

Individuals who see the good in the bad engage distinctive default network coordination
during post-encoding rest

Siddhant Iyer¹, Eleanor Collier², Emily S. Finn³, & Meghan L. Meyer¹
¹Columbia University, ²University of California, Riverside, ³Dartmouth College

Author names and affiliations:

- ¹: Columbia University, New York, NY, 10027
- ²: University of California, Riverside, CA, 92521
- ³: Dartmouth College, Hanover, NH, 03755

Abstract

Focusing on the upside of negative events often promotes resilience. Yet, the underlying mechanisms that allow some people to spontaneously see the good in the bad remain unclear. The broaden-and-build theory of positive emotion has long suggested that positive affect, including positivity in the face of negative events, is linked to idiosyncratic thought patterns (i.e., atypical cognitive responses). Yet, evidence in support of this view has been limited, in part, due to difficulty in measuring idiosyncratic cognitive processes as they unfold. To overcome this barrier, we applied intersubject representational similarity analysis (IS-RSA) to precisely test whether and how idiosyncratic neural responding supports positive reactions to negative experience. We found that idiosyncratic functional connectivity patterns in the brain's default network while resting after a negative experience predicts more positive descriptions of the event. This effect was largely driven by functional connectivity patterns between the ventromedial prefrontal cortex (VMPFC) and the rest of the default network and also occurred relatively quickly during rest. For the first time, we identified post-encoding rest as a key moment and the default network as a key brain system in which idiosyncratic responses correspond with seeing the good in the bad.

Significance

Negative experiences are unavoidable, which is why effective coping strategies are key to wellbeing. One health-protective strategy is seeing the positive features that arise from life's challenges. Yet, to date, the underlying mechanisms that allow some people to spontaneously see the good in the bad remain speculative. We found responses by the brain's default network immediately after hearing about life's hardships explain why some of us react with optimism while others with despair. Specifically, homogenous default network responses corresponded with negative reactions, whereas idiosyncratic default network responses corresponded with positive reactions. People who can see negative situations through rose colored glasses may be able to do so, in part, by wearing their own, unique lens after the event.

Introduction

It is often helpful to see the good in the bad. Emphasizing the positive consequences of a medical condition, such as how it brings into focus what matters in life, promotes mental and physical health in both patients and their caretakers (Kim et al. 2007; Pakenham 2005; Chung et al. 2022). Highlighting the positive ramifications of an interpersonal betrayal fosters forgiveness and reconciliation (vanOyen Witvliet et al. 2020; McCullough et al. 2006). Even outside of our immediate social sphere, adopting a hopeful perspective on strangers' plights increases costly donations to relevant charities (Brethel-Haurwitz et al. 2020). While multiple pieces of evidence point to the upside of positivity in response to negative situations, the underlying neurocognitive mechanisms by which people see the good in the bad remain vastly underspecified.

To help fill this knowledge gap, we attempt to answer the following questions: *how*, in terms of an underlying cognitive mechanism, are some people able to see the positives of a negative experience? *Where* in the brain does this mechanism occur? And *when* during a negative experience does the mechanism come online to generate positivity? Insight into the *how* question may come from the broaden-and-build theory of positive emotion. This account proposes that while negative affect corresponds with prototypical thought patterns, positive affect is linked to idiosyncratic thought patterns (Fredrickson 2004). For example, normative responses to creative problem-solving are associated with negative affect (Nijstad et al. 2010), whereas unusual and diverse responses—relative to group norms—are tied to positive affect (Isen et al. 1985). Research on foraging behavior tells a similar story about idiosyncrasy and positivity. In both human and non-human animals, exploring atypical paths is associated with positive affect, whereas exploiting known outcomes is associated with negative affect (Barnes et al. 2022; van Dooren et al. 2021; Heller et al. 2020). Collectively, work on explore-exploit behavior and the broaden-and-build theory of positive emotion suggests people who can see the good in the bad may do so through idiosyncratic cognitive processing.

To date, this possibility has not been tested, in part, because it is difficult to measure idiosyncratic cognition “in vivo.” To overcome this barrier, we capitalized on a recent advance in computational neuroscience that is designed to detect idiosyncratic (as well as normative) cognitive processing as it naturally unfolds. Intersubject representational similarity analysis (IS-RSA) quantifies the similarity in subjects' neural responses as a function of a behavioral metric, such as their interpretations to stimuli (Finn et al. 2020). Here, we specifically employed an IS-RSA “Anna Karenina” model (Finn et al. 2020), so named after the opening line of Tolstoy's famous novel, which goes, “All happy families are alike; each unhappy family is unhappy in its own way.” Although Tolstoy's line posits greater similarity for positive vs. negative experiences, this need not be the case; the Anna Karenina model simply tests whether there is idiosyncrasy in one set of responses compared to another. For the present study's hypotheses, our Anna Karenina model predicted that subjects who see a negative event more positively will show idiosyncratic neural responses, while subjects with more negative views will show highly similar neural responses.

If idiosyncratic cognition underlies positivity in the face of negative events, the next key question to answer is *where* in the brain does the idiosyncrasy occur? Idiosyncrasy may occur in the brain's default network, an interconnected set of cortical regions associated with subjective interpretations (Yeshurun et al. 2021), including subjective, affective interpretations (Satpute and Lindquist 2019; Chang et al. 2015; Thornton and Tamir 2020). While affective reactions (e.g., high arousal) are linked to limbic regions outside of the default network, the subjective representation of affective reactions (e.g., the construal of a high arousal state as tense versus excited) is

associated with default network regions (Chang et al. 2015; Thornton and Tamir 2020; Satpute and Lindquist 2019). Moreover, individuals with similar subjective beliefs (e.g., political partisans) demonstrate neural synchrony in default network regions while processing belief-relevant stimuli (Finn et al. 2018; Leong et al. 2020; van Baar et al. 2020; Simony et al. 2016; Broom et al. 2022). Two distinct findings, when considered together, further suggest that idiosyncratic responses in a particular portion of the default network—the VMPFC—may be key to generating positivity in response to negative events. First, VMPFC increases engagement within subjects when they are explicitly instructed to try to find positive meaning (vs. control conditions) in responses to negative stimuli with high internal validity (e.g., photographs of very upsetting images; (Doré et al. 2017)). Second, the VMPFC responds idiosyncratically across subjects while they view naturalistic stimuli designed to more closely mirror situations witnessed in everyday life (Chang et al. 2021). Collectively, these findings suggest idiosyncratic responding by the default network generally, and the VMPFC particularly, might underlie seeing the good in the bad spontaneously (i.e., without instruction). To investigate these possibilities, we tested whether idiosyncratic functional connectivity (i.e., timecourse correlations reflecting coactivation) 1) between all default network regions and 2) specifically between the VMPFC and other default network regions corresponds with positive reactions to negative information.

