Individual differences in habituation predict dishabituation magnitude in adults and infants

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Abstract

From infancy to adulthood, habituation and dishabituation enable learners to filter out repetitive information and orient to novel information. Because variability in these processes has been linked to differences in later cognitive outcomes, studying individual differences in habituation and dishabituation is crucial for building a more comprehensive model of early learning. Here, we leveraged large-scale datasets spanning infants, preschoolers, and adults to examine how individual differences in habituation predict dishabituation magnitude. We found that faster habituation and higher volatility predicted stronger dishabituation. Moreover, we showed that different measures of dishabituation sometimes yielded divergent patterns, suggesting that measurement choices can influence observed effects and should be carefully considered in developmental research. 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; dishabituation; looking time; mega-analysis; individual differences

Habituation and dishabituation are fundamental processes in learning. Habituation refers to the decrease in response to a repeated stimulus, while dishabituation describes the increase in response following the introduction of a novel stimulus. These processes 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, uninformative stimuli while remaining sensitive to new information.

These mechanisms have also become a cornerstone of research methods in cognitive development (Aslin, 2007; Cohen, 2004; Kucharskỳ, Zaharieva, Raijmakers, & Visser, 2024; Oakes, 2010). A typical infant study using the habituation paradigm involves repeatedly presenting an infant with the same stimulus until they exhibit a decline in interest and then presenting a novel stimulus. A dishabituation response—indicated by significantly longer looking time at the novel stimulus than the last display of the familiar stimulus— serves as a crucial index of memory and discrimination. In this work, we used existing data collected using this method to study individual differences in dishabituation, and whether individual-level predictors (e.g. habituation rate and age) and experiment-level predictors (e.g. stimulus complexity) relate to 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 models of early learning. In one influential model of habituation (Hunter & Ames, 1988), learners engage with stimuli to optimize learning. This theory predicts 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 received empirical support (Cao, Raz, Saxe, & Frank, 2023; Kidd, Piantadosi, & Aslin, 2012; Raz, Cao, Saxe, & Frank, 2025).

Individual differences of looking behavior also have been studied as cognitive markers with long-term implications. Habituation rates has been associated with foundational cognitive processes such as information processing speed (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; 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 III & Singer, 1983). Notably, prior meta-analytic findings suggest that the predictive strength of habituation versus dishabituation varies across studies, potentially due to sample characteristics, measurement variability, or statistical noise (Kavšek, 2004).

Infant looking is also sensitive to variability in the learning environment, for example 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 volatility 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,

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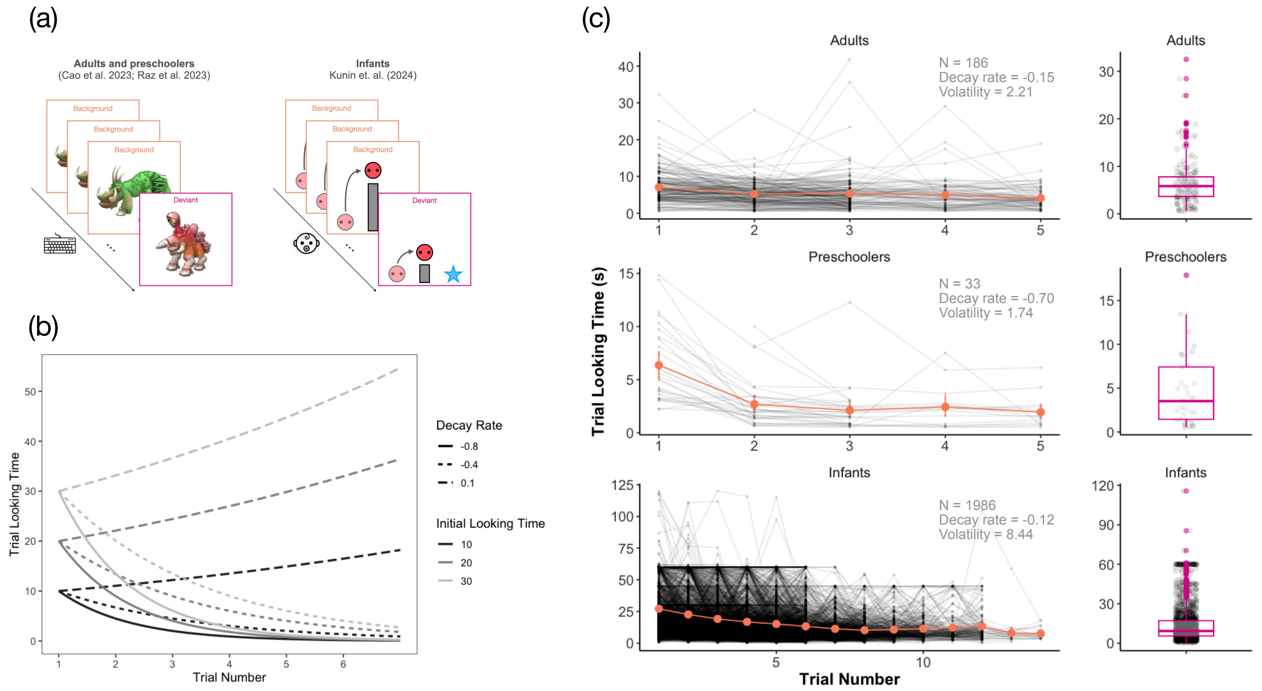

