Individual differences in habituation rate and behavioral volatility predict dishabituation in adults, preschoolers and infants

Anonymous CogSci submission

Abstract

From infancy to adulthood, habituation and dishabituation enable learners to filter out repetitive information and remain attentive to novelty. Here, we leveraged large-scale datasets spanning infants, preschoolers, and adults to examine how individual differences in habituation parameters (e.g., decay rate, attention variability) predict dishabituation. We found that faster habituation consistently related to stronger attention recovery to novel stimuli. In addition, higher variability in looking behavior during repeated stimulus exposures predicted greater dishabituation in adults. We also observed that different measures of dishabituation yielded somewhat divergent patterns, highlighting the importance of robustness checks on exploratory analysis. These findings reveal how endogenous factors are meaningful drivers of looking behaviors. Overall, our results underscore the need for large-scale data approaches to studying visual attention across the lifespan.

Keywords: habituation; looking time; mega-analysis; individual differences

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; Kucharský, 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. In this work, we used existing data collected using this method to study individual differences in dishabituation, and what individual-level predictors (e.g. habituation rate and age) and experiment-level predictors (e.g. stimulus complexity) account for those differences.

Endogenous and exogenous factors driving looking behavior Understanding how endogenous and exogenous factors– differences between individuals and differences between tasks– interact to guide looking behavior is crucial for developing a comprehensive model of early learning. In one influential model of habituation (Hunter & Ames, 1988), learners, including infant learners, engage with stimuli to optimize learning. This leads to the predictions that (i) more efficient learners (e.g. older infants) should habituate faster than less efficient learners (e.g. younger infants), (ii) learners should recover attention to novel stimuli as they become more habituated with familiar stimuli, and (iii) learners should engage with a stimulus relative to its information value. All of these predictions have enjoyed empirical support (Cao, Raz, Saxe, & Frank, 2023; Kidd, Piantadosi, & Aslin, 2012; Raz, Cao, Saxe, & Frank, 2025). Particularly striking are studies of individual differences, suggesting that some differences could serve cognitive markers with long-term implications. Habituation rate—how quickly an infant's attention declines in response to repeated exposure to a stimulus—has been 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—have been associated with stronger recognition memory (Fagan III, 1984; Fagan & Singer, 1983).

Another striking example comes from studies manipulating environmental volatility, or the predictability of upcoming stimuli. Poli et al. (2024) demonstrated that infant learners adjust their looking behavior in response to volatility: they initiate saccades more quickly when stimuli are highly unpredictable. Yet, we know less about whether volatility varies as a function of the learners, as well as the learning context. On

the one hand, behavioral variability has often been interpreted as random noise (Faisal, Selen, & Wolpert, 2008; Renart & Machens, 2014) or a lack of control (Todorov, 2004). In the context of habituation and dishabituation, these accounts would predict that greater behavioral volatility during habituation would be unrelated to subsequent dishabituation, or predict weaker dishabituation. On the other hand, behavioral volatility could also be adaptive, reflecting an enhanced sensitivity to potential environmental contingencies and more 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 leading to greater dishabituation by allowing learners to remain more responsive to novel stimuli.

The challenge of studying drivers of looking behavior Systematically studying how different endogenous and exogenous factors shape looking time in the habituation paradigm—especially across different age groups and stimulus contexts—remains challenging. Recruiting and testing large infant samples can be highly resource-intensive (De-Bolt, 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; Kucharský 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).

Here, 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 et al., 2023; Raz et al., 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