With respect to the *when* question, there are two competing possibilities regarding when during a negative experience idiosyncratic default network coactivation comes online to generate positivity. One possibility is that the phenomenon occurs during encoding—in the moment of witnessing negative information. Consistent with this possibility, past work shows negative affect increases default network similarity across subjects while encoding emotional narratives (Nummenmaa et al. 2012). Greater default network similarity while listening to an ambiguous story also corresponds with more negative interpretations of it (Finn et al. 2018). Critically, however, this past work narrowly focuses on negative affect and has not investigated the key tenet of the broaden-and-build theory, which is that idiosyncratic cognitive responses should relate to positive affect.

Moreover, encoding may not be the moment in which idiosyncrasy supports seeing the good in the bad. One prediction from the broaden-and-build-theory is the “undoing hypothesis” which suggests idiosyncratic cognitive processing occurs directly after a negative experience to generate a positive interpretation (Fredrickson 2004). Other work also finds that positive interpretations can occur after a negative event to make the memory less threatening (Speer et al. 2021). Thus, a second possibility is that idiosyncratic default network coactivity spontaneously occurs directly after a negative experience to generate a more positive interpretation. This possibility is further supported by research on memory consolidation, which suggests offline processes during rest after an experience, including offline processes in the default network, shape how it is remembered (Tambini and Davachi 2019; Meyer et al. 2019; Wamsley 2022; Hoffman and McNaughton 2002). Idiosyncratic cognitive processes may therefore emerge in the default network during rest after a negative experience to help generate a more positive lens on the event. If this were the case, it would suggest the need for a paradigm shift with respect to how seeing the good in the bad is experimentally measured and manipulated: rather than assessing the phenomenon *during* a negative experience, as is frequently done (López-Solà, Koban, & Wager, 2019; Norris & Wu, 2021; Moser, Hartwig, Moran, Jendrusina, & Kross, 2014; Doré et al. 2017), researchers may want to consider assessing it post-encoding.

To test whether, where, and when idiosyncratic neural responding corresponds with seeing the good in the bad, we had subjects undergo functional magnetic resonance imaging (fMRI) while they watched videos of patients diagnosed with cystic fibrosis discussing their experience with

the condition. Using videos of cystic fibrosis patients allowed us to test our hypotheses in a context where individual differences in positive versus negative affect meaningfully predict well-being (Slattery et al. 2017; Pakenham 2005). That is, when caregivers stay positive, it is better for the patients' mental and physical health outcomes as well as their (Chung et al. 2022; Pakenham 2005; Nieto et al. 2022; Rand and Shea 2013; Helgeson et al. 2006; Kim et al. 2007; Pakenham and Cox 2008, Byra et al. 2021; Chang and Chan 2015; Luthans et al. 2008). Here, our experimental setup mimics the type of situation a caregiver may face, in which a patient discloses difficult information to them, and the listener could (or could not) spontaneously focus on the good in the bad. If we observe idiosyncratic responding predicts positivity, it would shed light into the basic neurocognitive mechanisms that facilitate this resilient strategy.

Subjects also watched, inside the scanner, videos describing the biology of cystic fibrosis (e.g., the genetic basis of cystic fibrosis). These videos covered cystic fibrosis content that is less open to subjective interpretation than the patient videos, which allowed us to examine whether idiosyncrasy-related positivity occurs most strongly in response to negative stimuli open to interpretation. Before and after watching the videos, subjects completed rest scans. After completing the rest and video scans, subjects stepped out of the scanner and wrote descriptions of what they remembered from each video, separately. Subjects' descriptions were submitted to a sentiment analysis that quantified negative and positive content. We were therefore able to test 1) whether idiosyncratic neural responses predict more positive reactions to patients' experiences, 2) whether the idiosyncratic responses are present in the default network and 3) when—during encoding or post-encoding rest—the phenomenon occurs.

Results

Capturing Variability in Affect

To test our predictions about whether, where in the brain, and when idiosyncratic cognitive processing may generate positivity in response to negative information, we had subjects complete functional magnetic resonance imaging (fMRI) while undergoing the following experimental phases: the “patient encoding” phase comprised four, approximately 4-minute videos of cystic fibrosis patients discussing their experience with the disease, and the “science encoding” phase comprised four, approximately 4-minute Khan Academy videos describing the biology of cystic fibrosis. The order of patient and science encoding was counterbalanced across subjects. Prior to these phases, subjects completed a 6-minute *baseline* rest scan. Subjects also completed 6-minute rest scans following each encoding phase, here termed “post-patient rest” and “post-science rest.” After their scan session, subjects responded to a surprise free recall prompt on a computer, in which they viewed a snapshot of each video and were asked to type everything they recalled from the video. The paradigm is depicted in Fig. 1.

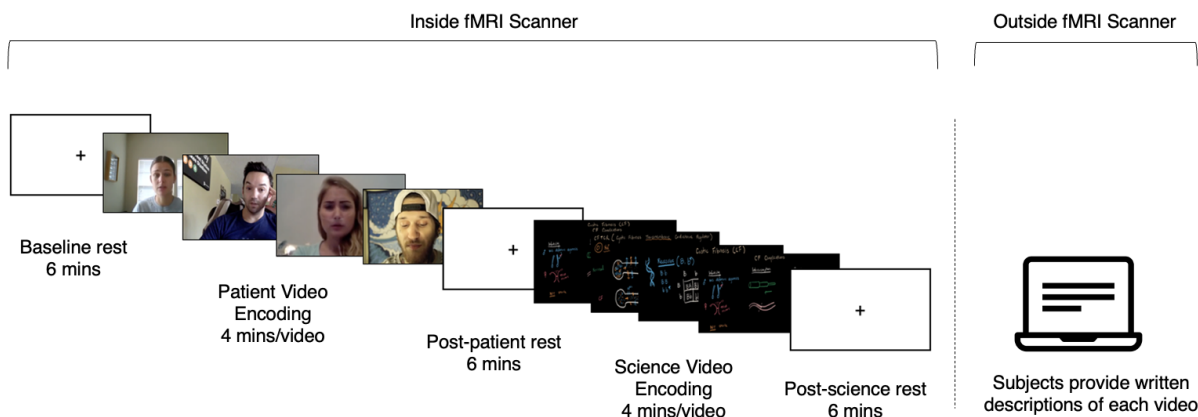


Fig. 1. Paradigm. Patient and science encoding were interleaved with rest scans to assess offline processing. Whether subjects first completed patient or science encoding was counterbalanced across subjects. After fMRI scanning, subjects wrote down everything they remembered from each video.

