Neural and verbal responses to attachment-schema narratives differ based on past and current caregiving experiences

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Abstract

Children's caregiving experiences impact the internal models they use to process new emotional events. Examining inter-subject functional correlation in 7- to 15-year-olds during narrative movies depicting separation and reunion, we find that secure attachment to current caregivers plays a larger role than early adversity in shaping prefrontal-amygdala connectivity. Secure attachment also decreased the emphasis in later memory on separation elements in the narrative.

Early caregiving experiences can play a major role in how children process and emotionally respond to interpersonal interactions throughout their lives. A recent review of the neural and behavioral impacts of caregiving-related early childhood adversities (crEAs, including caregiving instability, abuse, and neglect) hypothesized that these experiences specifically disrupt the construction of *affective schemas*: semanticized knowledge and predictions about how socio-emotional events are likely to unfold (Tottenham, 2020). This internal model of emotional expectations (about, for example, whether a caregiver will be responsive to the child's needs) can then impact how new experiences are experienced and remembered (Bowlby, 1969; Bretherton, 1992), though the same cognitive and neural mechanisms as other kinds of event scripts (Baldassano et al., 2018; Kurby & Zacks, 2008; Gilboa & Marlatte, 2017). Specifically, there are critical connections between regions in medial prefrontal cortex that track the activation of event scripts (De Soares et al., 2024) and subcortical systems involved in learning and emotion regulation, including the amygdala (Marusak et al., 2016).

In this study we aimed to test this hypothesis that crEAs can disrupt the typical function of this prefrontal-amygdala system during the processing of a naturalistic attachment episode. Rather than using static or highly-simplified stimuli to evoke an attachment schema, we presented children with one of two short movies that depicted a separation and reunion with a caregiver, and then asked them to freely recall the events of the video they watched. We also sought to understand how the effects of early caregiving instability can be modulated by the strength of attachment to a children's current caregivers, testing for differences in amygdala connectivity patterns and recall behavior as a function of instability and attachment.