Datatasets

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; 1004 F; 955 M; 27 NA).
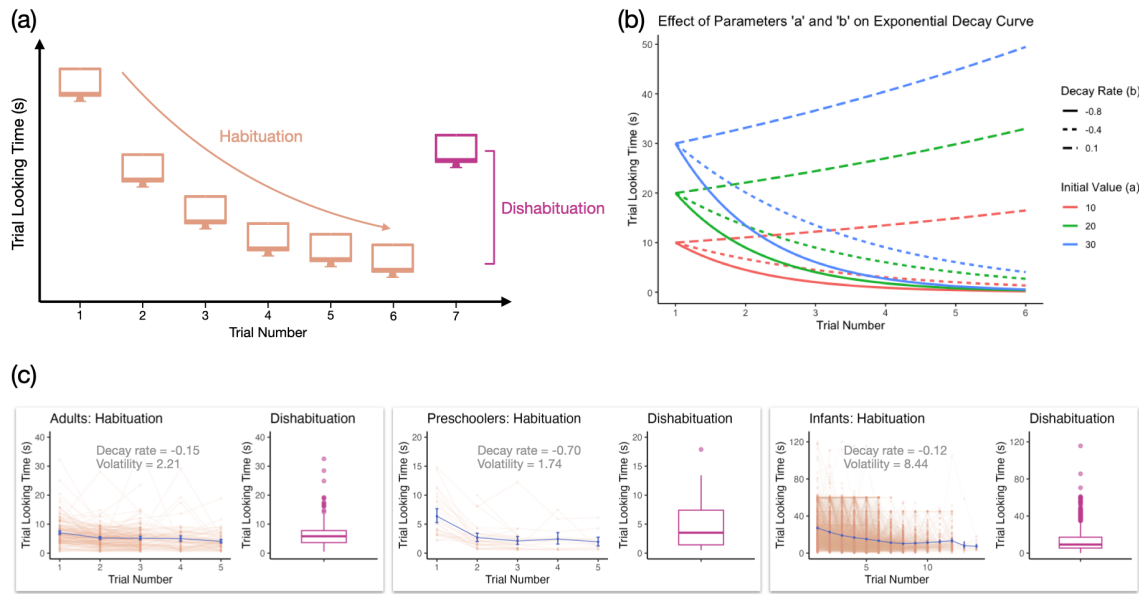
Figure 1: (a)Conceptual diagram illustrating habituation (looking times decrease with repeated exposures to the same stimulus) and subsequent dishabituation (a renewed increase in looking time when a novel stimulus is presented).(b) Exponential decay curves showing how variation in the initial value (*a*) and decay rate (*b*) affects the slope and starting point of the habituation trajectory. More negative *b* values reflect faster declines in looking time.(c) Empirical examples of habituation (left) and dishabituation (right) across adults, preschoolers, and infants. Each panel shows mean trajectories (lines), individual participant trajectories (light lines), and the corresponding boxplot of dishabituation. The group average decay rate and volatility (the standard deviation of residuals) are noted below each age group's plot, illustrating differences in habituation and dishabituation across the lifespan.

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 ~ 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 ~ lme(trial_looking_time ~ 1, random = ~ 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 in infants ($r = 0.65$). 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 = 33), 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 (Infants: $\beta = -0.09$, $SE = 0.02$, $p < .001$; Adults: $\beta = 0.09$, $SE = 0.07$, $p < .001$). In addition, we found that adults who showed higher volatility in their looking time also dishabituated stronger ($\beta = 0.55$, $SE = 0.08$, $p < .001$). We did not see this relationship with younger participants (Preschoolers: $p = 0.14$; Infants: $p = 0.89$). For infants, individuals who looked longer to the first

Table 1: Comparison of Residual-Based Model and Difference of Log LT Model

(A) Residual-Based Model					(B) Robustness Check			
Predictor	Coeff.	Std. Err.	t	p-value	Predictor	Coeff.	Std. Err.	t	p-value
Adults					**Adults**				
(Intercept)	0	0.06	0.03	.980	(Intercept)	0	0.07	0	1.000
Decay rate	-0.46	0.08	-6.09	**< .001**	Decay rate	0.05	0.09	0.53	.600
Age	0.09	0.07	1.36	.180	Age	0.03	0.07	0.34	.740
Volatility	0.55	0.08	7.30	**< .001**	Volatility	0.09	0.09	0.97	.330
Complexity	0.03	0.06	0.49	.630	Complexity	0.15	0.07	2.08	**.040**
Preschoolers					**Preschoolers**				
(Intercept)	0	0.14	0	1.000	(Intercept)	-0.04	0.17	-0.25	.810
Decay rate	0.49	0.17	2.91	**.010**	Decay rate	0.43	0.22	1.99	.060
Age	-0.06	0.15	-0.42	.680	Age	-0.19	0.18	-1.04	.310
Volatility	0.25	0.16	1.53	.140	Volatility	0.11	0.19	0.57	.580
Infants					**Infants**				
(Intercept)	0.08	0.03	2.63	**.010**	(Intercept)	0.13	0.04	3.59	**< .001**
Decay rate	-0.17	0.02	-8.31	**< .001**	Decay rate	-0.15	0.02	-6.62	**< .001**
Age	-0.09	0.02	-4.26	**< .001**	Age	-0.08	0.02	-3.56	**< .001**
Volatility	0	0.03	-0.14	.890	Volatility	0.04	0.03	1.27	.200
Complexity	-0.1	0.03	-3.24	**< .001**	Complexity	-0.16	0.04	-4.38	**< .001**
Initial LT	0.45	0.03	16.6	**< .001**	Initial LT	-0.06	0.03	-2.00	.050

Table 2: This table presents model estimates predicting dishabituation magnitude across age groups. All numeric predictors were z-scored within age groups for comparability. The categorical predictor, complexity, was contrast-coded using sum coding. Bold values indicate statistically significant results.

habituated stimulus (*a*) also dishabituated more (β = 0.45, *SE* = 0.03, *p* < .001).