Figure 1: (a) Experimental setup. Conceptual diagram illustrating habituation (looking times decrease with repeated exposures to the same stimulus) and subsequent dishabituation (a renewed increase in looking time when a novel stimulus is presented). (b) Effects of initial looking and decay rate on looking behavior, in principle. Exponential decay curves showing how variation in the initial value (*a*) and decay rate (*b*) affect the slope and starting point of the habituation trajectory. More negative *b* values reflect faster declines in looking time. These curves use simulated data for illustrative purposes only. (c) Empirical data. Habituation (left) and dishabituation (right) across adults, preschoolers, and infants in the current work. Each panel shows mean trajectories (orange lines), individual participant trajectories (gray lines), and both group and individual-level dishabituation (in pink). The group sample size, averaged decay rate, and volatility (the standard deviation of residuals) are noted below each age group's plot.

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). Higher volatility in looking time may indicate greater flexibility in attention, allowing learners to remain more responsive to novel stimuli and leading to greater dishabituation.

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, because of the noise in our measurements, and the resources required to recruit and test large samples (Dannemiller, 1984; DeBolt, Rhemtulla, & Oakes, 2020; Kucharskỳ et al., 2024; Oakes, 2017; Thomas & Gilmore, 2004). To overcome these limitations, 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, 2024; Sheskin et al., 2020).

Here, we used large-scale datasets, including data 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), we took 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 (i.e., fluctuations in looking time), age, and stimulus complexity. By comparing across three age groups, we showed developmental continuity and discontinuity in the relationships between habituation and dishabituation.

To preview our findings, we found that (1) Individuals who habituated faster showed stronger dishabituation; (2) In adults, but not younger participants, greater variability in looking time during habituation was associated with stronger dishabituation, and (3) Different ways of measuring dishabituation yielded some convergent and some 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 during an online study. 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 a 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 focused 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 consisted of 186 habituation-dishabituation sequences, each contributed by a unique English-speaking participant recruited through Prolific (Age: *M* = 28.98 Years, *SD* = 9.32 Years; 111 F; 72 M; 2 Not Available).

Preschoolers The design of the preschooler study was similar to the adult study, except that it was administered in person at a university-affiliated preschool in the US using a laptop. We applied the same preprocessing steps as in the adult dataset to maintain consistency. The final dataset included 33 habituation-dishabituation sequences, each from an unique participant (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 drawn from Kunin et al. (2024), a mega-analysis studying 3- to 12-month-old infants' looking behavior at unexpected and visually new stimuli. The topics of the experiments were infants' responses to inanimate objects, and animate agents. Infants underwent the habituation procedure described in the Introduction. The current analysis focused on perceptual dishabituation – that is, comparing looking at the visually new test trial to the last habituation trial. To ensure data quality, we excluded participants with fewer than three habituation trials. The final dataset includes 1986 habituation-dishabituation sequences, each from an unique infant (Age: *M* = 224.9 Days, *SD* = 96.45 Days; 1004 F; 955 M; 27 Not Available).

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 `https://github.com/anjiecao/habituation_cogsci2025`. These analyses were exploratory; see below for robustness checks.

Selecting exponential decay parameters for each age group We followed the conventions of a vast prior literature (Ashmead & Davis, 1996; Dannemiller, 1984; Sirois & Mareschal, 2002; Thompson & Spencer, 1966) and modeled habituation with an exponential decay function. Here, we fit a nonlinear mixed-effects (NLME) model with an exponential decay function of the form: `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(a) for schematic illustration of how *a* and *b* shapes the habituation trajectory).

First, we used a data-driven approach to ask 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.[1]

The infant dataset preferred the model with random effects on both *a* and *b*, and the adult and preschooler dataset preferred the model with random effect on *b* only. 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 (See SI: Table 1-3).

Additional predictors We examined three additional predictors: volatility (how much looking behavior varied during 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). Since the stimuli were held constant within each dataset, this measure reflects individual differences in how consistently participants looked across repeated exposures (higher volatility corresponds to more inconsistent looking). In the adult dataset, complexity was explicitly manipulated by creating two levels (complex versus simple; complex creatures had many body parts and simple creatures had fewer body parts). 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).