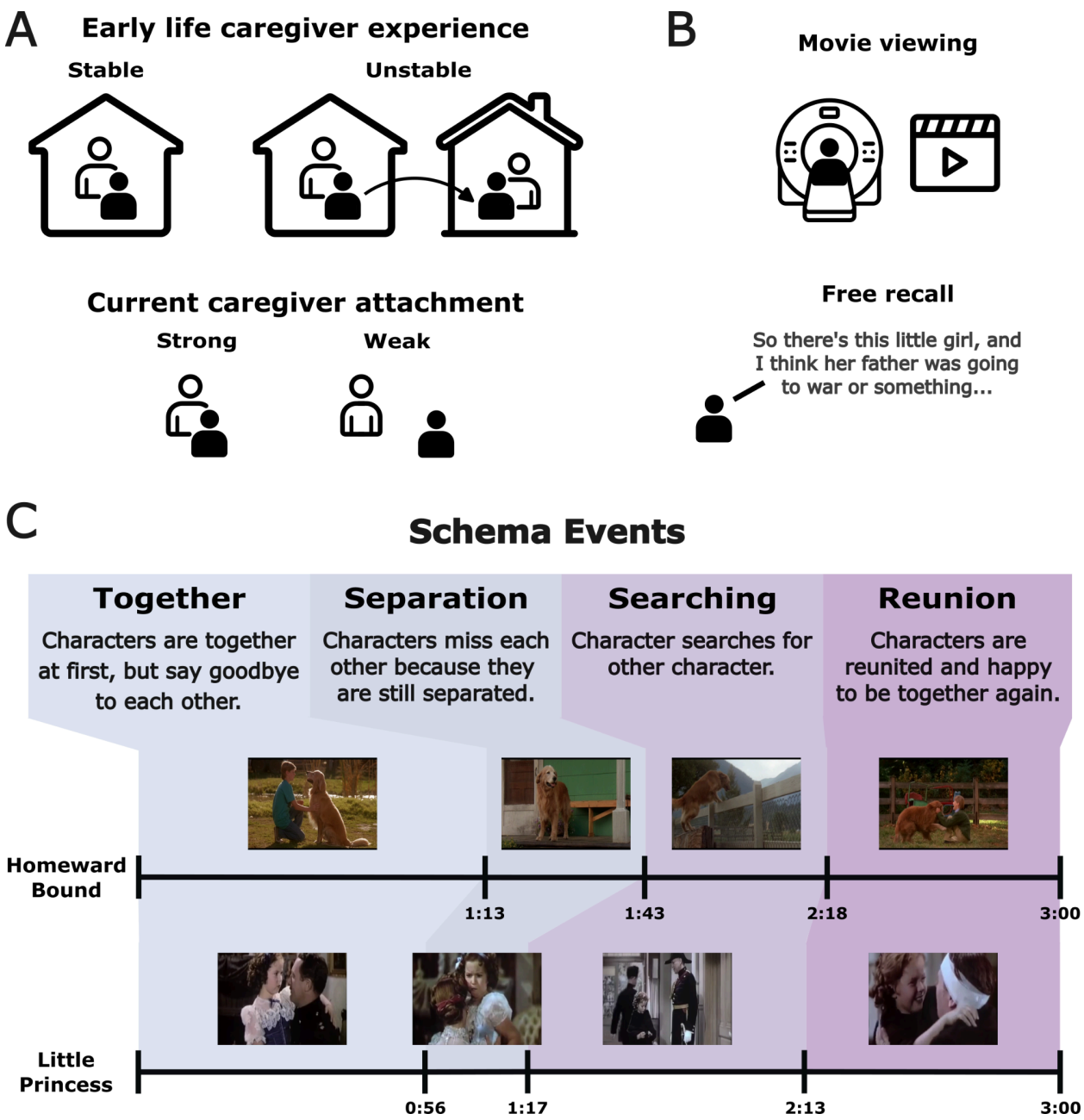

Figure 1: Study population and design. ***A***. *Children were characterized as having either stable or unstable early caregiving, based on whether they had experienced at least one change in their primary caregivers. Separately, the strength of each child's attachment to their current caregivers was measured, producing "strong" and "weak" attachment groups.* ***B***. *Participants watched a three-minute movie clip during an fMRI session and were later asked to recall what they remembered from the movie to an experimenter (Part 2) outside of the scanner.* ***C***. *Each movie clip (Homeward Bound or Little Princess) was edited to depict the same sequence of four events associated with an attachment schema.*

Participants (N = 187; ages 7 - 15) included children with a variety of caregiving experiences, assessed in two ways (Figure 1A). Children were labeled as having “stable” (N=70, N=104) or “unstable” (N=59, N=82) early caregiving environments, based on whether they had ever experienced a change in their primary caregivers (such as being removed from the care of their biological parents or moving between foster families). Additionally, we measured the attachment relationship quality between each child and their current caregiving parent, assessing whether they had a “strong” (N=54 for fMRI analyses, N=87 for recall analyses) or “weak” (N=48, N=79) level of current attachment. Brain activity was measured while each participant viewed a 3-minute movie clip depicting an attachment narrative, after which each participant verbally recalled the movie to an experimenter (Figure 1B). Two different narrative clips were constructed, using scenes from two different films (*Homeward Bound* or *The Little Princess*) in which a character is (1) initially together with their caregiver; (2) separated from their caregiver; (3) searching for their caregiver; and (4) reunited with their caregiver (Figure 1C).

