Predicting Affect Dynamics during Naturalistic Viewing from Sentiment Analysis and Brain Functional Connectivity

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Abstract

Affective experiences are critical components of human behavior, guiding our thoughts, feelings, and actions. Prior research has largely focused on dimensional theories of emotions, such as valence and arousal, which rely on self-reported sentiments and behavioral tasks using unimodal stimuli like pictures and faces. However, obtaining continuous measures of affective experience in naturalistic environments presents significant challenges due to the complexity and dynamics of the real-world context. In this study, we explore the feasibility of predicting individuals' dynamic affective experience during naturalistic viewing using semantic information extracted from annotated descriptions of the movie, as well as brain functional connectivity. By applying fine-grained sentiment analysis, we derive a continuous representation of the movie's sentiment during the movie-viewing experience. We then correlate these sentiments with behavioral valence and arousal ratings from an independent group of 60 participants and previously collected fMRI data from 17 participants who watched a TV show episode in the scanner (Chen et al., 2017). Our results suggest that automated sentiment analysis can effectively predict subjective valence on an event-level basis, even though it may not be a reliable predictor of affective experience at the sentence level. Meanwhile, we developed a more flexible approach to clustering sentiment scores based on meaningful shifts in the narrative such as topic, time, location, which provides a more accurate and contextualized analysis of sentiment. These findings provide new insights into how individuals' dynamic feelings of valence during movie-watching can be measured and predicted, contributing to the growing body of literature and methods in natural language processing, affective computing, emotion processing, and whole-brain functional connectivity.

Predicting Affect Dynamics during Naturalistic Viewing from Sentiment Analysis and Brain Functional Connectivity

Affective experience, or the subjective feeling that accompanies an individual's emotional response to an event or stimulus, plays a crucial role in shaping our daily lives. Whether it be the feeling of joy from spending time with loved ones, the stress of a deadline at work, or the anxiety caused by a frightening event, affective experiences color our perceptions of the world around us and can influence our behaviors, decision-making, and overall well-being (Fox, 2018; Phelps, 2006; Tiedens, 2004; & Keltner, 2010). As such, understanding and predicting affective experience has become an increasingly important area of research, with potential applications for perceiving others' beliefs and feelings, learning from the past, and understanding the social world (Adoplhs, 2010; Decety, 2010; & Immordino-Yang and Singh, 2013). Most studies have used self-reported and behavioral tasks but obtaining a continuous measure of affective experience in a laboratory setting is time-consuming, labor-tensive, and susceptible to human biases. In this study, we investigated our ability to predict affective experience during naturalistic movie-watching tasks from semantic information extracted from annotated descriptions of the movie as well as from fMRI functional connectivity, with the ultimate goal of providing a useful method for understanding and predicting how affective experiences fluctuate over time and in response to semantic information in our environment.

Literature review

Studies on affective experience focus on dimensional theories of emotions, describing emotions in terms of two fundamental dimensions: valence (i.e., hedonic level) and arousal (i.e., level of activation; Russell, 1980). The valence dimension refers to the degree of pleasantness or unpleasantness of an emotion and is often used to indicate the forces that influence an individual's attraction to desirable objects and repulsion from undesirable ones. It has been identified and classified in nearly all events and stimuli, including written or spoken language, faces, sounds, and pictures (Kauschke et al., 2019). Arousal, on the other hand, refers to a state of being mentally activated, awake, and highly reactive to stimuli, both psychologically and physically. It is often triggered by external stimuli that are emotionally charged, such as being in a potentially dangerous situation or experiencing fear while watching a horror movie (Fox, 2018), and it fluctuates along a single axis between calmest and most exciting (Lewis et al., 2007). Previous studies have demonstrated how both valence and arousal influence our cognition and behavior. For example, valence can impact our attention, memory, and decision-making, as it signals the importance and relevance of environmental stimuli (Storbeck & Clore, 2008). Meanwhile, arousal can have both beneficial and detrimental effects on cognitive performance and social interactions depending on its level, which can fluctuate over time. High levels of arousal, for instance, may enhance our ability to process information and remember details, but may also interfere with our ability to control our emotions and regulate our behavior (Immordino-Yang & Singh, 2013).