To derive an objective measure of the affect in subjects' descriptions, their written responses were submitted to a sentiment analysis, which is a natural language processing approach used to determine the degree to which language is positive, negative, or neutral. Specifically, we used Valence Aware Dictionary and sEntiment Reasoning (VADER, Hutto and Gilbert 2014), and specifically its Sentiment Intensity Analyzer module, which was created by leveraging and improving upon lexicons and techniques from existing natural language processing models (e.g., LIWC, ANEW), independent Amazon Mechanical Turk word ratings, and machine learning text classifiers.

Fig. 2 depicts the words used by two subjects to describe the patient videos, one of whom had a highly negative affect score (Fig. 2A) and the other a highly positive affect score (Fig. 2B). Negative words are shown in red, positive words are shown in blue; bigger words have stronger affect (highly negative or highly positive). It is noteworthy that subjects' affect scores were not significantly correlated with the length of their recall ($r = .243, p = .131$), suggesting affect was not confounded with the amount of information recalled. Subjects' affect scores were also not significantly correlated with the number of affective words written ($r = .096, p = .554$), indicating that their affect scores represent the "degree" of valence, rather than just the presence or absence of affective words. In keeping with the main analyses, all the above tests were computed using spearman correlation, such that inferences could be drawn regarding the *rank order* of subjects without assuming linearity between their affect scores and connectivity idiosyncrasies.

A. Words of relatively negative subjects



B. Words of relatively positive subjects



Fig. 2. Word clouds showing words used by subjects when describing the patient videos. A. Words used by subjects with the most negative descriptions. B. Words used by subjects with the most positive descriptions. Negative words are shown in red; positive words are shown in blue. Font size indicates strength of affect (highly negative or highly positive).

Importantly, there was no significant correlation ($r = -.101, p = .536$) or difference ($t = -1.720, p = 0.093$) in the affect scores between patient (i.e., patient; $\text{Mean}_{\text{social}} = -.148, \text{SD} = 1.894$) and science (i.e., Khan Academy; $\text{Mean}_{\text{nonsocial}} = .546, \text{SD} = 1.473$) responses. These results suggest, respectively, that subjects' affect in their patient descriptions is not conflated with their affect in their science descriptions, and that the overall affective content in descriptions was “matched” for the patient and science videos.

Collapsing across individual differences, subjects' functional connectivity is similar in each phase of the experiment

Before testing for idiosyncrasy-related positive affect, we simply assessed the extent to which subjects exhibited similar functional connectivity profiles in default network regions, as well as limbic regions, during encoding and rest. As depicted in Fig. 3, this analysis requires first extracting, for each subject, the timecourse of neural activity from each region of interest (ROI) and correlating these timecourses between each ROI-pair. Next, a vector is created for each subject, in which each vector cell is populated by the timecourse correlation of an ROI pair. Finally, all subjects' vectors (i.e., network connectivity profiles) are correlated with one another. This analysis assesses the extent to which subjects' functional connectivity profiles are similar to one another and helps ensure that across subjects, our measure of functional connectivity is reliable before examining its relationship to individual differences in affect.

Conceptually replicating prior work finding that neural synchrony is strong during naturalistic video watching (Finn et al. 2018; Broom et al. 2022; Yeshurun et al. 2017), functional connectivity similarity during patient and science encoding was significant between default network regions, as well as between limbic regions (with and without NAC; r 's $> .574, p$'s $< .001$). Interestingly, similarity in functional connectivity was also significant in these regions during the rest scans (r 's $> .475, p$'s $< .001$). This suggests that when collapsing across individual differences, subjects show similar functional connectivity profiles in brain regions relevant to subjective interpretation (default network regions) and emotional reactivity (limbic regions) during each phase of the experiment.

Further, inter-subject connectivity similarity was not significantly different for either default network regions or limbic regions during any of the experimental phases (r 's $< .132; p$'s $> .479$). Note that for these analyses, the r -value indicates dissimilarity, and thus significant r -values would indicate

significantly distinct patterns (see Methods). These results suggest that any intersubject differences detected in subsequent analyses are not a function of, and are thus robust to, the underlying level of similarity across subjects.

Default network idiosyncrasy during post-patient rest predicts positive descriptions of patients' experiences: Inter-Subject Representational Similarity Analysis (IS-RSA)

We used an Anna Karenina model to test whether, where in the brain, and when idiosyncratic responding may predict seeing the good in the bad. Our operationalization of the model predicts that subjects with highly negative descriptions would show similar neural responding while subjects with highly positive descriptions would show idiosyncratic neural responding. The approach involves comparing the mean affect of each subject pair ('inter-subject mean affect') with their connectivity dissimilarity ('inter-subject connectivity dissimilarity'). Note that we here use a dissimilarity measure instead of similarity, only for ease of interpretation (i.e., to reflect idiosyncrasy). Fig. 3 provides a conceptual depiction of the IS-RSA analysis approach.

