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Staying and Returning Dynamics of Sustained Attention in Young Children

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Abstract

Sustained attention is a dynamic process with rich temporal structure. Eye-tracking provides a tool for capturing rich temporal data relevant to sustained attention, but extracting relevant insights from this rich data is nontrivial. This paper studies eye-tracking data collected from children, aged 3-5, performing the TrackIt task, a visual object tracking paradigm designed for studying sustained attention development in young children. Building on a hidden Markov model paradigm recently proposed for analyzing eye-tracking data with TrackIt, we explore characterizations of participant behavior, such as continuously maintaining attention on an object and transitioning attention between objects, that provide richer insights than task performance alone. In particular, our results suggest that improvement in TrackIt performance that accompanies development in this age range may stem more from improved ability to return to task after distractions, rather than from improvements in ability to continuously maintain attention on the task.

Keywords: Sustained attention; eye-tracking; TrackIt

Introduction

A large amount of recent work has characterized sustained attention as a dynamic and fluctuating process involving the interplay of different attentional modes to achieve adaptive behavior over time (Rosenberg, Finn, Constable, & Chun, 2015; Case, Arruda, & VanWormer, 2016; VanRullen, 2018; Fiebelkorn & Kastner, 2019). Existing behavioral methods have identified temporal fluctuations in measures of on-task (versus off-task) behavior, including accuracy, reaction time, reaction time variability, and experience sampling, as well as more general characteristics of fluctuations such as periodicity (Rosenberg et al., 2015; Christoff, Gordon, Smallwood, Smith, & Schooler, 2009; Aue, Arruda, Kass, & Stanny, 2009). However, there is a lack of measures to probe locally and densely what attention shifting and distractions look like mechanistically and statistically, at least in the real-time context of consciously perceivable behavior (i.e., on timescale of seconds or minutes, rather than sub-seconds).

It is typical for sustained attention tasks to have "targets" with which participants are asked to engage. For the purpose of this paper, it is useful to decompose the behavior of performing a sustained attention task into the following four process states[1]:

1. Attending to the target
2. Transitioning from the target to a (goal-irrelevant) non-target or "distraction"
3. Attending to a non-target
4. Transitioning from non-target back to target or to another non-target

Sustained attention research has largely focused on characterizing State 1 and, to a lesser extent, State 3 (the "attending" states), and relatively limited data is available for understanding States 2 and 4 (the "transitioning" states). We believe this is in part due to a lack of experimental methods available for directly probing the transitioning states, which are typically very brief in duration and lack measurable behavioral signatures in many task paradigms.

In this paper, we present experimental results from the TrackIt task, a visual object tracking task designed for studying sustained attention in children, that, in combination with continuous eye-tracking data, provides a direct measure for probing transitions between attentive states. In particular, we use this framework to study how changes in different components of children's attending behavior contribute to improved task performance, with a focus on State 1, which we refer to as "Staying", and State 4, which we refer to as "Returning".

Methods for Probing Sustained Attention

Measures based on task performance, such as accuracy, reaction time, and reaction time variability can only determine the extent to which a participant is in State 1 (Staying). In particular, when a participant is not attending to the task, they could be in any of States 2, 3, or 4, which cannot be probed more informatively by such measures. For example, most versions of the continuous performance task (CPT), a well-established task for studying sustained attention, capture information only at the relatively infrequent timepoints that call for a participant response, typically once every few seconds (Rosvold, Mirsky, Sarason, Bransome Jr, & Beck, 1956). This may fail to detect if a participant becomes distracted but returns to task between responses, for example, and it provides little or no information about what participants are doing while distracted.

[1] This decomposition is meant purely to describe the behavior of attending, not the underlying cognitive processes.

Experience sampling (or the thought-probe method) which probes the participant about their conscious experience at random intervals (Stawarczyk, Majerus, Maj, Van der Linden, & D'Argembeau, 2011), has been used to study mind-wandering and can probe the distracted state (State 3) more descriptively, but lacks the temporal resolution to pinpoint transitions, and its intrusive nature can potentially alter the dynamics of natural attending behavior (Smallwood & Schooler, 2015). Post-task probing is one approach to alleviating the latter issue, but suffers from the limitations of participants' memory.