Nevertheless, previous methods are limited in their ability to capture the complexity and dynamics of affective experiences in naturalistic settings. For example, research on predicting emotional valence and arousal has predominantly relied on brief unimodal stimuli such as faces, pictures, sounds, and music (Kim et al., 2020), coupled with behavioral tasks and self-reported sentiments (Lindquist et al., 2016). However, obtaining continuous measures of affective experience is challenging, as it is often time-consuming and labor-intensive, and self-reported sentiment can be influenced by factors such as social desirability bias and mood-congruent memory. Conversely, naturalistic movie viewing, which simulates observing various real-world situations and provides rich affective components analogous to experiences in realistic settings (Sabatinelli et al., 2006), stands out as an alternative with high ecological validity. Previous studies have demonstrated the effectiveness of naturalistic movie stimuli in studies of attentional engagement (Song et al., 2021), memory recall (Chen et al., 2017), semantic representations (Nastase et al., 2017), and the evaluation of affective states (Kim et al., 2020; Kim et al., 2017). For instance, Kim et al. (2020) used movie stimuli to predict participants' subjective valence ratings while watching a movie, using a signed valence model from a separate group of fMRI participants with notably different viewing experiences. However, there is still room for improvement in the ecological validity of previous tasks, as the movie was paused every few seconds for participants to rate their valence, which may disrupt ongoing attention and cognition in realistic settings where experience is uninterrupted and continuous.

Current Study

The objective of this study is to investigate the potential for measuring and predicting people's dynamic affective experience during naturalistic viewing from movie scripts using sentiment analysis, as well as from brain functional connectivity using a connectome-based predictive model, independent of human subjective biases. To achieve this, we combined a naturalistic experimental paradigm with sentiment analysis and computational modeling built from fMRI functional connectivity. More specifically, we recruited participants to watch a naturalistic movie without interruption, rating their feelings of valence and arousal throughout the viewing. We then conducted fine-grained sentiment analysis to quantify the scene details in movie scripts into scaled scores between positive, negative, and neutral sentiments. Scene details play a fundamental role in the visualization and comprehension of a movie scene, as they provide readers with information about the setting, location, time, identity of characters, characters' feelings, appearance, dialogue, actions, facial expressions, and any other important details relevant to the scene. By analyzing the sentiment expressed in the scene details, this study contributes to a deeper understanding of the emotional content of the movie script. Meanwhile, we built a connectome-based predictive model (CPM) that predicts moment-to-moment behavioral ratings of valence and arousal from fMRI functional connectivity data of another group of participants who watched the same movie episodes under the fMRI scanner.

To evaluate our hypotheses, we relate ground-truth behavioral ratings to automated sentiment as detected by multiple sentiment analysis models, as well as to valence and arousal predicted by CPM from fMRI functional connectivity. We hypothesize that higher ratings of positive sentiment, as detected by automated sentiment analysis, would predict positive affective experience as measured by behavioral ratings of subjects watching a movie, as well as greater positive affect decoded by CPM. Similarly, we hypothesize that higher ratings of arousing sentiment, as detected by automated sentiment analysis, would predict affective arousal as measured by behavioral ratings of subjects watching a movie, as well as greater affect decoded by CPM.