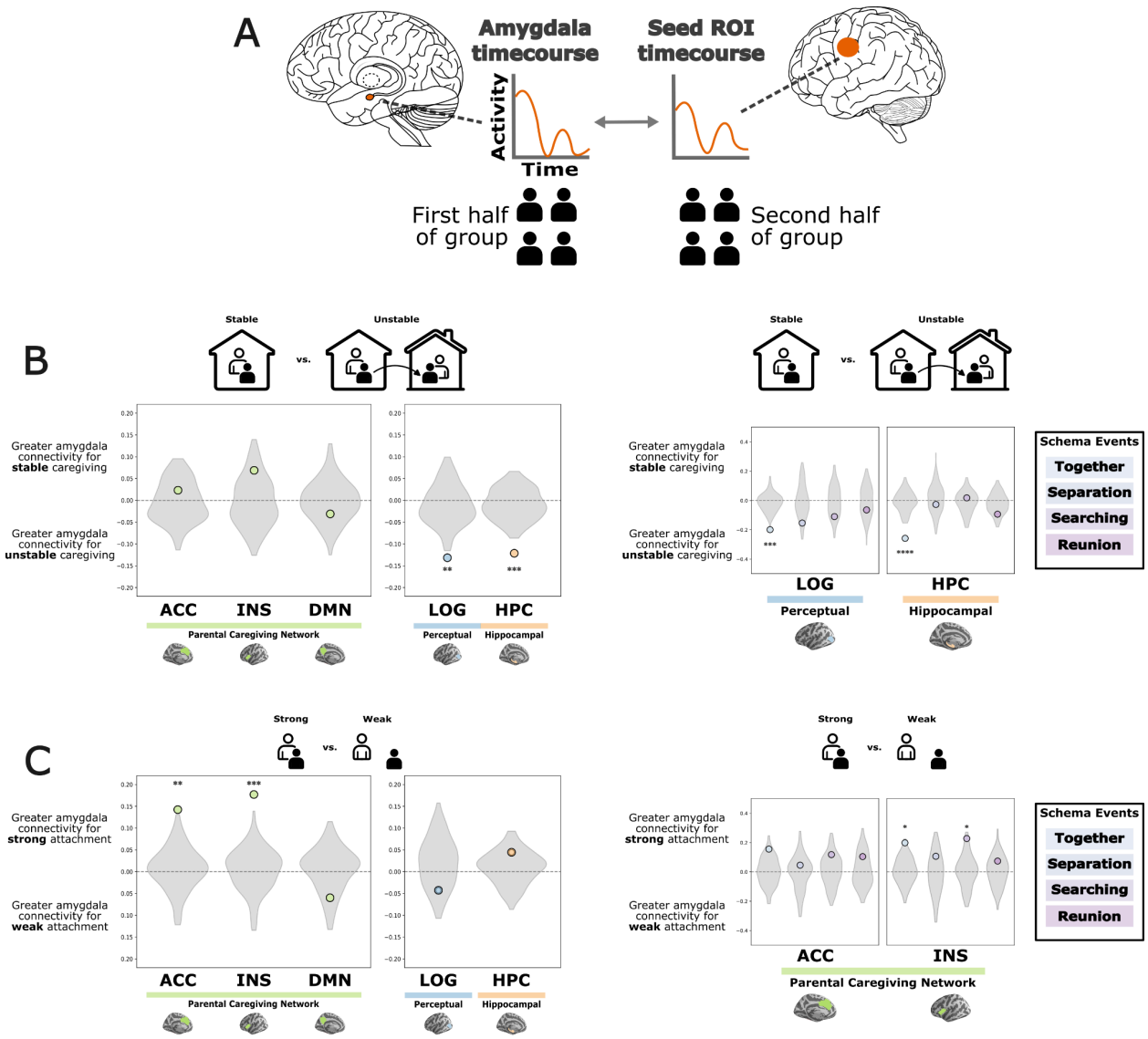

Figure 2: Intersubject functional connectivity with amygdala during movie viewing. ***A****. A specific group of participants (e.g. those with stable caregiving environments) is randomly divided in half. The mean amygdala response timecourse is computed in one half, and the mean response timecourse of a seed ROI is computed in the other half. The correlation between these two timecourses yields the ISFC for this seed ROI for this group.* ***B****. Unstable early caregiving environments in early childhood were associated with stronger coupling between amygdala to perceptual (LOG) and hippocampal (HPC) areas. Examining these effects for each of the four events, we found that this enhanced connectivity for unstable caregiving experiences was driven by event 1 (Together) for both the LOG and HPC.* ***C.*** *Across the entire viewing, strong levels of current attachment were associated with greater amygdala coupling in medial prefrontal (ACC) and insula (INS) regions. The ACC effect was not driven by specific events, but the enhanced INS connectivity was significantly driven by events 1 (Together) and 3 (Searching). * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$*

To measure the stimulus-driven connectivity between amygdala and regions in the cortex, we first computed the univariate timecourse (in each hemisphere) of activity in the amygdala and for five a priori regions of interest (ROIs). Three of these regions come from the previously-defined Parental Caregiving Network (Shimon-Raz et al., 2023), including anterior cingulate cortex (ACC) in medial prefontal cortex, the insula (INS), and a default mode network regions (DMN) in posterior medial cortex. We also included the hippocampus (to measure interactions with episodic memory systems) and a visual region in lateral occipital gyrus (LOG) previously found (Herrington et al., 2011) to be strongly connected to the amygdala (to measure interactions with sensory systems). Children within a specific subgroup (e.g. those with stable early caregiving) who watched the same clip were randomly divided into two halves, and we then measured the inter-subject functional correlation (Simony et al, 2016) between the average amygdala timecourse in one half and each ROI in the other half (Figure 2A). These ISFC values were averaged between the two movies and the two hemispheres of the amygdala and ROI, and then statistically compared between subgroups (i.e. strong versus weak current attachment or stable versus unstable early caregiving).