Finally, these methods' low temporal resolutions make it challenging to investigate whether the behavior of sustaining attention can be decomposed into more fundamental behaviors. In particular, a major complicating factor is that the transitioning states 2 and 4 are often very brief and hence can be probed only by measures with sufficiently high temporal resolution. Eye-tracking is a natural candidate method for obtaining this dense temporal data. Eye-tracking is especially informative in the context of the TrackIt task because the relevant aspects of participant behavior in this task (visually tracking the displayed objects) are directly coupled to the eye-tracking measurements. In particular, this paradigm allows us to probe all four of the process states described above.

TrackIt

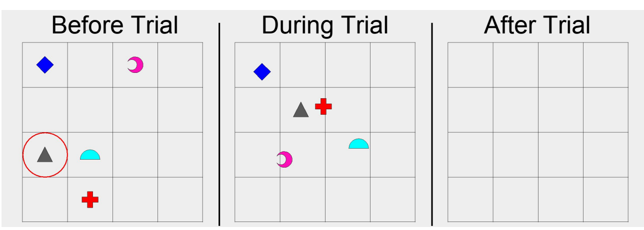

Figure 1: An example trial of the standard TrackIt task, on a 4×4 grid with 4 distractor objects. The target object here is the grey triangle, as indicated before the trial. A video of an example TrackIt trial can be found at https://osf.io/utksa/.

TrackIt, introduced by Fisher, Thiessen, Godwin, Kloos, and Dickerson (2013), is a child-appropriate visual object-tracking task recently developed to measure sustained attention, that can capture differential contribution of exogenous and endogenous control of attention and allow flexible assessment over a range of developmental years (including preschool years), with parameters for adjusting difficulty with age (Kim, Vande Velde, Thiessen, & Fisher, 2017). In the TrackIt task (illustrated in Figure 1), participants visually track a single target object moving about on a grid, among other moving distractor objects. At the end of each such trial, all objects vanish from the grid, and participants are asked to identify the target's final grid cell location (i.e., the grid cell the target occupied immediately before vanishing). The proportion of trials in which participant correctly identifies this grid cell is called "location accuracy", and has been the main quantity used to measure participant performance. Previous work has shown that children as young as 3 years old can consistently complete the TrackIt task and provide usable data (Fisher et al., 2013). Moreover, TrackIt has been shown to have good psychometric properties for measuring sustained attention, and research in several labs has linked performance on TrackIt to classroom learning, numeracy skills, prospective memory, and proactive control (Erickson, Thiessen, Godwin, Dickerson, & Fisher, 2015; Doebel et al., 2017; Doebel, Dickerson, Hoover, & Munakata, 2018; Brueggemann & Gable, 2018; Mahy, Mazachowsky, & Pagobo, 2018).

TrackIt has two conditions: a "Salient Target" (exogenous) condition and a "Non-Salient Target" (endogenous) condition. In the Salient Target condition, the target rhythmically "shrinks" and "unshrinks" (specifically, it alternates between its default size and a 50% reduced size, at 3 Hz) throughout the trial. This increases the salience of the target relative to the distractors to exogenously support maintenance of attention on the target.

Previous Related Work with TrackIt A number of previous studies using TrackIt have shown that childrens' location accuracy improves significantly between the ages of 3-5 years (Fisher et al., 2013; Kim et al., 2017). Kim et al. (2017) analyzed the errors (in location accuracy) made by children, suggesting that

(a) young children showed a preference (compared to chance levels) for selecting the final locations of distractor objects, suggesting that they were indeed distracted by these objects, and

(b) there was a reduction in these "distractor errors" that explained a significant proportion of the improvement in location accuracy with age.

Previous work using eye-tracking to study attention with TrackIt has focused on using eye-tracking as a secondary validation measure for location accuracy (Thiessen, Dickerson, Erickson, & Fisher, 2012). For analysis purposes, all previous work using eye-tracking with TrackIt has summarized the eye-tracking data by the proportion of time during which the participant's gaze was on the target, versus on a distractor (Thiessen et al., 2012; Kim, Singh, Vande Velde, Thiessen, & Fisher, 2018).

Both of these lines of work suggest that, as children develop, their performance (in terms of location accuracy) becomes less affected by distractors, but the work sheds little light on what changes in behavior underlie this improvement with respect to distractors. For example, do children improve on staying on the target and avoiding being distracted in the first place, or do they improve on returning to the target after distractions?