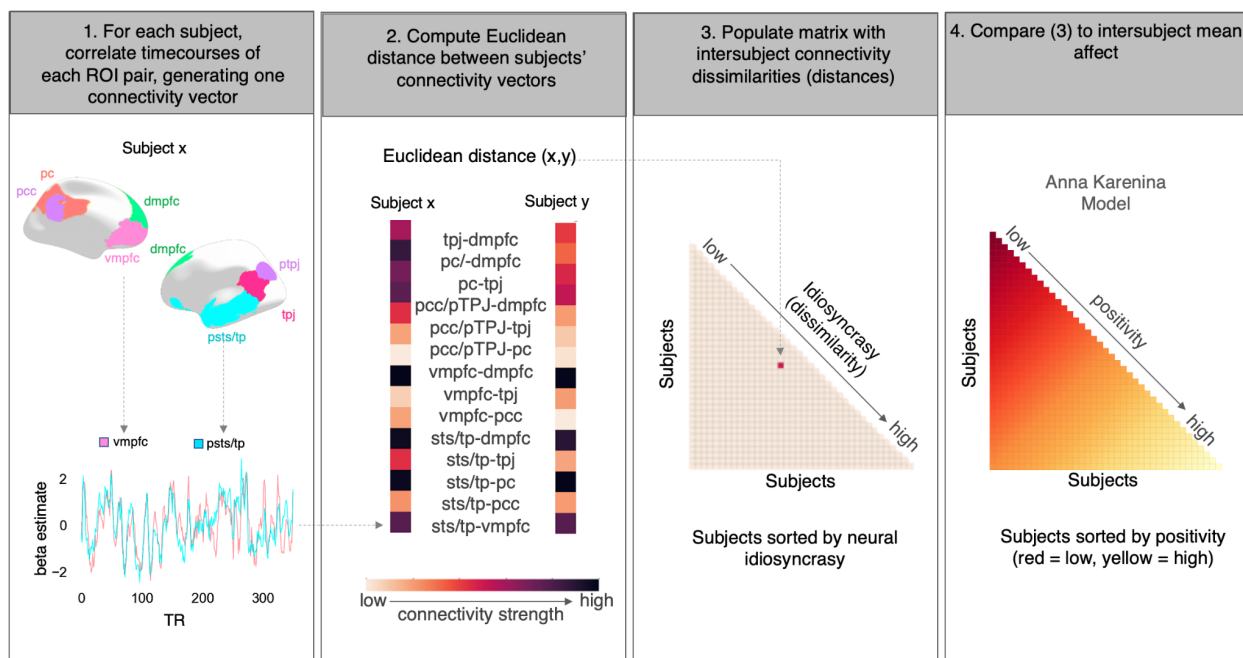


Fig. 3. Data analytic approach involving four steps. First, for each subject and for each phase of the experiment, activity timeseries from the default network ROIs were extracted and correlated with one another to generate connectivity vectors. Second, the euclidean distance metric was used to compute dissimilarity in connectivity vectors between subjects. Third, each subject pair's connectivity dissimilarity was populated into a subject-by-subject matrix. Fourth, the intersubject connectivity dissimilarity matrix was statistically compared to the theoretical Anna Karenina model. To examine the relative specificity of results to the default network, follow-up analyses were also conducted with limbic region ROIs.

We found evidence in support of the hypothesis that idiosyncratic default network coactivity comes online after observing negative information to help create a more positive reaction. The Anna Karenina model investigating default network functional connectivity during post-patient rest demonstrated a significant and positive relationship with the affect in subjects' descriptions of the patients' videos ($r = .226, p = .029$; Fig. 4A). This result indicates that subjects with highly negative

patient memories show similar default network functional connectivity profiles during post-patient rest, whereas subjects with highly positive memories show idiosyncratic default network functional connectivity patterns during post-patient rest (i.e., their patterns are different from other positive subjects, as well as other negative subjects). Interestingly, subjects' mean default network functional connectivity (i.e., the strength of their connectivity) did not significantly relate to affect scores ($r = -.142, p = .383$). The default network effects we observed are thus likely driven by idiosyncrasy in subjects' functional connectivity profiles (i.e., in how the regions communicate with one another), as opposed to simply average connectivity strength.

The Anna Karenina model testing the relationship between default network connectivity and affect in patient descriptions was not significant for the patient video encoding phase ($r = -.045, p = .646$). Parallel analyses testing for a link between the affect in science video descriptions and default network connectivity dissimilarity during 1) science encoding or 2) post-science rest were also non-significant (science encoding $r = -.018, p = .858$; post-science-rest $r = -.065, p = .511$). Finally, although affect scores were not significantly correlated with the number of correct facts recalled, to be certain that our Anna Karenina post-patient rest results in the default network are not related to the amount of information recalled, we ran an Anna Karenina model relating subjects' number of correctly recalled facts with their default network functional connectivity profiles from the consolidation phase. This model was also non-significant ($r = .005, p = .958$), indicating the observed affect results are not driven by memory accuracy more generally. Default network idiosyncrasy during post-encoding rest may thus be particularly important for generating a positive lens on negative information that is open to subjective interpretation.

The Anna Karenina model was also not significant when examining connectivity between limbic regions, another potential mechanism underlying these broaden-and-build effects. That is, given the emotional nature of the videos, and the reliance of sentiment analysis on affective words, it is possible that regions in the limbic system would exhibit idiosyncrasy in addition to the default network. To check for this, we ran our analyses in limbic regions associated with affective responding (dACC, AI, and amygdala and separately, dACC, AI, amygdala, and nucleus accumbens). The Anna Karenina model was not significant during any phase for the limbic region analysis (r 's $< |.137|$ p 's $> .210$). Overall, our results converge to suggest that idiosyncratic default network coactivity during offline processes *after* a negative experience open to interpretation helps generate a more positive lens on the event.

Default network idiosyncrasy occurring early in post-patient rest predicts more positive recall: temporal IS-RSA results

So far, results suggest idiosyncratic default network coactivity during rest after encoding negative information that is open to interpretation corresponds with seeing the good in the bad. We next wanted to know when, over the course of the 6-minute rest state scan, this effect is most pronounced. Do the subjects who engage idiosyncratic default network responding use the full six minutes of rest to do so? Or does idiosyncrasy happen fairly quickly after encoding to help generate a positive lens? To answer these questions, we investigated whether the relationship between default network functional connectivity and affect is particularly salient during certain periods of the offline processing after listening to the patients' negative experiences. First, we conducted our analyses separately on connectivity patterns during the first and second halves of the post-patient rest phase, finding significant effects only during the first half (IS-RSA $r_{first_half} = .232, p_{first_half} = .031$; IS-RSA $r_{second_half} = .139, p_{second_half} = .196$). Going one step further, we employed a sliding window approach, with each window still approximately half the duration of

the consolidation phase (i.e., 3 minutes), to more precisely quantify when during rest the Anna Karenina model is most meaningful. To this end, the Anna Karenina model was tested across 3-minute time windows starting at $t=0$ and shifting by 1s each time. For example, the first 5 windows were 1s-180s, 2s-181s, 3s-182s, 4s-183s, and 5s-184s. We found a roughly linear reduction in our model fit, though it included a peak effect for the 50s-220s window before sharply dropping to non-significance (Fig. 4B). These results suggest that idiosyncratic default network responses occur relatively quickly during offline processes *after* a negative experience to help generate a more positive lens on the event.