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[1] We explicitly assume *a* and *b* are uncorrelated because they are conceptually independent. Moreover, this constraint improves statistical parsimony by reducing model complexity.

The preschooler dataset did not manipulate complexity; participants saw complex creatures throughout. 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 had sufficient variation to estimate initial looking time for each individual, we included it as a predictor as well.

Selecting measures of dishabituation Our main behavior of interest – longer looking 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.

Here, we propose a new residual-based measurement of dishabituation that can control for individual participants' baseline looking tendencies, which confound naive comparisons of habituation speed and dishabituation magnitude. We defined individual differences in looking as the difference between an observed value and the predicted value, in two separate models: one modeling habituation, and one modeling dishabituation. Each participant i receives a set of habituation trials $j_{1,\dots,n-1}$, with the dishabituation trial being j_n, with a total of n trials in each set. Looking times on these trials are t_{i,j_k}. We compute unexplained variation in dishabituation magnitude on a particular trial set $V_{i,j}$ as the difference between two residuals: $r^D_{i,j}$, dishabituation residuals, and $r^H_{i,j}$, habituation residuals on the last trial before dishabituation.

$$V_{i,j} = r^D_{i_j} - r^H_{i_j}. \tag{1}$$

r^D is extracted from an intercept-only linear model fit to dishabituation looking times across all participants and all trials: $t_{i,j_n} \sim \alpha + \beta_j$. r^H was computed similarly but using the exponential random effects model over trials above:

$$t_{i,j_{1,\dots,n-1}} \sim (a + a_i)\exp[(b + b_i)j_k], \tag{2}$$

where $a_i \sim N(0, \sigma_1)$ and $b_i \sim N(0, \sigma_2)$ as in a standard mixed effects model.

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 (See SI Simulations).

In addition to this approach, as a robustness check, we also followed a classic operationalization of dishabituation (Csibra et al., 2016), calculating variation in dishabituation magnitude as a difference score:

$$V'_{i,j} = log(t_{i,j_n}) - log(t_{i,j_{n-1}}) \tag{3}$$

In this analysis, features of each participant's habituation trajectory (for all age groups, volatility and decay rate; for infants, volatility, decay rate, and initial looking time) was estimated using only the habituation trials preceding the last trial to avoid 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 residual variation in dishabituation magnitude $V_{i,j}$ based on decay rate, age, and volatility (for all age groups), stimulus complexity (infants and adults), and initial looking time (infants).

Results

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 SI: Figure 1-3). We found small to moderate correlations 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 (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 sources of signal and noise. 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? See Table 1(A) for a summary of the results. Since the preschooler dataset included significantly less data (N = 33), we focused on interpreting the results on the infant and adult datasets. First, we found that looking behavior during habituation predicted dishabituation in both infants and adults. Infants and adults who habituated more quickly (i.e. had more negative decay rate) looked longer when a new stimulus appeared (Infants: β = -0.17, SE = 0.02, $p < .001$; Adults: β = -0.46, SE = 0.08, $p < .001$). In addition, we found that adults who showed higher volatility in their looking time also dishabituated more strongly (β = 0.55, SE = 0.08, $p < .001$). We did not see this relationship with younger participants (Preschoolers: p = 0.14; Infants: p = 0.89). Infants who looked longer to the first habituated stimulus 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 (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 (p = 0.63).

Lastly, 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 adults (p = 0.18) or preschoolers (p = 0.68).

Table 1: Comparison of Residual-Based Model and Difference Score Model

(A) Residual-Based Model

Predictor	Coeff.	Std. Err.	t	*p*-value
Adults				
(Intercept)	0	0.06	0.03	.980
Decay rate	-0.46	0.08	-6.09	< **.001**
Age	0.09	0.07	1.36	.180
Volatility	0.55	0.08	7.30	< **.001**
Complexity	0.03	0.06	0.49	.630
Preschoolers				
(Intercept)	0	0.14	0	1.000
Decay rate	0.49	0.17	2.91	**.010**
Age	-0.06	0.15	-0.42	.680
Volatility	0.25	0.16	1.53	.140
Infants				
(Intercept)	0.08	0.03	2.63	**.010**
Decay rate	-0.17	0.02	-8.31	< **.001**
Age	-0.09	0.02	-4.26	< **.001**
Volatility	0	0.03	-0.14	.890
Complexity	-0.1	0.03	-3.24	< **.001**
Initial LT	0.45	0.03	16.6	< **.001**