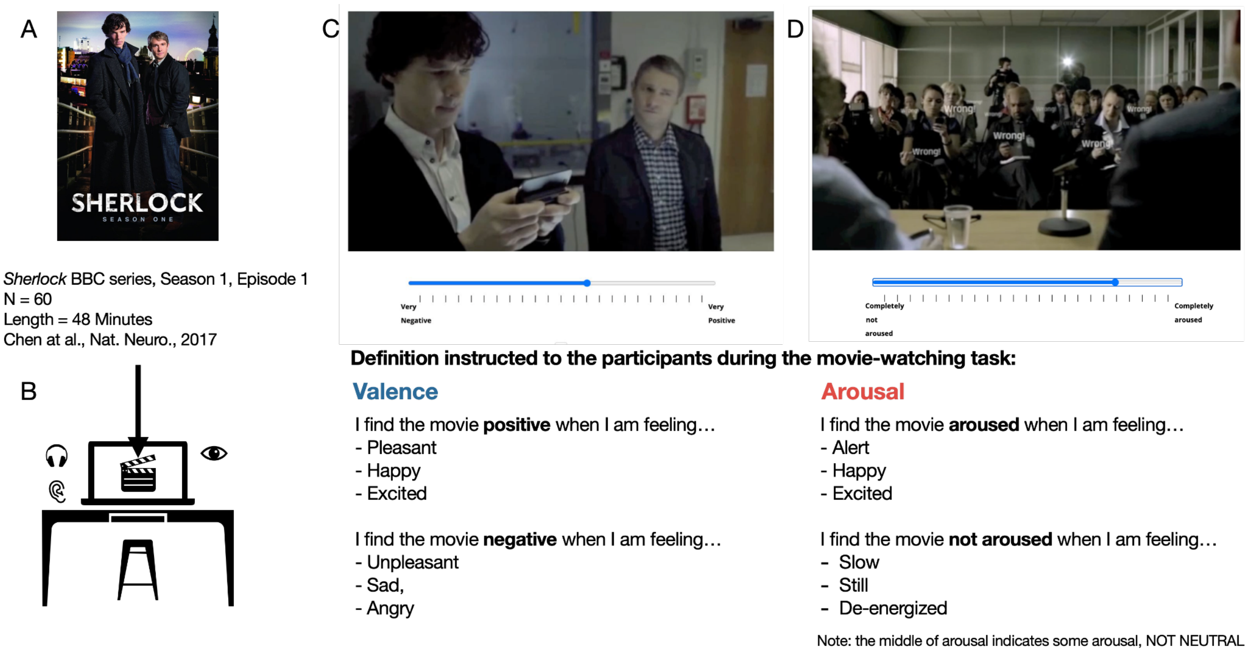
Method

Movie-watching task

Sixty individuals from the University of Chicago participated in a naturalistic movie-watching task in which they watched a 48-minute episode of the audio-visual TV show *Sherlock* BBC series, Season 1, Episode 1 (Figure 1A). All participants completed online informed consent and demographic forms and were compensated with one course credit for their participation. The study was approved by the Institutional Review Board of the University of Chicago.

Figure 1

Movie-watching task: Audio-visual TV show Sherlock BBC series, Season 1, Episode 1 (A), task environment (B), and example of tasks rating valence (C) or arousal(D) with instructions.



To collect continuous measures of affective experience during naturalistic movie viewing, while reducing disruption caused by pop-up ratings (every 4.5 seconds), we modified a movie-watching task previously used in research (Chen et al., 2017; Kim et al., 2020). Participants were instructed to wear headphones and sit in a quiet room with the room light set to the brightest (Figure 1B). They were required to turn off their phones and avoid any attentional distractions. The task began with detailed instructions about what was expected of the participants during the movie-watching task. Following this, participants watched a 1-minute practice video, before watching the main part of the movie. The main movie was segmented into a 23-minute clip and a 25-minute clip, with two cartoons placed before each clip began. During the movie-watching task, participants were randomly assigned to continuously rate how positive/negative (valence condition) or aroused/not aroused (arousal condition) they felt at each moment in the movie. For the valence condition, participants were told that a more "positive" rating indicated participants were feeling more pleasant, happy, and excited, while a more "negative rating" indicated participants were feeling more unpleasant, sad, and angry (Figure 1C). For the arousal condition, participants were told that a more aroused rating indicated participants were feeling more mentally or physically alert, happy, excited, while a more "not aroused" rating indicated participants were feeling more slow, still, and de-energized. Participants were instructed to rate their feelings by adjusting a scale bar from "Very Negative" to "Very Positive" (Figure 1C), or from "Completely not aroused" to "Completely aroused" (Figure 1D), using the left or right keys on their keyboard. The scale bar was constantly visible at the bottom of the computer monitor. All participants were verbally encouraged to update their ratings whenever they detected any emotional changes and as frequently as possible. After the movie ended, participants completed a post-task survey about their overall feelings of valence or arousal about the movie, and a debriefing questionnaire.

