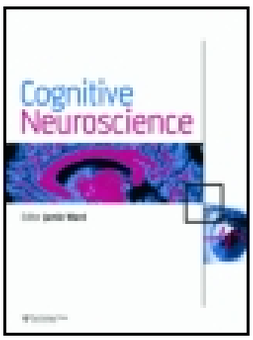

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REPORT

Decoding the emotional valence of future thoughts

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ABSTRACT

Affective future thinking allows us to prepare for future outcomes, but we know little about neural representation of emotional future simulations. We used a multi-voxel pattern analysis to determine whether patterns of neural activity can reliably distinguish between positive and negative future simulations. Neural patterning in the anterior cingulate and ventromedial prefrontal cortices distinguished positive from negative future simulations, indicating that these regions code for the emotional valence of future events. These results support prior findings that anterior medial regions contain representations of emotions across various stimuli, and contribute to identifying potential rewarding outcomes of future events. More broadly, these results demonstrate that the phenomenological features of future thinking can be decoded using neural activity.

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Future simulation; emotion; MVPA

Introduction

The emotional signals evoked by future thinking provide information and motivation for farsighted decisions (Bulley & Schacter, 2020). How does the brain represent affective future simulations? Studies employing univariate analyses have revealed specific brain regions recruited during emotional future simulations, including the amygdala, hippocampus, anterior cingulate cortex (ACC), ventromedial prefrontal cortex (vmPFC), and posterior cingulate cortex (PCC) (Benoit et al., 2014; D'Argembeau et al., 2008; Murphy et al., 2017; Sharot et al., 2007). However, few studies have examined patterns of neural activity when thinking about personal future events (e.g., Benoit et al., 2019; Hassabis et al., 2014), and no studies have examined neural patterning of emotional future events.

Recent attempts to classify the emotion of autobiographical memories have been successful in regions typically involved in episodic memory retrieval (Frid et al., 2020; Nawa & Ando, 2014). Given the similarity in neural activation when remembering the past and imagining the future (Addis et al., 2007), we may expect neural patterning in similar regions to carry information about emotion when simulating future events. However, previous work shows that memory and future thinking can exhibit differences in neural patterning even when overall activation is similar (Kirwan et al., 2014). Moreover, it has been shown that it is possible to classify emotional states when viewing impersonal stimuli, yet there is little overlap in brain regions expressing emotion-predictive patterns across studies, suggesting that different regions might represent affective quality depending on the type of stimuli being processed (Kragel & LaBar, 2016). As such, it is important to examine whether neural patterning when simulating *future* events carries information about emotion.

We used multi-voxel pattern analysis (MVPA) to examine whether patterns of neural activity can reliably distinguish between positive and negative future simulations. We focused on regions known to elicit univariate mean-signal differences in activity for positive and negative events: amygdala, hippocampus, ACC, vmPFC, and PCC. We expected that neural patterning in these regions would distinguish positive from negative simulations, indicating that these regions code for the emotional valence of future events.

Method

Participants

Twenty-two participants gave informed consent in a manner approved by Harvard University's ethics board, and were compensated with 20 USD/hour. Participants were 18–35 years old, fluent English speakers, right-handed, with no neurological or psychiatric impairments. One participant was dropped for task noncompliance, leaving 21 participants (*M* age = 22.05 yr, *SD* = 2.12, 8 males).

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Procedure

During a *pre-scan phase*, participants were randomly shown 48 of 72 scenarios with an ambiguous outcome (e.g., 'Bike ride'), along with a neutral description of the scenario (e.g., 'You and a friend decide to cycle along the river'), and an instruction to simulate an event going well (positive condition) or poorly (negative condition). Scenarios were randomly assigned to the positive or negative condition for each participant (24 of each). For each scenario, participants simulated a specific future event occurring within the next year at a specific time and place, describing the event aloud for one minute (see the Supplementary Information for detailed participant instructions). Participants rated the simulation from 1–5 for emotional valence (from strongly negative to strongly positive), vividness, emotional arousal, personal significance, plausibility, and similarity to previous experiences (from low to high). The pre-scan phase ensured that participants could simulate a detailed and emotionally provoking event for each cue. Participants first completed two practice trials to ensure that instructions were understood. Stimuli were shown via computer with E-Prime Version 3. The prescan phase took approximately 1 hour to complete.

