relationships between decay rate, age, and complexity showed some consistency across both measures, differences in the sensitivity of the decay rate effects and volatility effects indicate that these operationalizations of dishabituation magnitude do not always yield the same patterns of individual differences.

From birth, humans explore and learn about the world through our looking behaviors, and two canonical behaviors we display are (1) habituation to repeated stimuli, and (2) recovery of attention to novel stimuli. How do these behaviors vary across individuals, and what predicts them? Studying these questions are challenging because of limitations on measurement precision, and sample size, particularly in infants and young children. In this work, we leveraged three existing habituation datasets—from infancy to adulthood—to investigate relationships between individual differences in participant behaviors (habituation and dishabituation), demographics (age), and task factors (stimulus complexity). In particular, we studied the predictors of dishabituation, or orienting to novel stimuli. Overall, we found that individuals who habituate faster show a stronger rebound in attention to novel stimuli. We also observed an interesting relationship between the volatility of looking time and dishabituation magnitude, evident only in adults. Last but not least, our findings serve

as a cautious note for researchers that different operationalizations of dishabituation can yield somewhat divergent results, underscoring the importance of considering how each metric may capture different underlying processes. Overall, this work supports longstanding claims that habituation and dishabituation are not merely passive responses governed primarily by the dynamics and features of sensory inputs, but also by the endogenous properties of the observer (Köster, Kayhan, Langeloh, & Hoehl, 2020; Raz & Saxe, 2020). Below, we discuss each of our positive findings and their implications for developmental research.

Why do infants and adults who habituate more quickly to dishabituate more to novel stimuli? One possible explanation for this relationship is that individuals who habituate more quickly may process information more efficiently, allowing them to disengage from familiar stimuli and reallocate attention to novel ones more readily. Previous studies have shown that habituation and dishabituation reflect rational information gathering, where individuals allocate attention based on the trade-off between extracting useful information from a stimulus and the opportunity to explore new stimuli (Cao et al., 2023; Karni, Mattar, Emberson, & Daw, 2025; Raz et al., 2025). Under this framework, a steeper decay rate may indicate faster evidence accumulation, allowing individuals to determine more quickly when a stimulus is no longer informative and shift attention to novel inputs. This relationship also raises an intriguing reinterpretation of prior findings on individual differences. While substantial research has identified habituation and dishabituation as distinct measures predictive of later cognitive development, our findings suggest these measures may, at least in part, reflect a common underlying process. Specifically, the connection between fast habituation and strong dishabituation could imply that both are noisy measures of the same unifactorial construct, such as overall efficiency in processing and attention allocation. If so, this might explain why earlier studies have found overlapping correlations with cognitive outcomes—what appeared to be separate predictors could instead reflect different facets of the same mechanism.

Why do adults with more variable looking during habituation dishabituate more strongly than adults with more consistent looking? While prior work has investigated the relationship between environmental volatility (i.e. the unpredictability of the stimuli) and looking behaviors on a group level, here we are finding that internal behavioral volatility also predicts looking behavior. In one prior study Poli et al showed that infants were faster to saccade to visual stimuli when the stream of stimuli they watched was unpredictable, than when it was predictable. Together these findings suggest that observers can adapt to environmental instability, and that observers meaningfully vary in how unstable their looking behaviors are, even for repeated stimuli. In the current work, people whose attention fluctuates more, even when viewing the same stimulus repeatedly, are not necessarily inattentive or randomly shifting their gaze; rather, they may be more

attuned to potential changes and better prepared to respond when those changes occur. This interpretation aligns with models of adaptive attention, where variability in gaze patterns reflects an active strategy to monitor the environment for new information (Aston-Jones & Cohen, 2005; Wu et al., 2014). However, we only observed this relationship in adults. This might be due to younger participants exhibiting noisier looking behaviors, making it harder to detect systematic relationships between volatility and dishabituation.

Our current results and interpretations are constrained by several limitations. First, the heterogeneity of our data sources may weaken our developmental conclusions. While the adult and preschooler datasets share a comparable paradigm, the infant dataset integrates studies with diverse stimuli and procedures, introducing additional noise that complicates direct comparisons across ages. Relatedly, our analyses suggest that different measures of dishabituation may not always capture identical patterns across populations, highlighting the need for careful consideration when selecting operationalization. Given that most developmental studies rely on a single operationalization, our findings serve as a cautionary note that different operationalizations can shape observed effects and should be interpreted in the context of their underlying assumptions. Additionally, an important limitation is that we do not know whether we are capturing person-level individual differences, state-level individual differences, or a combination of both. Measures such as volatility, decay rate, and dishabituation magnitude may not be stable over time, given prior findings on the low test-retest reliability of habituation measures (Colombo, Mitchell, O'Brien, & Horowitz, 1987; Cristia, Seidl, Singh, & Houston, 2016; Hood et al., 1996). At the very least, participants who vary in behavior across a short span of time—whether due to intrinsic person-level traits, momentary state-level fluctuations, or an interaction between the two—demonstrate a stronger dishabituation effect. For future research, simulation work could provide a more systematic understanding of how different operationalizations influence observed effects, clarifying the extent to which methodological choices are sensitive to noise and error. By modeling different sources of noise—such as individual fluctuations in attention, measurement error, and trial-level variability—simulation studies could help determine whether observed effects are robust or driven by artifacts of the chosen operationalization.

By analyzing large-scale datasets that span infancy to adulthood, we demonstrated that individual differences in habituation trajectories, as well as the chosen metrics of dishabituation. Although methodological heterogeneity and smaller sample sizes in preschoolers limit our ability to make direct developmental comparisons, this work provides a strong basis for future research to understand the developmental changes of visual attention. Moreover, our findings highlight that fluctuations in looking behavior should not be dismissed as noise; rather, they could reflect adaptive strategies that facilitate information gathering. Taken together,

these insights underscore the need to view visual attention as an active process that contributes to learning across development.

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