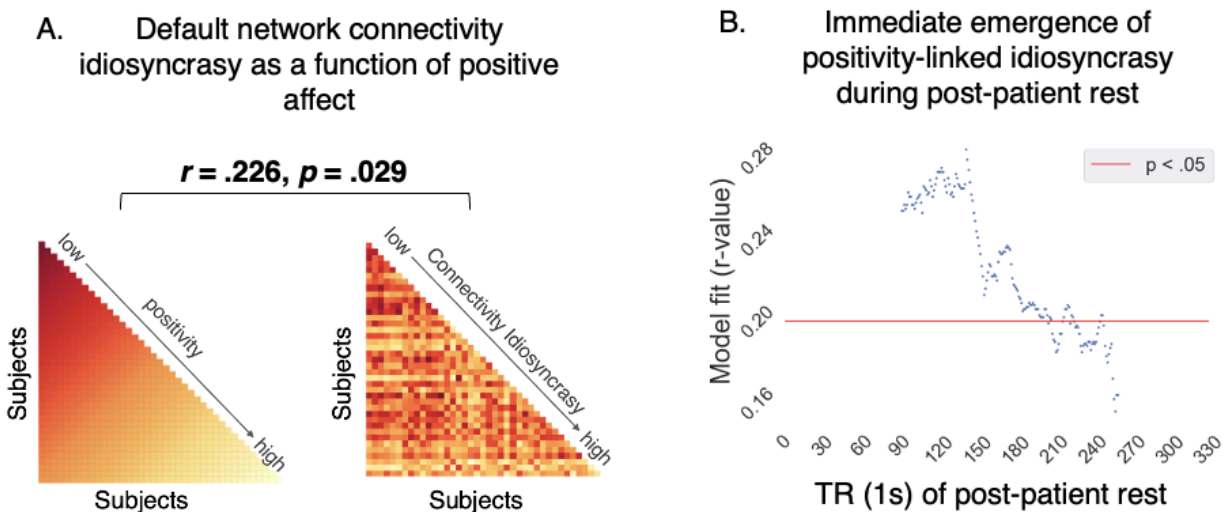


Fig. 4. Panel A) shows that the Anna Karenina model significantly predicts the affect in subjects' memories, with highly negative subjects showing similar default network functional connectivity profiles and highly positive subjects showing idiosyncratic default network functional connectivity profiles. Panel B) shows results from a sliding window analysis demonstrating that the Anna Karenina model is strongest and significant during earlier (vs. later) portions of the post-patient rest phase.

Default network idiosyncrasy driven by the VMPFC during post-patient rest predicts more positive recall: ROI-specific IS-RSA results

Prior work suggests that the VMPFC portion of the default network may be particularly key in idiosyncratically generating positive affect in the face of negative events (Roy et al. 2012; Doré et al. 2017). To assess this possibility, we next probed which ROIs in the default network were driving our results. Specifically, we tested which ROIs' exclusion from the network, individually or along with other ROIs, dissolved our results. To find this, we repeated our IS-RSA analyses with a default network region "subsetting method", i.e., we considered a default network subset of size 5 where 1 of the 6 ROIs is dropped from the analyses, then a subset of size 4 where every possible pair of ROIs is dropped from the analyses, then a subset of size 3 where every possible triad of ROIs is dropped from the analyses. Fig. 5 shows a schematic of the 'subsetting method'. Our analyses yielded VMPFC as the only ROI that was necessary in all of the subsets that showed significant effects. Specifically, among the three 5-ROI subsets, three 4-ROI subsets and two 3-ROI subsets that fit our model, only the VMPFC showed a consistent significant presence (r 's > .191, p 's < .036). Furthermore, in line with our findings that idiosyncrasies emerge particularly during early rest, we find that this necessity of the VMPFC persists even when analyzing the first

half of the post-patient rest period (one 5-ROI subset, three 4-ROI subsets, and one 3-ROI subset; r 's > .217, p 's < .039). These results suggest the default network may require the VMPFC to idiosyncratically generate positive affect in response to negative information.

Schematic of the subsetting approach isolating VMPFC as critical to idiosyncrasy in default network functional connectivity patterns

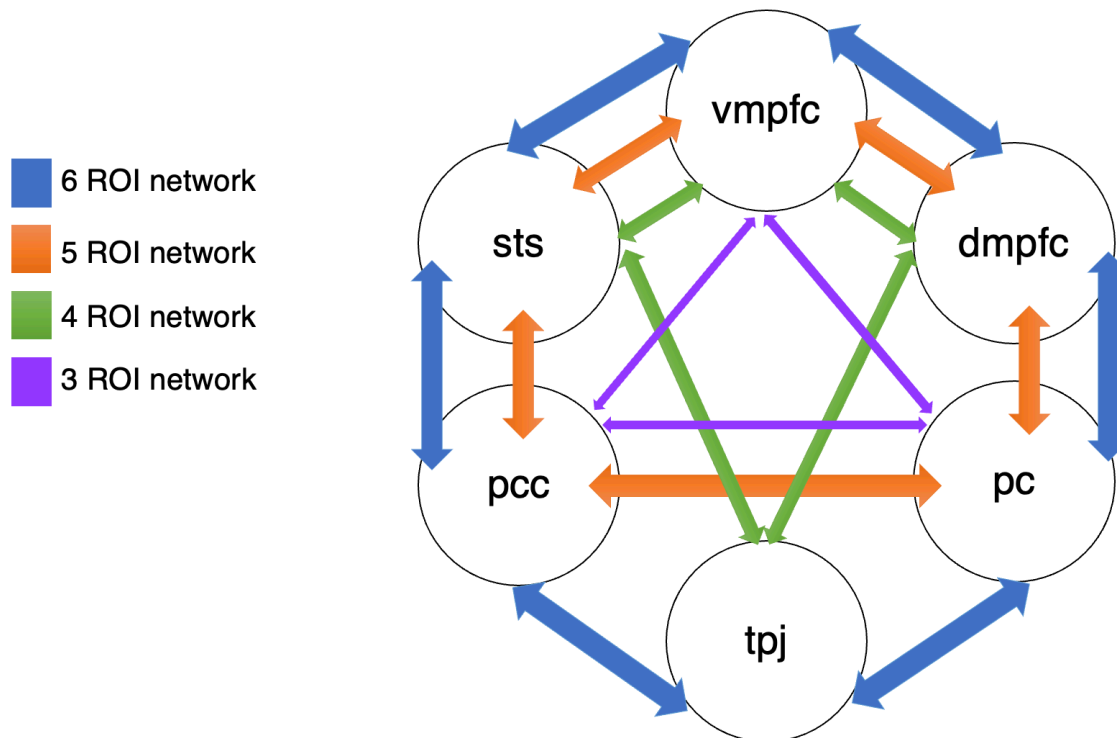


Fig. 4. Schematic of the subsetting method. The VMPFC is the only ROI that exists in all network subsets of sizes 3-6 that exhibit the Anna Karenina effect during post-patient rest. Network edge colors indicate subset size.