We found that both early life experiences and current feelings of attachment security had a significant association with amygdala connectivity patterns. Amygdala responses in children with unstable early caregiving experiences were more strongly associated with visual cortex and the hippocampus: LOG ($\Delta r = -0.13$, $p = 0.008$) and HPC ($\Delta r = -0.12$, $p = 0.001$) (Figure 2B). We conducted an exploratory analysis in which we separately examined ISFC within each of the four schematic events in the movies, and found that this effect was significantly driven only by event 1 ($p = 0.0004$; $p =$

00008). This suggests that, for children with an unstable caregiving history, the initial presentation of a caregiving relationship triggers interactions with the visual system (possibly through top-down attention to incoming sensory input) and with episodic memory (possibly involving reactivation of specific past caregiving episodes, rather than a semanticized schema).

Children with stronger current feelings of attachment security (Figure 2C), in contrast, exhibited greater amygdala coupling with medial prefrontal and insular regions (ACC: $\Delta r = 0.14$, $p = 0.005$; insula: $\Delta r = 0.18$, $p = 0.0004$). In a post-hoc analysis of the contributions of individual events, we found that the ACC effect was not significantly driven by any specific event and that the INS effect was significant for events 1 and 3 ($p = 0.04$; $p = 0.04$); all events in both regions showed numerically greater connectivity for children with strong attachment. When testing directly for changes in response timecourses in individual regions (rather than connectivity with the amygdala), we found significant differences between children with strong and weak attachment security in both left and right ACC responses ($p = 0.02$ and $p = 0.05$, respectively).

Additionally, we tested for interactions between caregiving stability and current attachment on amygdala connectivity. We found a significant interaction in the hippocampus ($p = 0.02$); unstable caregiving increased hippocampal-amygdala connectivity *only* for children with weak current attachment security. This suggests that a strong attachment to current caregivers may mitigate disruptions to activating and encoding attachment-related experiences for children who experience unstable early caregiving.

