Affective Experience Predicts Narrative Engagement during Naturalistic Viewing

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Abstract

People are more engaged in a narrative during emotional moments. However, we lack a fine-grained understanding of the type of emotions that drive narrative engagement. Here, we used a connectome-based predictive model to predict narrative engagement from dynamic functional connectivity as participants watched an episode of the TV show *Friday Night Lights (FNL)*. Correlation between dynamic intersubject correlation (dynamic ISC) and engagement revealed that areas in the dorsal attention network, ventral attention network, and control network were more synchronized across participants during moments of high engagement. We then used a ridge regression model to investigate the relationship between narrative engagement and the affective experience of 16 emotions. Our results suggest that people are more engaged in a narrative when they are subjectively experiencing high arousal negative emotions.

Keywords: emotion; engagement; arousal; connectome-based predictive model (CPM)

Background

People engage with the world by attending to the abundant perceptual information in the external environment. Attention fluctuates overtime[1] and is naturally captured and driven by the content of the stimuli when people comprehend naturalistic stimuli[2], for example, listening to a story or watching a movie. Narrative engagement has been defined as the experience of being deeply immersed in a story and connecting to its plots and characters[3], and emotional engagement is considered as a key dimension of it[4]. Previous work suggests that emotional arousal enhances attention[5,6], and emotional valence is also an influential factor of how attention operates[7]. Consistent with this past work, a recent study found that people are more engaged during emotional moments in a narrative[2].

Human affective experience, however, is rich and complex. Do different emotions capture engagement differently? Most prior studies have focused on a limited subset of emotion categories and do not fully capture the complexity of affective experience while listening to a story or watching a movie. The Friday Night Lights (FNL) dataset includes emotion ratings on 16 emotions while watching the episode and provides a unique opportunity to characterize the relationship between affective experience and narrative engagement. To that end, we examined if and how the 16 emotions predict narrative engagement.

Specifically, we trained a supervised machine learning algorithm (ridge regression model) to build a predictive model of narrative engagement, as indexed by a connectome-based predictive model (CPM) trained on time-varying functional connectivity data, from behavioral ratings along 16 different emotional dimensions while participants watched an episode of Friday Night lights. Using this model, we examined how fluctuations in the 16 dimensions of affective ratings tracked changes in narrative engagement measured using the CPM.

Results

Neural synchrony across participants tracks narrative engagement. We trained a support vector regression model (SVR model) to predict moment-to-moment (i.e at every TR) behavioral ratings of narrative engagement from dynamic functional connectivity. The model was trained on the *Sherlock* dataset[11] and tested within the same dataset. Leave-one-out (LOO) cross-validation was conducted, such that this model was trained on all but one subject, and tested on a held out subject. The LOO procedure was then repeated across all subjects with a different subject held out each time. Pearson's correlation between the predicted engagement and actual behavioral engagement ratings was calculated, the Fisher's z-transformation of which was averaged across cross-validation folds and considered as the indicator of the predictive accuracy, along with the mean squared error (MSE), and R^2. These predictive accuracy indicators were tested for statistical significance by comparing them with the results from permutations (n=1000) in which null models were generated by using the trained model to predict time-randomized behavioral engagement. The results suggested that predictive accuracy for this predictive model was significantly higher than the generated null models (Pearson's r, MSE, $R^2, p < .001;$). This model was then applied to the *FNL* dataset to predict moment-to-moment engagement from calculated dynamic functional connectivity.

We first asked whether the model-predicted engagement measure would be associated with stimulus-driven patterns of neural activity shared across participants. Dynamic intersubject correlation (ISC), a method of isolating shared brain activity related to processing the same stimuli at the same moment, was computed for all pairs of participants for each of the 122 ROIs (see *Methods* for brain parcellation details) across the time course. To investigate neural synchrony during time-varying engagement states, correlations were calculated between predicted engagement and dynamic ISC. The correlation values were then averaged across participant pairs, resulting in a correlation value for each of the 122 ROIs. Figure 1 showed the regions in which dynamic ISC significantly correlated with predicted engagement (corrected for multiple comparison, FDR-corrected $p < .05$), which included areas in the dorsal attention network, ventral attention network, control network, left hippocampus, left thalamus, and right basal ganglia.