Analysis Plan

Behavioral Ratings

To accommodate variations in the number of behavioral ratings provided by participants, we utilized a resampling and interpolation procedure. For each participant, behavioral ratings falling within the range of two cartoons were truncated (the total length is 52 TRs, where 1 TR equals 1.5 seconds), and the remaining ratings were resampled to one rating per TR.

We then assessed the reliability of each participant's ratings by calculating pairwise intersubject correlations (ISC) with all other participants and averaging the correlation values of those who rated valence or arousal. Participants with an ISC lower than 0.10 were excluded from the sample.

To further improve the signal-to-noise ratio of the data, we averaged the behavioral ratings within the group and smoothed the group average using a sliding window procedure. Specifically, we convolved them with a hemodynamic response function (HRF) and applied a tapered sliding window of 30 TRs (45 seconds) with a step size of 1 TR and a Gaussian kernel of σ = 3 TRs. The resulting behavioral rating was a time series with 1894 TR time points.

Fine-grained Sentiment Analysis

The present study utilized fine-grained sentiment analysis to analyze the sentiment of the “scene details” in the *Sherlock* movie script (Chen et al., 2017). The movie script was independently transcribed by a coder who had no prior knowledge of the experimental design or results, which contained 1000 pieces of scene details. The *Sherlock* movie episode was divided into 50 events based on major shifts in the narrative, such as changes in location, topic, and/or time, and ranging from 11 to 180 seconds in length. Each event was labeled descriptively (e.g., “War scene”), and for the purposes of the study, two identical cartoons (events 1 and 28) were removed from the script. This resulted in 879 pieces of scene details across 48 total events, which were rearranged from the first to the 48th event. To process the scene details, we followed several steps, including lowercase conversion, tokenization, punctuation, and stop-word removal.

Figure 2 presents examples of scene details extracted from the modified version of Chen et al (2017).’s movie script on a continuous movie-watching experience. For instance, during the 45-49 TR interval, participants observed a scene that was described as follows: “The sunrises, light fades into the room and John’s figure fades out of the room, signifying a passage of time. John walks into the room with a gown on and walks toward his desk with his cane in his right hand (Table 1).” Similarly, during the 1184-1185 TR interval, participants viewed another scene described as follows: “Sherlock says joyfully: “We’ve got ourselves a serial killer. I love those. There’s always something to look forward to.” Sherlock continues down the next flight of stairs quickly. He passes by another policeman standing guard by another door on that floor (Table 1).

Table 1

Examples of scene details on a continuous movie-watching experience.

Start time	End time	Scene Details	Event
…		…	…
45	49	The sunrises, light fades into the room and John's figure fades out of the room, signifying a passage of time. John walks into the room with a gown on and walks toward his desk with his cane in his right hand.	*#3.Watson Morning*
…		…	…
971	974	Sherlock abruptly turns round to Lestrade on his right mind-thought and says: “Shut up.”Lestrade, startled, exclaims: “I didn’t say anything!” John looks at Sherlock as well. Sherlock replies: “You were thinking, it’s annoying” then goes back to looking at the corpse.	*#27.Crime scene intro*
…		…	…
1184	1185	Sherlock says joyfully: “We’ve got ourselves a serial killer. I love those. There’s always something to look forward to.” Sherlock continues down the next flight of stairs quickly. He passes by another policeman standing guard by another door on that floor.	*#32.Where’s the suitcase?*
…		…	…
1242	1246	Donovan, standing at the tape alongside a policeman, sees him and says: “He’s gone. John asks Donovan: “Sherlock Holmes?” Donovan: “Yeah, he just took off. He does that.” John asks Donovan: “Is he coming back?” Donovan: “Didn’t look like it.”	*#33.Watch out for SH*
…		…	…