Discussion

How, where in the brain, and when are some people able to see the good in the bad? Answering this question is critical to developing a complete scientific model of resiliency and may offer insight into how to intervene to generate optimism in response to negative events. We discovered that idiosyncratic coactivity in the brain's default network during rest after exposure to negative information predicts more positive reactions. The findings add critical support for the broaden-and-build theory of positive emotion, which posits that idiosyncratic cognitive processes may help “undo” negative reactions to generate positivity (Fredrickson 2004). Previously, it was difficult to demonstrate support for this prediction, in part, due to the limited ways to measure idiosyncrasy. To overcome this barrier, we capitalized on a new data analytic approach designed to detect idiosyncrasy between participants. For the first time, we identified that in response to negative information, 1) post-encoding rest is a key moment and 2) the default network is a key brain

system in which homogenous responses correspond with negative affect, whereas diversified responses correspond with positive affect.

The results are remarkably specific to idiosyncratic default network coactivity during post-encoding rest. The Anna Karenina model, which tested the possibility that people who described the videos negatively versus positively may show different functional connectivity profiles, was significant for default network regions, but not limbic regions, and only during the post-patient rest phase. The lack of IS-RSA results during baseline rest rules out the possibility that results are driven by persistent, trait-level differences in default network functional connectivity. The lack of IS-RSA results during patient encoding further rules out the possibility that post-patient rest results are redundant with differences in perceptual processing *during* encoding. The lack of IS-RSA results during science encoding and post-science rest phases further points to the specificity of the results to seeing the good in the bad when there is room for subjective interpretation. Further, the lack of IS-RSA results in the limbic regions suggest that while affect may be modulated by these regions, idiosyncratic processing of subjective, affective stimuli are governed by the default network. Moreover, subjects' *mean* default network functional connectivity during post-encoding rest was also unrelated to memory affect, further suggesting results pertain to intersubject (dis)similarities in functional connectivity patterns.

Finally, the IS-RSA results are also highly specific to affective content, rather than other, potentially confounding psychological variables contributing to subjects' written descriptions of the videos. For example, subjects' affect scores were not significantly correlated with the number of facts recalled from the videos and an IS-RSA model using the number of facts recalled was similarly non-significant. Additionally, we assessed the total number of words, the number of affective words, and the 'affective intensity' (i.e., the sum of absolute or unsigned affect scores) of subjects' recall, and none of these variables were associated with subjects' affect scores. These further rule out the possibility that our results are driven by alternative constructs.

It is noteworthy that while we did not observe a relationship between intersubject differences *during* video watching and memory affect, previous research has shown intersubject differences can occur during encoding. For example, priming and trait biases have been leveraged to evoke individual differences in the default network while viewing ambiguous (van Baar et al. 2020) and polarizing (Leong et al. 2020) stimuli, respectively. Highly emotional content has also been used to show that negative emotions correspond with greater intersubject neural synchrony (Nummenmaa et al. 2012). However, the optimal trade-off between a stimulus' ability to elicit intersubject, individual differences in neural responding vs. synchronous responding across subjects is unknown (Finn et al. 2020). Our study, to our knowledge, is the first to use stimuli which evokes synchrony during encoding while successfully eliciting individual differences only during the post-encoding phase. This may be because the patient videos are overall predominantly negative and we did not recruit different groups of participants who were slated to respond to the videos differently, as is the case, for example, among political partisans from different groups. This further points to the potential importance of post-encoding rest in spontaneously generating individual differences that may not emerge immediately during encoding. Future work is needed to determine whether intersubject variability *during* encoding, if generated, can carry over to post-encoding rest, and what the individual contributions of encoding and post-encoding phases are on idiosyncratic cognitive processes. Regardless, our results are consistent with other work indicating that post-encoding processes explain unique variance in subsequent memory (Gruber et al., 2016).

The results also speak to the possibility that intersubject differences in the default network emerge particularly strongly in response to socioemotional events. Intersubject differences in neural responding are thought to reflect “subjective construal”, or the way each of us as an individual interprets the world (Griffin and Ross 1991). Thus, these differences may occur in response to stimuli that are open to interpretation (Nastase et al. 2019; Finn et al. 2018), which are encountered a lot more in social, relative to non-social, situations. For example, in contrast to visual stimuli that portray “the facts on the ground”, other people’s affect, intentions, and beliefs cannot be overtly seen and instead must be interpreted. In fact, when a large group of participants from the human connectome project observed the same animations of shapes moving around a screen, the more certain participants were that the shapes conveyed interpersonal interactions, the more strongly they engaged default network regions (as well as some regions outside of the default network; Varrier and Finn 2022). Here, we found that intersubject, default network effects in seeing the good in the bad occurred after hearing patients discuss their experience with cystic fibrosis, but not in response to hearing about the biology of cystic fibrosis. This was the case despite the fact that participants did not express significantly dissimilar amounts of affect when describing both types of videos. This observation, paired with prior work finding that default network regions preferentially consolidate social (vs. non-social) information during rest (Meyer et al. 2019), speak to the particularly important role of the default network in generating subjective interpretations of the social world.

Two sets of follow-up analyses revealed additional insight into the spatio-temporal basis of these effects. First, temporal analyses revealed that our intersubject results emerge during *early* post-patient rest. The Anna Karenina model was significant during the first, but not second, half of the post-patient rest phase and sliding window analyses further revealed that the effect occurs in the first ~3.5 minutes of rest. The temporal immediacy may be driven by multiple factors. One possibility is that most post-encoding effects occur during early rest, reflecting a type of recency effect in mind wandering. Alternatively, it is possible that specifically *interpersonal* information, as was conveyed in the patient videos, may be temporally prioritized by the brain during post-encoding processes. It has been argued that goal-relevant information may be “tagged” for prioritized memory consolidation at rest (Cowan et al. 2021). Given that 1) humans have a strong, endogenous goal to feel connected to others (Baumeister and Leary 1995) and 2) default network regions engage “by default” during rest (Raichle 2015), interpersonal information may be prioritized during post-encoding rest, with individual differences in affect codified quickly. Future work that manipulates 1) when rest occurs after interpersonal interactions (e.g., immediately versus delayed) and 2) the duration of rest, will clarify which of these competing possibilities best explains the temporal immediacy of interpersonal learning and memory.