(B) Robustness Check

Predictor	Coeff.	Std. Err.	t	*p*-value
Adults				
(Intercept)	0	0.07	0	1.000
Decay rate	0.05	0.09	0.53	.600
Age	0.03	0.07	0.34	.740
Volatility	0.09	0.09	0.97	.330
Complexity	0.15	0.07	2.08	**.040**
Preschoolers				
(Intercept)	-0.04	0.17	-0.25	.810
Decay rate	0.43	0.22	1.99	.060
Age	-0.19	0.18	-1.04	.310
Volatility	0.11	0.19	0.57	.580
Infants				
(Intercept)	0.13	0.04	3.59	< **.001**
Decay rate	-0.15	0.02	-6.62	< **.001**
Age	-0.08	0.02	-3.56	< **.001**
Volatility	0.04	0.03	1.27	.200
Complexity	-0.16	0.04	-4.38	< **.001**
Initial LT	-0.06	0.03	-2.00	.050

Table 1. 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. Therefore, the intercept represents the mean dishabituation response for that age group. Bold values indicate statistically significant results.

Robustness check Next, we repeated our analyses using the alternative measure of dishabituation (the difference between the dishabituation trial and the last habituation trial in log seconds). We repeated the model selection procedure and analysis plan as above. The model selection procedure yielded the same results as the primary analysis: the adult and preschooler dataset preferred the model with random effect on b, and the infant dataset preferred model with random effect on both a and b (See SI: Table 4-6).

Despite this consistency of which exponential decay model was selected as the best fitting model, the specific results differed somewhat when using the difference score measure (See Table 1(B)). In adults, only complexity was a significant predictor of dishabituation magnitude. In preschoolers, decay rate was only marginally positively associated with dishabituation (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 ps < 0.01). The initial looking time was negatively associated with the dishabituation magnitude, 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: $R^2_{adjusted} = 0.04$).

Discussion

From birth, humans explore and learn about the world by looking, and we display 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 datasets to investigate relationships between individual differences in participant behaviors (habituation and dishabituation), demographics (age), and task factors (complexity). In particular, we studied the predictors of dishabituation, or orienting to novel stimuli. Overall, we found that individuals who habituated 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 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? One possible explanation is that individuals who habituate more quickly may process information more efficiently, allowing them to disengage from familiar stimuli and reallocate attention to novel stimuli 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 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 cognitive development, our findings suggest these measures may, at least in part, reflect a common underlying process. The connection between fast habituation and strong dishabituation could imply that both are noisy measures of the same construct, such as overall efficiency in processing and attention allocation. If so, this might explain why earlier studies have found that both measures are correlated with cognitive outcomes: these measures reflect the same factor. Measuring and studying a variety of partially related constructs in the same, large datasets, makes it possible for researchers to discover the latent, unifying processes that underlie what appear to be separate constructs.

Why do adults with more volatile looking dishabituate more strongly? Our results suggested that observers can meaningfully vary in how unstable their looking behaviors are, even for repeated stimuli. In the current work, adults whose attention fluctuated more during habituation, were not necessarily inattentive or randomly shifting their gaze; rather, they may have been 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, or because behavioral volatility genuinely does not predict dishabituation in infants.

The current work has a number of limitations. First, we were limited by our data. Although the adult and preschooler datasets share a similar paradigm, the preschooler dataset is very small, and the infant dataset includes studies with diverse stimuli, adding variability that complicates direct comparisons across age groups. 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 including vs. excluding animate agents. These challenges highlight the need for large-scale, coordinated data collection. For example, the upcoming MB5 study aims to test the Hunter & Ames (1988) model of attentional preference using a multi-lab design (Kosie et al., 2024), offering a promising avenue to disentangle true developmental patterns from methodological variability.

Discrepancies between our primary and secondary results highlight that these individual differences in looking are sensitive to the operationalization of the measure. In both adults and preschoolers, no predictor was consistently robust, and neither group showed significant dishabituation across measures (All ps > 0.05), contrasting with previous studies that found significant dishabituation effects using just raw looking time on the deviant trials (Cao et al., 2023; Raz et al., 2023). In contrast, results from infants remained stable: infants dishabituated, and steeper habituation rates, simpler stimuli (inanimate objects), and younger age predicted greater dishabituation. However, the relationship between initial looking time and dishabituation varied by method, with residual-based estimates being positive and difference score based estimates negative. Given that many developmental studies choose just a single measure for their dependent variable, we suggest that researchers consider robustness checks for exploratory analyses of developmental data.

One 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 some of these constructs display low test-retest reliability, especially in children (Colombo, Mitchell, O'Brien, & Horowitz, 1987; Cristia, Seidl, Singh, & Houston, 2016; Hood et al., 1996). Therefore, the most conservative interpretation of our results is that participants who varied 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—demonstrated a stronger dishabituation effect. For future research, formal computational modeling could provide a more systematic understanding of how different measures of dishabituation relate to each other, and clarify 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.

In summary, individual differences in habituation predict dishabituation in infants and adults. 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, subject to both endogenous and exogenous factors, that contributes to learning across development.

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