The *scanned phase* occurred following a 30 minute break. During this phase, participants silently re-simulated the same 48 scenarios for 15s each, focusing on the emotional aspects, then rated the event for emotional valence and vividness (3s each). Trials were interspersed with a variable fixation cross (3.5, 5, or 6.5s). There were three task runs, each lasting 10 minutes with 16 scenarios presented in a random order. Participants also completed 24 semantic control trials which are not relevant to the current analysis. The scanned phase took approximately 1 hour to complete.

fMRI acquisition and analysis

Images were acquired on a 3 T Siemens Prisma scanner equipped with a 32-channel head coil. Anatomic images were acquired with a magnetization-prepared rapid gradient echo sequence (matrix size of 256x256, 1mm^3 resolution, 176 slices). Functional images were acquired with a multiband echo-planar imaging (EPI) sequence (repetition time [TR] = 2s, echo time [TE] = 30 ms, matrix size 124x124, 87 slices, 1.7mm^3 resolution, multiband factor of 3, in-plane GRAPPA acceleration factor of 2). Slices were auto-aligned to an angle 20° toward coronal from anterior-posterior commissure alignment. fMRI data were analyzed using Statistical Parametric Mapping (SPM12). Preprocessing included slice-time correction, two-pass spatial realignment, and normalization into Montreal Neurological Institute (MNI) space (using the SPM12 TPM template; no resampling). Anatomic images were also normalized into MNI space.

Feature selection

We selected five regions of interest (ROIs), and conducted MVPA separately in each hemisphere: amygdala (number of left/right voxels = 355/349), hippocampus (1379/1267), ACC (2094/2003), vmPFC (1008/1218), and PCC (500/311). ROIs were identified using WFU PickAtlas v3.0, with voxels restricted to gray matter by inclusively masking ROIs with the default SPM gray matter probability map thresholded at $p > 0.2$. A univariate analysis confirmed that the contrast of positive versus negative future simulation identified neural regions that overlapped with those defined by the WFU PickAtlas. Our choice to employ anatomical, as opposed to univariate-defined, ROIs was based on prior studies (Benoit et al., 2014; D'Argembeau et al., 2008; Murphy et al., 2017; Sharot et al., 2007) and ensured that our feature selection procedure was wholly independent of the data employed for the MVPA.

MVPA

For each participant, a general linear model (GLM) was constructed where each trial was modeled as separate regressor, yielding one model with a beta image corresponding to each trial (Rissman et al., 2004; Ritchey et al., 2013). Trials were modeled with a boxcar function convolved with a canonical hemodynamic response function for the 15s stimulus duration (72 regressors of interest, concatenated across the three runs). The GLM included regressors modeling the 6s rating window (72 total), six regressors representing movement-related variance, and regressors modeling each run. Temporal smoothing was conducted using a high-pass filter of 128s. The resulting parameter estimates were extracted from each ROI for each simulation trial, and z-scored within each ROI both across trials and voxels. We conducted MVPA on the resulting values using the Princeton MVPA Toolbox and custom MATLAB scripts.[1]

Classification was implemented with regularized logistic regression (L2) using an a priori penalty parameter (λ) of 10.[2] Within each ROI, we used a three-fold cross validation approach where a classifier was trained

[1]Code and experimental materials are available upon request.
[2]To confirm similar results using other penalties, we ran a post-hoc classification analysis for each ROI using a range of penalties (0.01–100), and found no significant differences in accuracy.

Table 1. Mean behavioral ratings of positive and negative future simulations (1–5 scale).