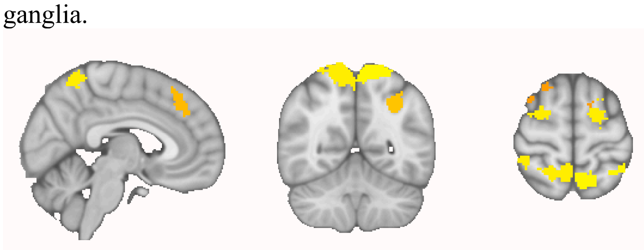
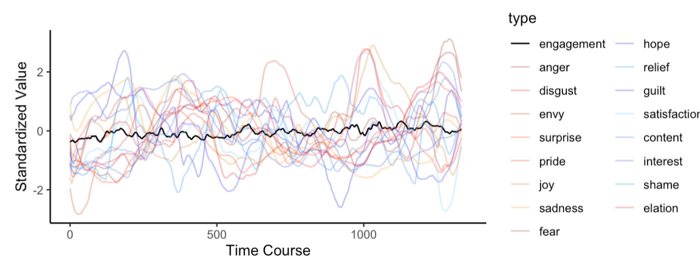


Fig. 1. Dynamic ISC scales with changes in engagement. Regions that show significant correlation between dynamic ISC and group-average engagement ($p < .05$)

Affective Ratings Predict Engagement. We trained a supervised machine learning model to assess the relationship between narrative engagement and the 16 categories of emotion ratings. A ridge regression model was built to use subjective ratings of 16 emotions to predict the engagement measure derived from dynamic functional connectivity (Figure 2A). The dataset was randomly divided into 70% training set and 30% testing set for cross-validation The results for the ridge regression model (R^2 = .62) showed that among the sixteen emotions, fourteen of them (all except elation and guilt) were significant predictors of engagement ($t = .3941, p = .69; t = 1.1580, p = .24$). We labeled pride, joy, elation, anger, disgust, envy, sadness, surprise, and fear as high arousal emotions, and interest, content, hope, satisfaction, relief, shame, and guilt as low arousal emotions. The results showed that high arousal emotions (e.g., anger and disgust) positively predict engagement while low arousal emotions (e.g., satisfaction and relief) are negative predictors of engagement (Figure 2B), suggesting that emotional arousal may play an important role in narrative engagement. For emotions that predict high engagement, negative emotions (e.g., anger, disgust) were more predictive of high engagement than positive emotions (e.g., pride, hope). Similarly, for emotions that predict low engagement, negative emotions (e.g., shame, fear) were more predictive of low engagement than positive emotions (e.g., satisfaction, relief). Taken together, our results suggest that people are more engaged when they are experiencing high arousal negative emotions and less engaged when they are experiencing low arousal negative emotions.

Exploratory Independent Component Analysis. In exploratory analyses, we performed an independent component analysis (ICA) to decompose the 16 affective ratings into two independent components (IC) (See **Supplementary Table 1**). A linear regression analysis was conducted to predict engagement from IC1 and IC2. The overall model was significant ($F(1,1332) = 280.71, p < .001, R^2 = .375$), with IC1 negatively predicting engagement ($\beta = -.302, p = .042$) and IC2 positively predicting engagement ($\beta = 3.481, p < .001$). Visual inspection of the IC loadings suggests that IC1 corresponded to valence, but IC2 did not neatly correspond to arousal (e.g., low arousal emotions had highly positive and highly negative loadings, while high arousal emotions did not load onto the IC). Future studies that collect subjective ratings of valence and arousal will allow us to more explicit test the hypothesis that high arousal negative emotions are more like to capture narrative engagement.

A.



B.