Current Study

The current study begins to explore operational measures for probing the above four process states, based on a combination of eye-tracking and TrackIt. In particular, we study the distinction between "staying" and "returning", which respectively correspond to process states (1) and (4) in our process state breakdown.

Methods

Open Practices Statement All analyses in this paper were preregistered on the Open Science Framework (OSF)[2]. All data analyzed in this paper is publicly available on OSF[3]. All code underlying the analyses is available on GitHub[4].

Data

In this paper, we reuse a dataset of TrackIt and eye-tracking data originally provided by Kim, Singh, Thiessen, and Fisher (2020). Kim et al. (2020) used this data to validate a hidden Markov model (HMM) algorithm for inferring the object to which a participant is attending at each timepoint. The output of this algorithm is a high-frequency (60 Hz) sequence of objects that the participant is estimated to be tracking, over time. Each timepoint in this 60 Hz sequence is refered to as a "frame". After applying preprocessing steps (as described in Kim et al. (2020)), we apply this HMM algorithm and use the output as a starting point for our analysis.

Participants 50 typically-developing children, aged 3.5-6 years ($M = 4.60$, $SD = 0.67$), each performed 11 TrackIt trials, including 1 initial practice trial during which the experimenter explained the task. Practice trials were omitted from analysis, giving 10 usable trials per participant in each condition. Data from 8 participants was discarded due to eye-tracking data quality issues, leaving 42 children, ages 3.5-6 years ($M = 4.65$, $SD = 0.71$) included in the analysis. Participants performed Salient Target and Non-Salient Target conditions on separate days (approximately 1 week apart), with order counter-balanced.

Procedure Participants were asked to visually track ("follow *with your eyes*") a single target object as it moved around on the grid, among moving distractor objects (with exact parameter settings as described under "TrackIt Settings" below). As shown in Figure 1, before trial start, the target was indicated by a red circle around it, which disappeared upon the start of the trial (initiated by button press). The target then flashed white repeatedly for a half-second before all objects began to move around the grid. At the end of each trial, all objects vanished from the grid, and the child was asked to indicate (by pointing) the final grid cell the target occupied before vanishing.

TrackIt Settings Based on previous work calibrating TrackIt to the 3-5 year old age group (Kim et al., 2017), the following TrackIt settings were used: object speed was 500 pixels per second, grid size was 6×6, number of distractors was 6, and minimum trial length was 10 s (the actual length of the trial was randomized between 10-20 s, under the constraint that the target ended in the center of a grid cell, in order to reduce predictability of trial end).

[2] https://osf.io/4vtpc/

[3] https://osf.io/u8jbs/

[4] https://github.com/sss1/behavioral_eyetracking

Measures of Performance

Each of the below performance measures was computed per trial and then averaged over trials (within participant and condition) to provide one value of each performance measure per participant and condition; all discussion in the "Results" section is in terms of these participant/condition-level measures. The measures are defined in terms of "runs", i.e., maximal subsequences of consecutive frames in which the tracked object (as estimated by the HMM) is constant. Between each pair of consecutive runs, a "transition" occurs from one object to the next.

In order to reduce sensitivity to factors such as overall switch frequency (which is strongly influenced not only by eye-tracking noise but also by choices of parameters in the HMM), we normalized each measure to have a simple, fixed expected value under the null hypothesis that participants' attention was identically distributed among the 7 displayed objects. This also improves interpretability of the measures, because values can be compared to the null values.

Returning: Proportion of Transitions from Distractors to Target (PTDT) Of all transitions from a distractor object, PTDT is defined as the proportion that go to target. In expectation, PTDT is the transition probability from distractors to targets in the HMM, and hence, in the absence of any target bias, PTDT has a mean value of $1/6$.

Staying: Normalized Duration on Target (NDT) is defined as the difference in mean duration of runs on target and runs on any object. In the absence of any target bias, NDT has an expected value of 0. Note that we used the difference (rather than the ratio) of run lengths because this ratio would be extremely sensitive to short runs off target and, moreover, this ratio would not have the benefit of interpretation as a proportion anyway.

Results

Target Preference In both Salient and Non-Salient Target conditions, both returning (PTDT) and staying (NDT) had means significantly higher than their respective chance values of $1/6$ and 0 ($ps < .001$, according to two-tailed, one-sample t-tests, reported in Table 1). This indicates that children have a consistent behavioral preference for staying on and returning to the target object (as opposed to distractor objects).