After preprocessing the data, a fine-grained sentiment analysis was conducted using the Valence Aware Dictionary for Sentiment Reasoning (VADER) model, a parsimonious rule-based approach that maps lexical features to emotion intensities, which has been effective in previous studies (Hutto & Gilbert, 2014). The VADER lexicon contains words that are rated on a scale from -4 to 4 based on their sentiment polarity, where negative or positive values indicate negative or positive sentiment, respectively. To measure sentiment at the sentence level, VADER applies a set of rules to combine the sentiment scores of individual words in a given text and produces a “compound” score that indicates the overall sentiment for the sentence. These rules take into account the context of the words, the grammatical structure of the sentences, and the presence of emoticons, capitalization, and punctuation marks.

For each of the 879 scene details, VADER scanned the text for known sentimental features, modified the intensity and polarity of sentiment according to the rules, summed up the scores of words within the sentence, and normalized a compound score ranging from -1 (extremely negative) to +1 (extremely positive), with scores closer to zero indicating a more neutral sentiment.

To obtain a continuous measure of sentiment, a resampling procedure was implemented, which assigned one sentiment score for each of the 1924 TRs of the whole movie. The same sliding-window smoothing procedure was applied to the sentiment scores that had been resampled, resulting in a time series with 1894 TR time point. To assess whether the behavioral ratings of valence and arousal were predicted by sentiment, sentiment was z-scored, and Pearson’s r was calculated between the ground-truth measures of valence and sentiment, and between the ground-truth measures of arousal and sentiment.

To determine the statistical significance of the results, we conducted a permutation test. The aim of this test was to generate null distributions by randomly permuting the phase of the behavioral valence and arousal time series. This process was repeated 1000 times, and the correlation between the permuted data and automated sentiment was computed. Next, we conducted a one-tailed significance test and calculated the p-value using the following formula: $p = (1 + \text{number of null r values} \geq \text{empirical r}) / (1 + \text{number of permutations})$. This approach enabled us to determine whether the correlation between the ground-truth measures of valence/arousal and automated sentiment was statistically significant.

Subsequently, we performed the same analysis procedure on an event-level by averaging the automated sentiment within each of the 48 events and correlating them with the averaged ground-truth measures of valence and arousal by event. This enabled us to assess the relationship between the sentiment of the events and the participants' behavioral ratings of valence and arousal.

Connectome-based Predictive Model (CPM)

A leave-one-subject-out cross-validation technique was employed to develop a support vector regression model that predicts moment-to-moment ratings of emotional valence and arousal using moment-to-moment functional connectivity between large-scale brain networks, as outlined in Ke and Leong’s (2022) work. The dataset comprised 17 participants who underwent fMRI scanning while viewing the first episode of the Sherlock BBC series (Season 1, Episode 1), obtained from Chen et al. ’s (2017) openly available dataset. Various preprocessing techniques were applied to the fMRI data, including slice timing correction, motion correction, linear detrending, high-pass filtering, co-registration, affine transformation to the MNI space, and resampling to 3-mm. The blood-oxygen-level-dependent (BOLD) activity time series of participants were extracted from 114 cortical and 8 Brainnectome subcortical regions of interest, including the bilateral amygdala, hippocampus, basal ganglia, and thalamus. Feature selection was performed by selecting only functional connections between brain regions that are significantly correlated with behavior in training subjects, as per Shen et al.'s (2017) approach.