Second, we found that the effect of complexity predicted dishabituation 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) (β = -0.1, *SE* = 0.03, *p* < .001). Complexity did not predict dishabituation in adults and the preschooler dataset did not contain variability in stimulus complexity (Adults: *p* = 0.63).

Last but not least, participant age predicted dishabituation, but only in infants: While younger infants showed greater dishabituation (β = -0.09, *SE* = 0.02, *p* < .001), age did not predict dishabituation in neither adult nor the preschooler dataset (Adults: *p* = 0.18; Preschoolers: *p* = 0.68). 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). We repeated the same model selection procedure and analysis plan as above, except that for fitting the habituation and volatility parameters, we dropped data from the last habituation trial to avoid spurious correlations between these parameters and our dependent measure. The model selection procedure yielded the same results as the primary analysis: sufficient variability in b in all three datasets, and sufficient variability in a for infants.

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 was a significant predictor of dishabituation magnitude (β = 0.15, *SE* = 0.07, *p* = 0.04). In preschoolers, decay rate was only marginally positively associated with dishabituation (β = 0.43, *SE* = 0.22, *p* = 0.06). (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 (all *p*s < 0.01). The initial looking time was negatively associated with the dishabituation magnitude (β = -0.06, *SE* = 0.03, *p* = 0.05), whereas in the residual-based method, the estimate was marginally positive.

Comparing the fit of the models across all three age groups, across the primary and secondary analyses, we found that the same predictors explained substantially more variance in the primary residual-based dishabituation measure (Adults: $R^2_{adjusted}$ = 0.25; Preschoolers: $R^2_{adjusted}$ = 0.33; Infants: $R^2_{adjusted}$ = 0.28) than in the secondary difference score measure (Adults: $R^2_{adjusted}$ = 0.02; Preschoolers: $R^2_{adjusted}$ = 0.11; Infants: $R^2_{adjusted}$ = 0.04)

From birth, humans explore and learn about the world through our looking behaviors, displaying two canonical behaviors: (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 that adults who demonstrated more volatile looking during habituation dishabituated more strongly. 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 primary findings and their implications for developmental research, and then discuss the discrepancies between the results from our primary and secondary analyses.

Why do infants and adults who habituate more quickly also 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. Measuring and studying a variety of partially related constructs in the same, large datasets, makes it possible for us to discover the latent, unifying processes that underlie what appear to be separate measures.

Why do adults with more variable looking during habituation dishabituate more strongly than adults with more consistent looking? Prior work has investigated the relationship between environmental volatility (i.e. the unpredictability of the stimuli) and looking behaviors on a group level; for example, 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. Here, we found that internal behavioral volatility also predicts looking behavior. Together these findings suggest that observers can adapt to environmental instability, and that observers can also meaningfully vary in how unstable their looking behaviors

are, even for repeated stimuli. In the current work, adults whose attention fluctuates more during habituation, 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 (truly) 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 preschooler dataset was very small, and the infant dataset integrates studies with diverse stimuli and procedures, introducing additional noise that complicates direct comparisons across datasets. For example, it is unclear whether the way we operationalized stimulus complexity truly captures the same contrast across adults, who watched stimuli of animate agents that were more vs less complex, and infants, who watched stimuli of including vs excluding animate agents.

Discrepancies between our primary and secondary results highlight that individual differences in looking behavior depend on the measure of dishabituation used. In both the adult and preschooler datasets, no predictor was consistently robust, and neither group showed significant dishabituation across measures ($ps > 0.05$), contrasting with previous studies that found significant effects using a different operationalization of dishabituation (Cao et al., 2023; Raz et al., 2023). In contrast, infant results remained stable: infants generally dishabituated, with steeper habituation rates, simpler stimuli (inanimate objects), and younger age predicting greater novelty recovery. However, the relationship between initial looking time and dishabituation varied by method, with residual-based estimates being positive and log-transformed estimates negative. Given that many developmental studies choose just a single measure for their dependent variable, our findings serve as a cautionary note that different operationalizations can shape observed effects and researchers should consider robustness checks for exploratory analyses of developmental data.

A last limitation is that while we found individual-level predictors of dishabituation, it is unknown whether these predictors reflect 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, and indeed display low test-retest reliability (Colombo, Mitchell, O'Brien, & Horowitz, 1987; Cristia, Seidl, Singh, & Houston, 2016; Hood et al., 1996). The most conservative claim way to interpret our re-

sults is that 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, formal computational modeling 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—this approach could help determine the conditions under which we should expect robust results vs those that are more sensitive to operationalization decisions, or state-level shifts in participant state.

By analyzing large-scale datasets that span infancy to adulthood, we demonstrated that individual differences in habituation trajectories predict dishabituation magnitude. 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 simply dismissed as noise; rather, they could also 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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