Condition Difference Since the Salient Target condition was expected to be more challenging than the Non-Salient Target condition (at least for younger children), we next

Table 1: Means and standard deviations (across participants) of staying (NDT) and returning (PTDT) measures in Salient (S) and Non-Salient (NS) task conditions. t-statistics and p-values are for two-tailed, one-sample t-tests against chance population means ($1/6$ for PTDT, 0 for NDT).

Cond.	Measure	M	SD	$t(41)$	p
S	Returning	0.49	0.20	10.56	$< .001^{***}$
NS	Returning	0.48	0.22	9.01	$< .001^{***}$
S	Staying	1.00	0.53	12.03	$< .001^{***}$
NS	Staying	0.88	0.58	9.70	$< .001^{***}$

checked whether condition influenced participant performance. As expected, location accuracy was somewhat higher in the Salient Target condition than in the Non-Salient Target condition, according to a two-tailed, paired t-test ($M_{\text{Salient}} = 0.46$, $SD_{\text{Salient}} = 0.32$, $M_{\text{Non-Salient}} = 0.40$, $SD_{\text{Non-Salient}} = 0.29$, $t(41) = 2.38$, $p = 0.02$). However, both returning (PTDT) and staying (NDT) failed to show significant differences between the Salient Target and Non-Salient Target conditions (according to two-tailed, paired t-tests for the means and standard deviations in Table 1, $t(41) = 0.50$, $p = 0.62$ for PTDT and $t(41) = 1.21$, $p = 0.23$ for NDT). This was somewhat surprising, since we had expected target salience to assist either with re-grabbing attention when following a non-target or with re-locating the target when searching for the target with intention to return, either of which should improve returning.

Regression over Location Accuracy As mentioned previously, one of the goals of this paper was to see whether children's performance, measured in terms of location accuracy, can be decomposed into components of staying on and returning to target. Hence, we checked how strongly returning (PTDT) and staying (NDT) are related to Location Accuracy. As illustrated in Figure 2, both quantities increased significantly with Location Accuracy in both Salient Target and Non-Salient Target conditions ($ps < 0.05$). Univariate regression statistics are provided in Table 2.

Table 2: Simple linear regressions of returning (PTDT) and staying (NDT) over location accuracy.

Condition	Measure	R^2	$F(1,40)$	p-value
Salient	Returning	.52	43.23	$< .001^{***}$
Non-Salient	Returning	.44	31.86	$< .001^{***}$
Salient	Staying	.12	5.27	$.027^{*}$
Non-Salient	Staying	.25	13.07	$< .001^{***}$

Regression over Age Motivated by previous observations that 3-5 year old children's location accuracies improve with age, we asked whether children's abilities to stay on and return to target also improve with age. Hence, we regressed each of location accuracy, returning (PTDT), and staying (NDT) over age. As illustrated in Figure 3, in both Salient Target and Non-Salient Target conditions, returning (PTDT) increased significantly with age ($ps < 0.001$), whereas staying (NDT) failed to exhibit a significant increase with age ($ps > 0.05$). Univariate regression statistics are provided in Table 3.

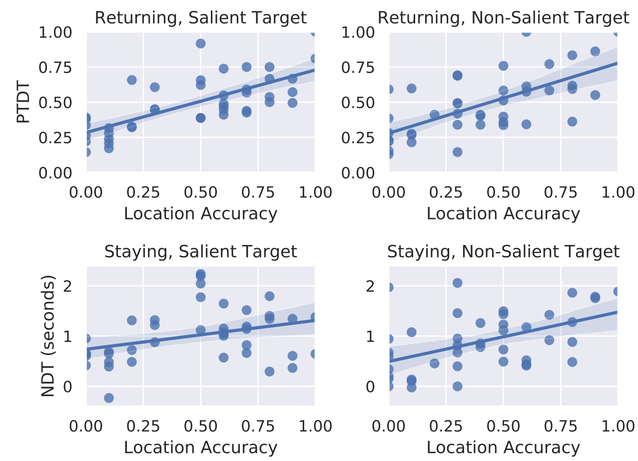

Figure 2: Linear regression of returning (PTDT) and staying (NDT) over location accuracy (proportion of trials on which the participant correctly identified the target's final location). Shaded regions indicate bootstrapped 95% confidence bands.