The second set of follow-up analyses revealed VMPFC as a key player driving the default network results. We used a “subsetting” approach to the IS-RSA default network post-encoding rest analyses in which we considered how removing an ROI impacts results. This approach showed VMPFC as the only ROI that was necessary for the IS-RSA results. VMPFC is associated with generating affective interpretations, particularly positive ones (Roy et al. 2012). Moreover, recent work implicates VMPFC in supporting idiosyncratic responses (Lieberman et al. 2019), particularly in response to naturalistic social stimuli (Chang et al. 2021). Our results therefore nicely complement and extend prior research on VMPFC, highlighting for the first time that this region plays a key role in asymmetrically predicting affect, with homogenous connectivity with default network regions predicting negative affect and idiosyncratic connectivity with default network regions predicting positive affect.

The VMPFC is part of the dopaminergic system, which is critical to reward and motivational processing. Interestingly, one recent study found that engaging the VMPFC during post-encoding rest helps subjects unlearn negative associations, an effect amplified by psychopharmacological increases in dopamine (Gerlicher et al. 2019). Future work can examine whether the relationship between idiosyncratic, post-encoding VMPFC-default network coactivity is thus mediated by dopamine. Additionally, the VMPFC has bidirectional links to brain regions that generate the physiological stress response (e.g., hypothalamus) and positive affect has also been shown to reduce stress (Koban et al. 2021; Eisenberger and Cole 2012). It may thus also be fruitful to assess the role of idiosyncratic, post-encoding VMPFC-default network coactivity in dampening physiological markers of stress.

More broadly, the results hint at a new way to think about the neurocognitive mechanisms supporting resilience and the “broaden and build” theory of positive emotion. In terms of resilience, extensive psychological research suggests that finding positive meaning in response to negative situations, such as a stressor bringing people together, promotes mental and physical health (Helgeson et al. 2006). When caretakers find the benefits of a patient’s experience with a disease, both the patient and caretaker experience better well-being (Kim et al. 2007; Chung et al. 2022; Pakenham 2005; Nieto et al. 2022; Rand and Shea 2013; Byra et al. 2021; Chang and Chan 2015; Luthans et al. 2008). Our paradigm mirrors this situation, as our subjects listened to patients with cystic fibrosis share their experience with the diagnosis. This parallel, paired with the fact that prior work found VMPFC increases activity when subjects are explicitly instructed to find positive meaning in response to negative stimuli (Doré et al. 2017), points to the possibility that idiosyncratic VMPFC responding during consolidation may support the resilient strategy to see the good in the bad. Moreover, the broaden-and-build theory of positive emotion has previously suggested that idiosyncratic cognitive processes are associated with positive affect, but with limited insight into how this occurs. Our results update this literature, showing that the idiosyncratic thoughts that promote positive affect may occur spontaneously (i.e., without instruction) during post-encoding rest. The present work generates the novel prediction that inducing idiosyncratic thinking directly after a negative event may help people walk away with a more optimistic view.

Conclusion

It is impossible to avoid negative experiences in life, which is why effective coping strategies are key to protecting mental and physical health. One well-known coping strategy is positive thinking (Taylor et al. 2000), including the tendency to stay positive in the face of life’s challenges (Kim et al. 2007; Pakenham 2005; Chung et al. 2022; vanOyen Witvliet et al. 2020; McCullough et al. 2006; Brethel-Haurwitz et al. 2020). Yet, to date, the underlying mechanisms that allow some people to spontaneously employ this resilient strategy have been unclear and speculative. We found idiosyncratic responses by the brain’s default network, when we rest immediately after hearing about life’s hardships, explain why some of us react with optimism while others with despair. People who can see negative situations through rose colored glasses may be able to do so, in part, by wearing their own, unique lens after the event.

Methods

Participants

Forty right-handed subjects (26 female; mean age = 29 years, SD = 11, 65% white; 23% Asian; 8% Hispanic) completed this study. Subjects either received \$20 per hour of participation or were

awarded course credit for completing the experiment. Subjects provided informed consent in accordance with the Dartmouth College institutional review board. The data used here has been reported on in prior work (Collier and Meyer 2020), though notably all analyses reported here are orthogonal to those previously reported.

Procedures

During the rest scans, subjects saw a blank screen and rested while awake. During the patient encoding scans, subjects watched four videos in which people with cystic fibrosis discuss their experiences with the disease, with each patient video lasting approximately 4-minutes. During the “science encoding”, subjects watched four, approximately 4-minute Khan Academy videos describing the biology of cystic fibrosis. The order of patient and science encoding was counterbalanced across subjects. Subjects also completed an anatomical scan which was used for fMRI image processing.

Sentiment analysis of memory recall

Directly after the fMRI scanning, subjects wrote down descriptions of the videos. Each subject’s typed responses to the 4 patient videos were combined into one paragraph per subject and the recall of the 4 science videos were combined into another paragraph per subject. The paragraphs were cleaned to exclude non-alphabets, common ‘stop-words’ (prepositions) as defined by python’s Natural Language Toolkit (NLTK; Bird 2006), as well as neutral (non-affect words). Next, we performed sentiment analysis (VADER, Hutto and Gilbert 2014) on each word, such that negative words were affect scored between -1 and 0 (with more negative words scoring closer to -1), and positive words were affect scored between 0 and 1 (with more positive words scoring closer to 1). Finally, we summed the word affect scores across the entire paragraph to obtain one affect score per subject. We chose to use the sum instead of the average affect score because the variance and skew across summed affect scores showed it to be the more appropriate metric to analyze (summed affect $var = 3.68$, $skew = .135$; mean affect $var = -.004$, $skew = -.9$). To rule out confounds, we ensured that the affect scores were not significantly correlated with the number of affect words ($r = .096$, $p = .554$) or number of overall words ($r = .243$, $p = .131$).

fMRI Data Acquisition

Scanning was performed on a Siemens Prisma 3-T Trio. Functional images were acquired using an EPI gradient-echo sequence (2.5 × 2.5 × 2.5 mm voxels, repetition time = 1000 msec, echo time = 30 msec, 2.5-mm slice thickness, field of view = 24 cm, matrix = 96 × 96, flip angle = 59°, multiband acceleration factor = 4). A T2-weighted structural image was acquired coplanar with the functional images (0.9 × 0.9 × 0.9 mm voxels, repetition time = 2300 msec, echo time = 2.32 msec, 0.9-mm slice thickness, field of view = 24 cm, matrix = 256 × 256, flip angle = 8°).

fMRI preprocessing

Functional and anatomical brain images were reoriented using SPM and skull-stripped using the Brain Extraction Tool in FSL. Data were preprocessed using FSL. Specifically, data underwent high-pass filtering (.009 Hz cutoff), motion correction, skull-stripping, spatial smoothing (6 mm radius), and registration to the anatomical image using Boundary-Based Registration. Nuisance variables, which included six standard motion parameters, their derivatives, as well as white matter and cerebrospinal fluid data, were regressed out using GLMs. Additionally, to correct for extreme motion, global (average brain) signal and motion scrubbing (volumes with framewise displacement > .2mm) artifacts were regressed out. All analyses are applied to the residual images from this nuisance-variable GLM.