Rating	Positive (SD)	Negative (SD)	*t*	df	*p*
Pre-scan phase					
Valence	3.80 (0.50)	1.92 (0.34)	−11.31	20	.000*
Vividness	3.55 (0.49)	3.50 (0.55)	−0.64	20	.533
Arousal	2.93 (0.49)	3.16 (0.61)	2.09	20	.050
Plausibility	3.07 (0.55)	2.56 (0.50)	−5.25	20	.000*
Personal significance	2.81 (0.54)	2.38 (0.55)	−3.88	20	.001*
Similarity to previous events	2.40 (0.59)	1.93 (0.39)	−4.57	20	.000*
Scan phase					
Valence	4.03 (0.42)	1.90 (0.34)	−13.52	20	.000*
Vividness	3.71 (0.61)	3.58 (0.68)	−2.00	20	.060

Note. * indicates significant at $p < .05$.

on data from two runs and tested on the remaining run. Accuracy was defined as the proportion of correct study trial assignments (positive vs. negative) across the three iterations of training and testing. Accuracy was binarized to give a score of 1 for correct and 0 for incorrect classification for each trial. Classification was deemed accurate if the average returned classifier evidence for the correct category was greater than .5 (i.e., chance). To ensure that 50% was an accurate estimate of chance accuracy, permutation analyses were conducted for each ROI (100 permutations) by scrambling the study trial assignments before cross-validation. Permutation analyses revealed that accuracy was not significantly different from .5 (all means = .50, SD = 0.007–0.01; *t*s (20) < 1.51, *p*s > 0.15).

Results

Behavioral results

During the pre-scan phase, positive relative to negative events were rated as more positive, plausible, personally significant, and similar to previous experiences. During the scan, positive events were again rated as more positive, but not more vivid than negative events (see Table 1).

Table 2. Mean classifier accuracy compared to chance (0.5).

Region and emotion condition	Classifier accuracy (SD)	*t*	df	*p (one-tailed)*
Amygdala negative	0.54 (0.07)	3.06	20	0.003*
Amygdala positive	0.50 (0.07)	−0.20	20	0.421
Hippocampus negative	0.56 (0.11)	2.53	20	0.010
Hippocampus positive	0.53 (0.09)	1.39	20	0.090
Anterior cingulate cortex negative	0.61 (0.07)	6.80	20	0.001*
Anterior cingulate cortex positive	0.57 (0.11)	2.82	20	0.005*
Ventromedial PFC negative	0.59 (0.10)	4.46	20	<0.000*
Ventromedial PFC positive	0.57 (0.11)	2.91	20	0.004*
Posterior cingulate cortex negative	0.57 (0.08)	3.79	20	0.001*
Posterior cingulate cortex positive	0.53 (0.10)	1.62	20	0.060

Note. * indicates significant at corrected $p < .005$. PFC = prefrontal cortex.

MVPA results

An ANOVA examining classifier accuracy across ROIs, emotion conditions, and hemispheres revealed a main effect of ROI ($F(2.93, 58.59) = 5.67$, $p = .002$, $\eta^2_p = 0.22$), and of condition ($F(1, 20) = 17.73$, $p < .001$, $\eta^2_p = 0.47$), where accuracy was higher for negative ($M = 0.57$, SD = 0.07) than positive simulations ($M = 0.54$, SD = 0.07). Because there was no main effect of hemisphere, we collapsed accuracy across hemispheres.

Next we conducted one-tailed t-tests comparing classification accuracy to chance (.5) for each ROI and emotion condition, with a Bonferroni correction for multiple comparisons (α = .05/(5 ROIs x 2 conditions), yielding a corrected *p*-value of .005). Classifier accuracy was above chance for positive and negative events in the ACC and vmPFC (Table 2 and Figure 1). Additionally, classifier accuracy was above chance for negative events in the amygdala and PCC.

Discussion

We show that medial PFC regions that track the emotion of future events using univariate mean-signal analyses also carry information about emotional valence in their multi-voxel neural patterning. These results support findings that the medial PFC codes for emotion across various stimuli (Kim et al., 2015; Kragel & LaBar, 2016), and extend them to include simulations of personal future events. Our findings also align with theories that anterior medial regions like the ACC and vmPFC process reward value (e.g., D'Argembeau, 2013; Roy et al., 2012), and are involved in identifying potential rewarding outcomes of future events (Benoit et al., 2014) and simulations (Lin et al., 2015). Since vmPFC dysfunction is implicated in depression and anxiety disorders (Drevets et al., 1997), a question for future research is whether