Figure 3: Linear regression of returning (PTDT) and staying (NDT) over age. Shaded regions indicate bootstrapped 95% confidence bands.

Mediation Analysis Since returning was found to significantly improve with both age and location accuracy, we next used mediation analysis to directly study the extent to which the improvements in location accuracy that come with age can

Table 3: Simple linear regressions of returning (PTDT) and staying (NDT) over age.

Condition	Measure	R^2	$F(1,40)$	p-value
Salient	Loc. Acc.	.40	26.70	$< .001^{***}$
Non-Salient	Loc. Acc.	.28	15.82	$< .001^{***}$
Salient	Returning	.30	17.16	$< .001^{***}$
Non-Salient	Returning	.34	20.71	$< .001^{***}$
Salient	Staying	.05	2.25	.141
Non-Salient	Staying	.08	3.64	.064

be explained by improvements in returning. Table 4 shows the results of this analysis. As expected from the previous analyses, we see that returning (PTDT) plays a strong mediating role between age and location accuracy, explaining 46% of the relationship between age and location accuracy in the Salient Target condition and 59% in the Non-Salient Target condition.

Differential Regression over Age Finally, we investigated whether age *differentially* affects staying and returning. To do this, we first replaced Returning (*PTDT*) and Staying (*NDT*) with their ranks (*RPTDT* and *RNDT*, respectively) across subjects, within each condition, in order to make them directly comparable. We then pooled RPTDT and RNDT and regressed them over (1) *age*, (2) a binary indicator variable *measure_type* indicating whether the measure was RPTDT (coded as 0) or RNDT (coded as 1), and (3) the interaction of *age* and *measure_type*. Results of this analysis are provided in Table 5. The significant negative coefficient $\beta_{age \times measure\_type}$ confirms that age differentially affects ranks of returning (RPTDT) and staying (RNDT); specifically, returning improves more with age than does staying.

Discussion

In this paper, we introduced new measures of attentional returning and staying based on eye-tracking in TrackIt. We provided experimental evidence suggesting that improvement in children's TrackIt performance may be better explained by an improvement in their ability to return to the target after a distraction than by an improvement in their ability to continuously track the target. This finding can also be expressed in terms of the four-state decomposition of attentional processes provided at the beginning of this paper. In particular, our results suggest that, over the course of development, the behavioral changes that underlie improved task performance may lie not so much in attention to the target (in State 1) as in transitions from a distraction (State 4).

One model in the sustained attention literature that is especially relevant this discussion is the supervisory attentional system proposed by Stuss, Shallice, Alexander, and Picton (1995), which includes four processes: monitoring goal activation, re-energizing goal activation, inhibition, and monitoring the match between current behavior and the goal. This fourth component is especially relevant for returning to current-goal-relevant behavior after being distracted. (For a meta-analysis review on neural bases of these components, see (Langner & Eickhoff, 2013)). This proposed system provides a candidate model for the cognitive machinery supporting dynamic attention. In particular, it outlines mechanistic pieces to support the *movement* or transitions of attention between various states of focus.

Another relevant model is the LC-NE (locus coeruleus-norepinephrine) theory of adaptive gain (Aston-Jones & Cohen, 2005) in neuropsychiatry, which outlines a model of adaptive attending behavior in which activity in LC neurons and their noradrenic projections interface with reward and cost judgments to drive perceptual modes of attending. The modes outlined are enhanced processing of current-goal-relevant features, disengagement from the environment altogether, or disengagement specifically from the current task set with continued general engagement in the environment in search of other potential tasks when the utility of the current task begins to diminish. Besides providing a breakdown of the attentional modes and providing a rough mechanistic theory for movement between these, Aston-Jones and Cohen articulate an intuitive justification or functional value for the "distractible" attentional mode, which is that it allows for exploration of alternative goals, given that a behavior that is most beneficial to an organism in one moment may no longer be in the next.

LC activity has been successfully tracked with measurements of pupil dilation (Gilzenrat, Nieuwenhuis, Jepma, & Cohen, 2010). Additionally, there is work on mind-wandering which also uses pupil dilation measurements to track and describe attentional lapses (Konishi, Brown, Battaglini, & Smallwood, 2017). Hence, in future work, it may be desirable to integrate the TrackIt-eyetracking paradigm with measurements of pupil dilation, in order to more richly characterize attentional lapses.