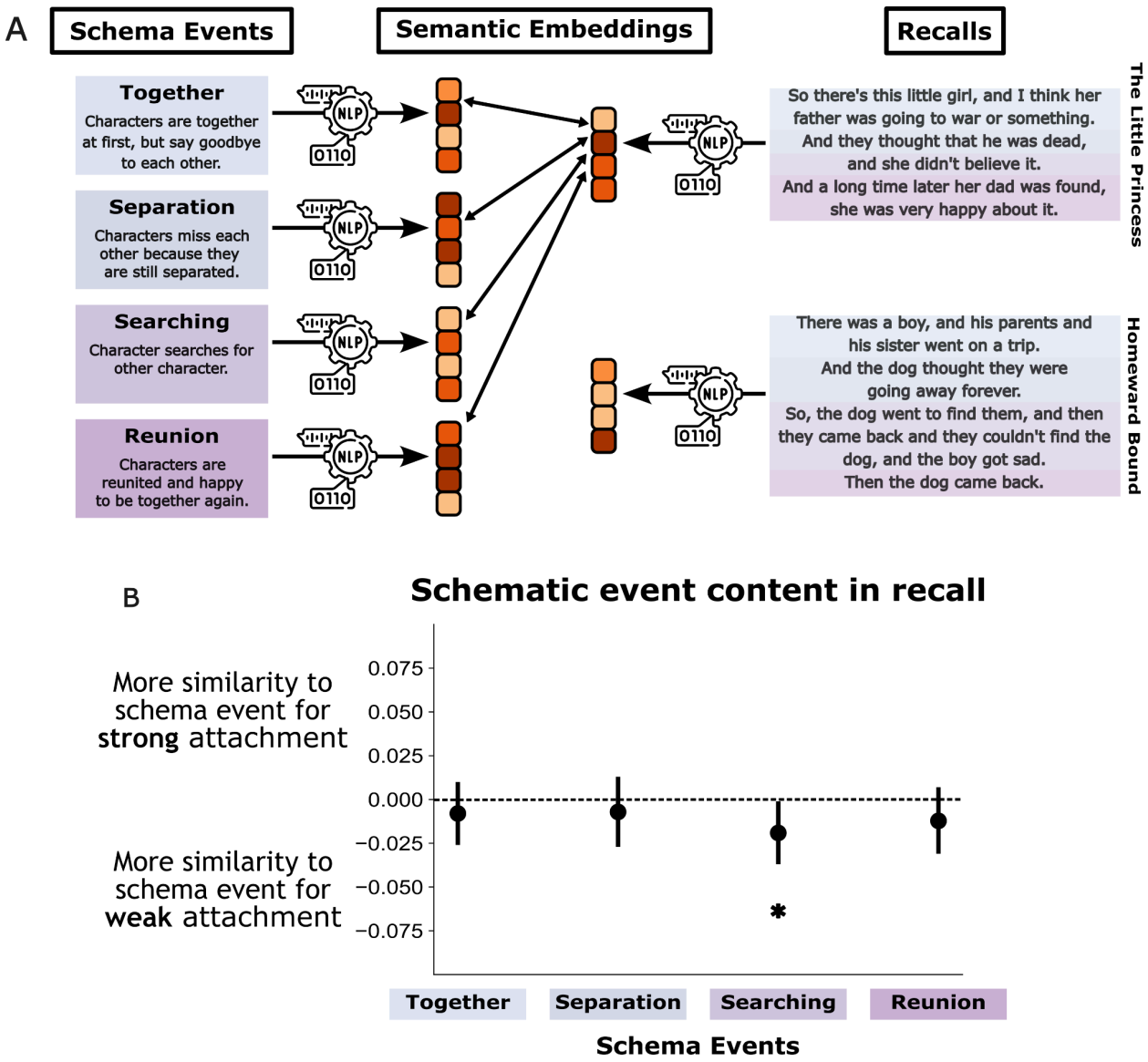

Figure 3: Analysis of semantic content of participant recalls. ***A.*** *Vector embeddings of each event in the attachment schema and each participant's recall are generated using a sentence transformer model. Recall embeddings were compared to each of the schematic event template embeddings using cosine similarity, with high similarity indicating a high degree of semantic similarity between a recall and a particular component of the attachment schema.* ***B****. Children with weaker current caregiver attachment had recalls with significantly more semantic content related to the Searching event, when the characters in the story are apart from each other and reunion is uncertain . * $p < 0.05$*

To examine whether caregiving was related to the content of free recall, we applied recently-developed tools from Natural Language Processing (NLP) to the recall transcripts. We input a text description of each of the four stages of our attachment script (Figure 3A) to a transformer-based language model (Devlin et al., 2018), producing a vector representation of the semantic content of each event. After applying the same NLP model to the recalls, we could then compute the semantic similarity between a child's recall and each of the four attachment events, providing a quantitative measure of the degree to which each schematic event was reflected in their recall. We tested whether there was a significant difference in similarity scores for children with differing caregiver stability or current attachment, using a linear regression model to control for participants' age, verbal IQ, and gender. We found that children with weaker attachment security had recalls with significantly more semantic content related to the Searching phase of the attachment script ($p = 0.04$) (Figure 3B), suggesting that weak attachment security biases memories of caregiving experiences to produce an overrepresentation of events in which the characters are separated.

In summary, we found that both instability in early caregiving environments and weaker current attachment security impacted functional connectivity and memory recall in response to a naturalistic attachment video. In the brain, the pattern of amygdala coupling to other brain regions showed a marked dissociation between the effects of early instability and current attachment. Prefrontal (and insular) connectivity to the amygdala, hypothesized to be critical for leveraging schematic knowledge for affective meaning making (Tottenham, 2020), was disrupted specifically in children with low levels of attachment security rather than in all children who experienced crEAs. Early

instability did have an effect on other components of amygdala connectivity, increasing interactions with sensory and episodic memory systems.

These results reveal the critical importance of a child's current attachment schema for processing and remembering interpersonal narratives. Anterior cingulate cortex tracks narrative event scripts (Baldassano et al., 2018; De Soares et al., 2024), and the insula has been shown to exhibit predictive signals for movie stimuli (Lee, Aly, & Baldassano, 2021). Strong amygdala connectivity to these regions suggests that, when presented with a narrative in which a caregiver leaves, children with well-formed attachment schemas can make schema-based predictions (i.e. that the caregiver will return) to modulate amygdala responses. In the absence of this internally-activated schema, the constructed situation model may instead be dominated by the current sensory input (i.e. that the character is currently separated from and searching for their caregiver), resulting in the greater focus on the separation period of the narrative observed in the recalls of participants with weak attachment security.

We did not observe this prefrontal-amygdala disruption in our crEA group (defined as having an early-life switch in caregivers), suggesting some degree of plasticity for affective schemas based on more recent experiences. This group did exhibit increased connectivity between the amygdala and the hippocampus, consistent findings in animal models that chronic stress can cause persistent abnormal coupling between the amygdala and hippocampus (Ghosh et al., 2013). This effect, however, was significantly modulated by attachment security; only children with weak current attachment exhibited this effect, suggesting that strong attachments to caregivers can serve a protective function in children with a history of crEA exposure.