Neural time series extraction

We wanted to objectively define default network brain regions while also ensuring that the regions selected are functionally relevant to psychological constructs. For this reason, we used the $k=50$ whole brain parcellation that used k -means clustering to isolate meta-analytic coactivations (de la Vega et al. 2016) from Neurosynth (Yarkoni et al. 2011). This parcellation includes six parcels that comprise the default network: the ventromedial prefrontal cortex (VMPFC), dorsomedial prefrontal cortex (DMPFC), temporo-parietal junction (TPJ), precuneus (PC), posterior cingulate cortex functionally combined with posterior TPJ (pcc/pTPJ), and the superior temporal sulcus extending into temporal poles (STS/TP; default network regions depicted in Fig. 2). The whole brain parcellation also includes limbic regions traditionally associated with affective responding: dorsal anterior cingulate cortex (dACC), anterior insula (AI), amygdala, and nucleus accumbens (NAc). We therefore were able to examine functional connectivity (i.e., timecourse correlations reflecting coactivation) for each subject for 1) the default network, 2) limbic regions, and 3) across the whole brain (i.e., all 50 parcels). These and all subsequent analyses were performed on default network regions, as well as separately, brain regions in the limbic system as well as brain regions across the entire brain. We ran limbic region analyses two ways: first, with just the dACC, AI, and amygdala and second, with these regions as well as the nucleus accumbens (NAc), given its reliable role in positive affect. This two-pronged approach was taken because the dACC, AI, and amygdala are associated with both negative and positive affect (Cunningham and Brosch 2012), whereas the NAc is more consistently associated with positive affect only (Knutson et al. 2001; Koch et al. 1996).

For each subject, the z-scored time series of neural activity in each parcel was extracted for each phase of scanning – rest scans and video encoding scans. Following recommendations from prior work (Nastase et al. 2019), we not only excluded the pre- and post-video fixation seconds, but also the first 10 seconds of the videos themselves, to prevent the onset of videos from inflating inter-subject similarity in connectivity. Similarly, we excluded the first 10 seconds of the baseline and consolidation phases each (i.e., the first 10 seconds of each rest period).

Intersubject Dissimilarity in Functional Connectivity

To calculate a subject's default network functional connectivity, we computed the Pearson correlation of the neural time series between each default network parcel pair (separately for each experimental phase, obtaining a 6×6 matrix of parcel-pair connectivity per subject). For inter-subject dissimilarity analyses, default network functional connectivity vectors were created for each subject by vectorizing the lower triangle of a subject's default network functional connectivity matrix (see Fig. 3). Specifically, following previous work's methodology (Hyon et al. 2020), we measured the dissimilarity in default network functional connectivity between subject pairs as the *Euclidean distance* of the pair's z-scored functional connectivity vectors, obtaining an $N \times N$ inter-subject functional connectivity dissimilarity matrix. We examined subjects' functional connectivity patterns (rather than, for example, a given region's timecourse) given prior work suggesting 1) offline processing during rest occurs via communication between brain regions (Tambini and Davachi 2019) and 2) when no stimuli are present as is the case during rest, between-subject dissimilarity in functional connectivity profiles are more interpretable than between-subject dissimilarity in regional timecourses (Hyon et al. 2020; Mars et al. 2016; Liu et al. 2019).

These steps were also taken in a series of follow-up analyses designed to assess the specificity of the results to default network regions. First, with the limbic regions dACC, AI, and amygdala, which created a 3×3 matrix of parcel-pair connectivity per subject, and then separately with nucleus accumbens (NAc), dACC, AI, and amygdala, which created a 4×4 matrix.

To test whether inter-subject connectivity dissimilarity was significantly different in any particular experimental phase, we conducted a non-parametric test in which we generated the inter-subject connectivity dissimilarity matrices for each phase using a bootstrapped sample (with repetition) of 40 subjects. The dissimilarity of a subject with oneself, if present due to resampling, was discarded. Next, by subtracting every pair of matrices and computing the median of the resultant matrix, we obtained the chance (null) difference in inter-subject connectivity dissimilarity between phases. We simulated this procedure 1000 times to generate null distributions, and counted the proportion of times that the actual difference in inter-subject connectivity dissimilarity was greater than the null difference, which served as our p-value.

IS-RSA Model creation and testing

We first converted subjects' affect scores into ranks, such that negative subjects were ranked low and positive subjects were ranked high (range of ranks = 0-39 for N=40). Our Anna Karenina model modeled subject pair's dissimilarity in functional connectivity as the mean of the pair's ranks, such that the higher the pair's rank (indicating more positive recall), the greater their dissimilarity in functional connectivity (indicating more idiosyncratic connectivity), and vice-versa. We thus obtained our 40*40 *connectivity similarity matrix model*. The Anna Karenina model is depicted in Fig. 3.

Finally, to test our hypothesis, we correlated our connectivity dissimilarity matrix *model* with our connectivity dissimilarity matrix *data* (we used spearman correlations to not assume linearity between the two matrices). To determine the statistical significance of a model's fit, we needed to account for the non-independence in our data: specifically, each data point (matrix cell) represented a subject *pair*, and thus each *subject* was represented in multiple (N-1=39) data points. To this end, and consistent with prior work (Finn et al. 2018), we conducted a non-parametric permutation test, wherein we randomly shuffled and reassigned subjects' functional connectivity vectors 5000 times, each time correlating the resultant simulated matrix with our model matrix, thus generating a (null) distribution of IS-RSA (correlation) values. We then summed the number of times our simulated null correlation value exceeded our observed model-data correlation, yielding the probability that our results were generated by chance. Finally, we compared this probability against a significance threshold of alpha = .05 to discern statistical significance.

Conflict of interest statement: The authors declare no competing interests

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Code & Data Availability:

Code & data are available at https://github.com/siyer7/default_network-socioaffective-memory-variability

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