The fluid and cycling movement of sustained attention between ideal engagement, disengagement, distraction, and anywhere in between, has also been documented and studied in several additional research areas. Recently growing literature on mind-wandering and its dynamics identifies and studies periods of distraction away from task, whether those periods are characterized by rumination of past events or planning or imagining of future events (Smallwood & Schooler, 2015). Finally, burgeoning work on meditation in health psychology often draws on the idea of practicing "returning" after a distraction, or after the mind has wandered, to a space of focus whether on the breath, another intended object of attention, or just general focused awareness. Because of the recent positive interest in meditation and its psychological and functional dynamics, this work may be of interest to health psychologists and the general community discourse on meditation as well.

Table 4: Results of mediation analysis of PTDT as a mediator of the relationship between age and location accuracy. 95% confidence intervals and p-values are based on a bootstrap procedure as described in Preacher and Hayes (2008) with 10,000 bootstrap samples; p-values are for the null hypothesis of 0 indirect effect.

Condition	Measure	Standardized Indirect Effect	95% Confidence Interval	Mediation Proportion	p-value
Salient	PTDT	0.29	$(0.15, 0.48)$	46%	$< .001^{***}$
Non-Salient	PTDT	0.31	$(0.16, 0.49)$	59%	$< .001^{***}$

Table 5: Multiple linear regression of performance (RPTDT/RNDT) over age, measure_type, and their interaction. t-statistics and p-values are based on a two-tailed t-test for the individual regression coefficients, against a null population coefficient of 0.

Covariate	β	$t(164)$	p-value
age	10.2	6.09	$< 0.001^{***}$
measure_type	24.6	2.21	0.028^{*}
age $\times$ *measure_type*	-5.3	-2.24	0.027^{*}

Limitations and Future Directions

While our results suggest that improvements in returning (measured by PTDT) might mediate as much as half of the improvement in location accuracy with age, it is not clear what other factors contribute to the remaining improvement. While improvements in staying (measured by NDT) might contribute a small portion (as NDT showed a significant improvement with location accuracy and a trending but not significant improvement with age), other possibilities include improvements in motor function, task comprehension, or task compliance, any of which might improve the location accuracy of participants who can already correctly track the target. Some of these possibilities could be further probed by examining relationships between gaze behavior and different types of location accuracy errors, such as the "spatial resolution" and "distractor" errors characterized by Kim et al. (2017).

On the other hand, this and prior work (Kim et al., 2018, 2020) using the hidden Markov model to infer attentional state from eye-tracking during TrackIt has assumed that children predominantly rely on overt attention (i.e., attention associated with eye movements toward the object of attention) for tracking the target, supported in part by the fact that participants are explicitly instructed to follow the target *with their eyes*. Still, there remains a possibility that participants could attend to the target covertly, allowing for improvements in location accuracy that are not accompanied by improvements in eye-tracking based performance metrics. To understand whether this occurs, future work could investigate trials with significant "off-task" gaze behaviors that are followed by correct location accuracy responses.

Though the current study focused on pulling apart staying and returning in terms of measurement during sustained attending, and explored their differential development over age, it did not focus on questions of underlying cognitive mechanism. For example, it is not clear whether staying and returning might operate on a shared cognitive or neural mechanism, or are subserved by qualitatively different processes.

Theoretically, one could conceive of staying as just a version of high-frequency returning, wherein the participant continuously shifts their attention back to the target over very fast timescales. In this theory of a single mechanism, improvement in returning over age may simply reflect an improvement in the mechanism's capacity to return after longer and longer time gaps.

On the other hand, there is evidence (e.g., Aston-Jones and Cohen (2005)) suggesting that externally directed attention moves between modes of enhanced goal-relevant stimulus processing and more distractible diffuse processing, which could respectively differentially support staying or returning. For example, the more distractible, diffuse processing mode which promotes switching between objects of attention, may support returning, but not staying. These findings could support the possibility of separate mechanisms behind staying and returning. Though the question of shared or different mechanisms is not directly explored in this study, the differential trends over age that we found in our results lends some initial support to a theory in which separate mechanisms support the two constructs.

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