Online Methods

Participants

222 children (7 - 15 years) were recruited as a part of a larger longitudinal study on disruptions in caregiving (see Fields et al., 2021 and Nikolaidis et al., 2022 for recruitment details). 135 of the cohort experienced disruptions in caregiving (e.g., institutionalization, domestic and international foster care, temporary/permanent separations from parents) and a comparison group of children did not (N = 87). All recruitment and data collection procedures were approved by the Columbia University IRB.

Caregiving instability was characterized by whether or not a child had a switch in primary caregiver or not, regardless of group (disrupted or comparison). This was assessed from a verbally reported timeline of each child's lifetime caregiving placements from their current legal guardian. A caregiving switch was characterized as a separation from biological parents (including those at, or shortly after birth to account for switches between the pre- and post-natal environment), orphanage placements, foster care placements, kinship care placements, or moves from one biological parent's home to another (on-going co-parenting arrangements did not count).

Attachment security was assessed from the 30-item Attachment strategies questionnaire (Finnegan et al., 1996). Based on prior work, children with scores below 3.0 were defined as the "weak" security group, while those with scores above 3.27 made up the "strong" security group.

Both groups, current attachment security and caregiving stability, were further examined for over-representation in age, gender, and verbal proficiency. First, none of the attachment security levels were significantly over-represented in either of the caregiving stability groups (Cramer's V = 0.13). Neither gender, male or female, were over-represented in the caregiving stability groups (Cramer's V = 0.04) or the attachment security levels (Cramer's V = 0.03). Next, a one-way ANOVA was conducted to confirm that there were no significant effects of age in either of the caregiving stability groups [$F(1, 98) = 0.60$, $p = 0.44$] or in the attachment security groups [$F(2, 97) = 0.18$, $p = 0.84$]. And lastly, the effects of verbal proficiency in both groups were examined with a one-way ANOVA, with no significant differences between attachment security groups [$F(2, 97) = 1.63$, $p = 0.20$]. However, there was a significant difference in verbal proficiency between the two caregiving stability groups [$F(1, 95) = 6.84$, $p = 0.01$]. Regardless of significance, we add all factors (age, gender, and verbal proficiency) as regressors in our linear regression models to evaluate recall transcripts.

Stimuli

Children saw one of two video stimuli, each three minutes in duration: a compilation from The Little Princess (1939) or a compilation from Homeward Bound (1993). Each stimulus was chosen and carefully edited to contain four scenes describing different fundamental themes of attachment: (1) Together, (2) Separation, (3) Searching, and (4) Reunion.

MRI scanning protocol and preprocessing

Prior to scanning all participants completed a mock scanning session to acclimate to the scanner environment and practice lying still for data collection. Data was collected on a Siemens Trio 3.0 tesla MRI scanner using a standard radiofrequency 12-channel head coil. A whole-brain high-resolution T1-weighted anatomical scan (MPRAGE; 256 × 256 in-plane resolution; 256 mm FOV; 176 × 1 mm sagittal slices) was acquired for each participant for registration of functional data. Children were randomly assigned to watch one of the video stimuli which were presented via an MR-compatible screen and mirror attached to the head coil. The MRI data included in this manuscript were preprocessed using fMRIprep 20.2.1 (Esteban et al., 2018; Esteban, Blair, et al., 2018).

Free recall protocol

After participants had completed their MR scan, an experimenter asked them to recall as much as they could from the video stimulus that they had viewed in the scanner. Their recall was recorded and transcribed.

Anatomical and functional data preprocessing

The MRI data results included in this manuscript come from preprocessing performed using fMRIPprep 20.2.1 (Esteban et al., 2018; Esteban, Blair, et al., 2018; RRID:SCR_016216), based on Nipype 1.5.1 (Gorgolewski et al., 2011; Gorgolewski et al., 2018; RRID:SCR_002502). A total of two T1-weighted (T1w) images were present