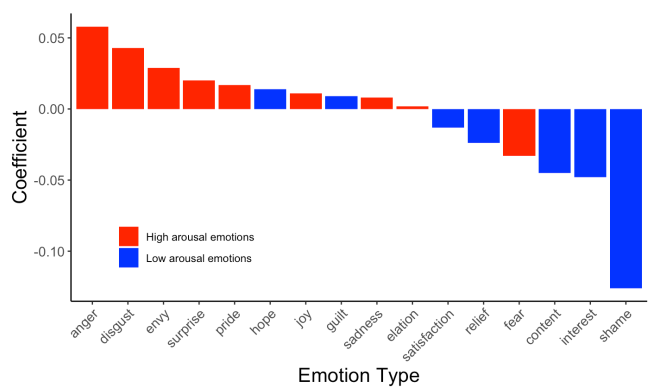


Fig. 2. Ridge Regression Modeling. (A) Overview of the relationship between engagement and 16 emotions. Red and orange lines represent high arousal emotions, blue lines represent low arousal emotions. (B) Coefficient for 16 emotions in predicting engagement.

Conclusions

Using data from the *Sherlock* and *FNL datasets*, we built a SVR model to predict engagement from dynamic functional connectivity patterns. Results from intersubject correlation show that dorsal and ventral attention network, and control network are synchronized when people are engaged. Using a ridge regression model, we found that people are more engaged when they are subjectively experiencing high arousal negative emotions. Further, we conducted a exploratory emotion decomposing analysis (ICA) and built a linear regression model to predict engagement from independent components. In conclusion, this study provided preliminary evidence that arousal plays a central role in engagement. Following studies could use different dataset to gain insights about the role of high and low arousal emotions in different context.

Methods

Behavioral Data Acquisition and Preprocessing. The behavioral subjective feelings on 16 different emotional dimensions were downloaded from OpenNeuro[9]. Participants (n=188; 105 females; mean [SD] age = 37.11 [10.71] years) from Amazon Mechanical Turk watched the 45-min the first episode of the Friday Night Lights (FNL). The episode was paused over the whole-time course at random intervals of 200 to 280s sampled from a uniform distribution. Each participant rated the intensity of 16 different emotional dimensions: contempt, surprise, relief, anger, envy, shame, interest, elation, satisfaction, guilt, sadness, hope, pride, fear, joy, and disgust. Ratings are downsampled to 1 Hz and used to create a subject-by-time sparse matrix (188×2728). We then averaged every two time points (188×1364) and a sliding window of the size of 30 TR was applied to the dataset which resulted in a 188×1334 subject-by-time matrix. The matrix was then averaged across participants for each emotion, resulting in a 16×1334 emotion-by-time matrix. The dataset was normalized (z-scored across time course) for each emotion.

fMRI Image Acquisition and Preprocessing. The fMRI images from the *FNL* dataset were downloaded from OpenNeuro. Functional blood oxygen level-dependent (BOLD) images were from Chang et all.[10-11] Preprocessing steps followed slice timing correction, motion correction, linear detrending, high-passing filtering (140-s cutoff), coregistration, and affine transformation to the MNI space. The functional images were resampled to 3-mm^3 voxels.

The preprocessed images from the *Sherlock* dataset were downloaded from Princeton University's DataSpace repository[11]. Functional images were from Chen et al.[12] Preprocessing steps followed slice timing correction, motion correction, linear detrending, high-passing filtering (140-s cutoff), coregistration, and affine transformation to the MNI space. The functional images were resampled to 3-mm^3 voxels.

Whole-Brain Parcellation. We followed Yeo et al.[12] for whole brain parcellation. Cortical regions were parcellated into 114 ROIs based on a seven-network cortical parcellation estimated from the resting-state functional the resting-state functional data of 1000 adults[13]. Sub-cortical regions were parcellated into 8 ROIs, which was extracted from the subcortical nuclei masks of the Brainnetome atlas[14], including bilateral amygdala, hippocampus, basal ganglia, and thalamus.

Data Availability. Behavioral emotional rating data and fMRI data from FNL dataset are available at OpenNeuro, https://openneuro.org/datasets/ds003521/versions/2.1.0; fMRI data from Sherlock dataset is available at DataSpace, https://dataspace.princeton.edu/handle/88435/dsp01nz8062179.

Supplementary. Supplementary is available here: https://github.com/Bigearkk/Supplementary

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