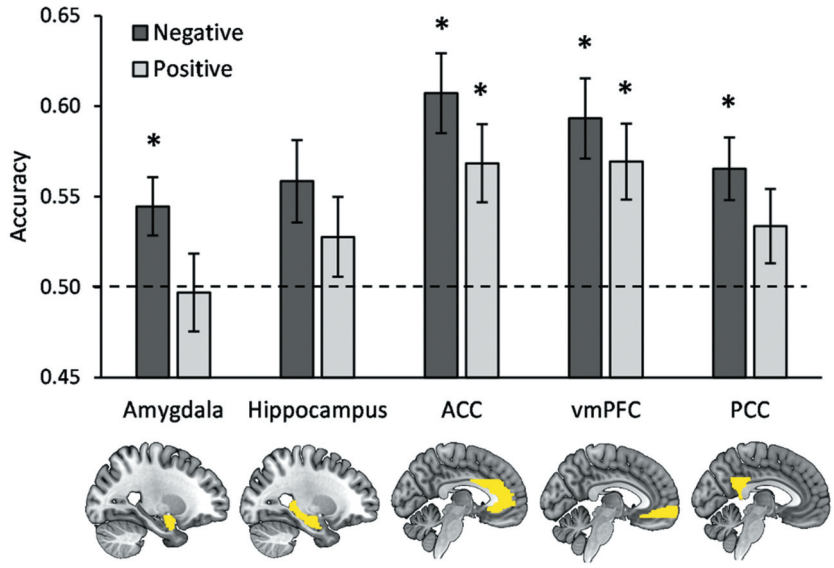

Figure 1. Classifier accuracy for each of the regions analyzed, split by emotion condition. Error bars denote standard error. Masks for each region of interest (ROI) are depicted in yellow (analyses were conducted in each hemisphere separately for each ROI, see main text for details). Note. * indicates significant at corrected $p < .005$, dotted line indicates chance classifier performance, ACC = anterior cingulate cortex, vmPFC = ventromedial prefrontal cortex, PCC = posterior cingulate cortex.

dysphoric individuals show differential coding of positive and negative events in this region.

Overall, negative events were more accurately classified than positive events. In addition to the ACC and vmPFC, negative events were classified above chance in the amygdala and PCC. It is possible that the content and subjective experience of negative events is more consistent across scenarios/trials, leading to more consistent neural patterning, whereas positive events are more variable in nature, leading to reduced classifier accuracy. The subjective ratings support this view; negative simulations were rated as less plausible, personally significant, and similar to previous events than positive simulations, which might contribute to decreased simulation variability and increased consistency in neural patterning. Alternatively, these phenomenological differences raise the possibility that negative events were more difficult to simulate than positive events. However, the prescan phase was designed to mitigate differences in simulation difficulty, and the equivalent vividness and arousal ratings suggest that participants were able to successfully simulate a novel event regardless of emotion condition.

Above chance classifier accuracy in the amygdala and PCC for negative simulations is also interesting in comparison to autobiographical memories. While anterior medial regions have been reported as representing autobiographical memory valence (Frid et al., 2020), the amygdala and PCC have not, raising the possibility that these regions differentially represent phenomenological content when thinking about past versus future. This possibility merits further study because MPVA can highlight neural differences between memory and future thinking missed by univariate analyses (Kirwan et al., 2014).

A limitation of the current paradigm is that future events had been previously simulated in the prescan phase. While this design ensured that participants simulated emotionally evocative future events, it introduces an episodic memory component, in that future events are not simulated for the first time in the scanner. Previous studies examining future thinking have used a similar repeated simulation design with emotional future events (e.g., D'Argembeau et al., 2008; Devitt et al., 2020; Szpunar et al., 2015, 2014), and obtained broadly similar results as studies in which events are simulated in the scanner for the first time. Because the present study is the first to decode emotional valence during future simulation, the reliability of the current findings should be examined in future work.

In conclusion, we find that neural patterning can reliably distinguish positive from negative future simulations in the ACC and vmPFC, indicating that these regions code for the emotional valence of future events. These results demonstrate that we can decode the phenomenological features of future simulation, and afford a starting point for decoding other features of personal future events using neural activation.

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Disclosure statement

No potential conflict of interest was reported by the authors.

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