for the majority of the dataset. T1w images were corrected for intensity non-uniformity (INU) using `N4BiasFieldCorrection` (Tustison et al., 2010), distributed with ANTS 2.3.3 (Avants et al., 2008, RRID:SCR_004757). The T1w-reference was then skull-stripped using `antsBrainExtraction.sh` workflow (from ANTs), using OASIS30ANTs as a target template. Brain tissue segmentation of cerebrospinal fluid (CSF), white-matter (WM) and gray-matter (GM) was performed on the brain-extracted T1w using fast (FSL 5.0.9, RRID:SCR_002823, Zhang, Brady, and Smith 2001). A T1w-reference map was computed after registration of T1w images (after INU-correction) using mri_robust_template (FreeSurfer 6.0.1, Reuter, Rosas, and Fischl; 2010). Brain surfaces were reconstructed using recon-all (FreeSurfer 6.0.1, RRID:SCR_001847, Dale, Fischl, and Sereno 1999), and the brain mask estimated previously was refined with a custom variation of the method to reconcile ANTs-derived and FreeSurfer-derived segmentations of the cortical gray-matter of Mindboggle (RRID:SCR_002438, Klein et al. 2017).

The amygdala was defined using an MNI template in standard space (MNI152NLin2009cAsym). Nonlinear registration to this template was performed with antsRegistration (ANTs 2.3.3) using brain-extracted versions of both the T1w reference and the T1w template. The following template was selected for spatial normalization: ICBM 152 Nonlinear Asymmetrical template version 2009c (Fonov et al., 2009), RRID:SCR_008796; TemplateFlow ID: MNI152NLin2009cAsym).

Functional data preprocessing

First, a reference volume and its skull-stripped version were generated using the custom methodology of fMRIPrep. A B0-nonuniformity map (or fieldmap) was estimated based on two echo-planar imaging (EPI) references with opposing phase-encoding directions, with 3dQwarp Cox and Hyde (1997) (AFNI 20160207). Based on the estimated susceptibility distortion, a corrected EPI (echo-planar imaging) reference was calculated for a more accurate co-registration with the anatomical reference. The BOLD reference was then co-registered to the T1w reference using bbregister (FreeSurfer) which implements boundary-based registration (Greve and Fischl 2009). Co-registration was configured with six degrees of freedom. Head-motion parameters with respect to the BOLD reference (transformation matrices, and six corresponding rotation and translation parameters) are estimated before any spatiotemporal filtering using mcflirt (FSL 5.0.9, Jenkinson et al. 2002). The BOLD time-series were resampled onto fsaverage6 for analyses on the cortical surface and MNI152NLin2009cAsym space for analysis of the amygdala. The BOLD time-series were resampled onto their original, native space by applying a single, composite transform to correct for head-motion and susceptibility distortions. These resampled BOLD time-series will be referred to as preprocessed BOLD.

Several confounding time-series were calculated based on the preprocessed BOLD: framewise displacement (FD) and three region-wise global signals. FD was computed using two formulations following Power (absolute sum of relative motions, Power et al. (2014)) and Jenkinson (relative root mean square displacement between affines, Jenkinson et al. (2002)). The DVARS variable was derived from the derivative of

the estimated relative (frame-to-frame) bulk head motion calculated using the root mean squared approach of Jenkinson et al. (2002). FD is calculated for each functional run using the implementation in Nipype (following the definitions by Power et al. 2014). The three global signals are extracted within the CSF, the WM, and the whole-brain masks. The confound time series derived from head motion estimates and global signals were expanded with the inclusion of temporal derivatives and quadratic terms for each (Satterthwaite et al. 2013). Frames that exceeded a threshold of 0.5 mm FD or 1.5 standardized DVARS were annotated as motion outliers. Participants whose timeseries contained more than 45 TRs (20% of all TRs) of motion outliers were excluded from further analyses due to excessive motion. The number of participants excluded did not significantly differ between groups (caregiving stability: $t(40)=-0.08$, $p=0.94$; attachment security $t(28)=0.54$, $p=0.59$). Discrete cosine filters were extracted with 125 s cut-off. The nuisance regressors, as well as the head-motion estimates, were placed in a confounds file and subsequently regressed out of the BOLD time series separately for the cortex and the amygdala using custom python scripts. All resamplings can be performed with a single interpolation step by composing all the pertinent transformations (i.e. head-motion transform matrices, susceptibility distortion correction when available, and co-registrations to anatomical and output spaces). Gridded (volumetric) resamplings were performed using antsApplyTransforms (ANTs), configured with Lanczos interpolation to minimize the smoothing effects of other kernels (Lanczos 1964). Non-gridded (surface) resamplings were performed using mri_vol2surf (FreeSurfer).

Many internal operations of fMRIPrep use Nilearn 0.6.2 (Abraham et al. 2014, RRID:SCR_001362), mostly within the functional processing workflow. For more details of the pipeline, see the section corresponding to workflows in fMRIPrep's documentation. After these preprocessing steps were taken, the cortical surface was parcellated into the 100 parcel, seven network parcellation from Schaefer et al., 2018.

Inter-subject functional correlation (ISFC) and inter-subject correlation (ISC) analysis

After the fMRI data was preprocessed and the cortical data was parcelated on the cortical surface (Schaefer et al., 2018) subjects were divided based on the number of caregiver switches that they had experienced and their current attachment security. The following ISFC and ISC analyses were run within two distinct groupings of the data: those who had experienced caregiving switches vs. those who had not, and those who felt a high level of attachment security with their current caregiver vs. those who feel a low level of attachment security with their current caregiver.

An ISFC analysis was then run within each group, following previous research (Simony et al., 2016). For this analysis, we followed a protocol to measure inter-subject correlation established previously (Cohen, Tottenham, & Baldassano, 2022) wherein each group was randomly split into two subgroups. In one subgroup all of their responses from one cortical parcel were averaged, and in the other subgroup, all of their responses from one hemisphere's amygdala were averaged. These group-averaged responses were then correlated to establish an ISFC value between each parcel and one hemisphere's amygdala. As we did not expect hemispheric

differences in amygdala connectivity, the ISFC values for each cortical parcel were averaged across the amygdala from each hemisphere. Similarly, we then averaged ISFC values across both hemispheres of each ROI. To compare the ISFC values between groups (e.g. caregiver switches vs. no caregiver switches) we subtracted the ISFC values for one group from those of the other for all cortical parcels. All of these analyses were run separately for subjects that had watched one of the two video stimuli, and then averaged across stimuli.

ISFC values for event-specific timecourses were computed in a similar fashion as the full timecourse, but with responses from each individual's amygdala and ROI taken only from a selection of consecutive TRs belonging to each respective event (Event 1: 0 - 70 TRs and 0 - 91 TRs in The Little Princess and Homeward Bound, respectively; Event 2: 71 - 96 and 92 - 129; Event 3: 97 - 166 and 130 - 173; and Event 4: 167 - 225 and 174-225). All group and hemisphere averaging across ISFC values were performed as for the full-timecourse analysis described above.

Interaction effects of attachment and caregiving were examined by dividing participants into four groups, based on a 2x2 split according to both stable vs unstable caregiving environments and strong vs weak attachment. ISFC was computed within each of the four groups. An interaction effect was defined as the root mean square deviation of each subgroup (e.g. participants with both strong current attachment and unstable early caregiving environment) from the grand mean after taking into account both the main effects of attachment and caregiving. All averaging across groups, amygdala hemispheres, and ROI hemispheres were consistent with the main analysis.

In the ISC analysis, each group was randomly split into two subgroups, as described above. Responses from each hemisphere (e.g. left and right ACC) were averaged within each subgroup. Group-averaged responses were then correlated within subgroups, establishing a within-group response ISC value. Across group response ISC values were then computed by correlating subgroups from a subgroup in its counterpart group (e.g. a strong attachment security subgroup was compared to a weak attachment security subgroup). Next, geometric correlations were computed as a ratio of across group ISC values to the geometric mean of within group ISC values. To establish statistical significance, ISFC and ISC values were again measured 100 times in groups in which the life experience and attachment variables of interest were randomly shuffled across subjects. All values were then normalized (z-scored) before fitting with a survival function, evaluating real values relative to their corresponding null distribution. The p-value computed for the real value is then reported as the cumulative probability in the fitted distribution.

Free recall analysis

To examine narrative recall, we measured the proximity between each child's transcribed recall and the attachment narrative. We created four schematic event templates abstractly describing each of the four events. After removing stop-words from recall transcripts, we extracted sentence embeddings from a transformer-based language representation model (Sentence BERT) representing each of the four schematic event templates and recall transcripts. We then generated 4 proximity scores per participant by taking the cosine distance from recall embeddings to each event's

embeddings and subtracting the distance from 1, where larger values denote more proximity between the event and recall. Similar to the ISFC analysis, we examined proximity scores between targeted groups (e.g. high/low attachment security, N = 186 after exclusions, where 87 children reported attachment security scores in the highest group and 79 reported scores in the lowest group; ever/never switched, N = 186 after exclusions, where 104 children never experienced a switch in caregiver). We fit a linear regression model to each of the 4 events' proximity scores, adding participants' age, verbal IQ, and gender as regressors. Both target groups and interaction terms were examined for significance.

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