To assess the performance of the CPM in predicting subjective valence and arousal, Fisher's z-transformed Pearson's r was computed between the ground-truth measures of valence and predicted valence, and between the ground-truth measures of arousal and predicted arousal. To assess the relationship between brain activity and sentiment, Pearson's r was computed between the automated sentiment of valence and predicted valence, and between the automated sentiment of arousal and predicted arousal. The same permutation test approach was employed to determine whether the correlations between the ground-truth measures of valence and arousal, automated sentiment of valence and arousal, and predicted valence and arousal were statistically significant. All three variables, i.e., subjective behavioral ratings, automated sentiment, and CPM predictions, were given equal consideration and evaluated interchangeably in this study.

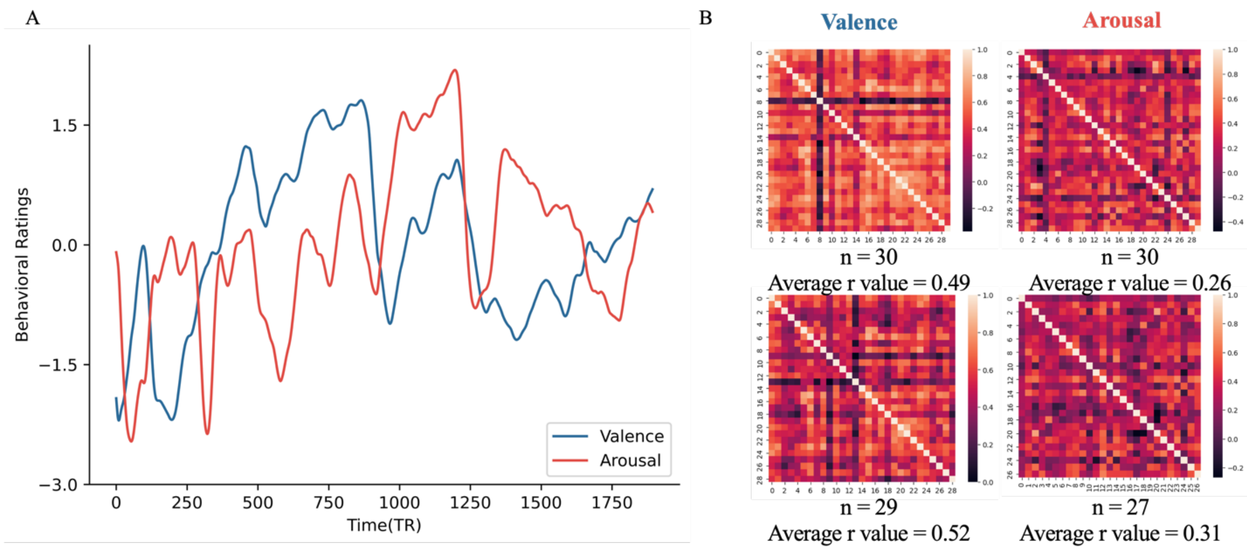
Results

Dynamic Affective Experience during Movie-watching is Synchronized across Individuals

Two independent group-level ratings of valence (blue lines depicted in Figure 3A) and arousal (red lines depicted in Figure 3A) were obtained from participants while they performed the movie-watching task. We computed the pairwise intersubject correlation (ISC) matrix of valence and arousal ratings with all other participants. As shown in Figure 3B, the average Pearson's r value before exclusion was 0.49 for valence (n = 30) and 0.26 for arousal (n = 30). Subject 1031 was excluded from the valence group as they had a negative correlation with all other participants (r = -0.11). Similarly, subjects 1010 (r = 0.01), 1026 (r = -0.02), and 1102 (r = 0.02) were excluded from the arousal group because their Pearson's r values were equal to or below 0.10 compared to all other participants. The ISC analysis revealed synchronization of valence (r = 0.52, n = 29) and arousal (r = 0.31, n = 27) across participants, indicating that the dynamic affective experiences of the participants were synchronized during the movie-watching task.

Figure 2

Ground-truth measures of valence and arousal (A). Note: Both measures were smoothed using a sliding window with a size of TR = 30. Intersubject correlation matrix (B) between participants who rated valence or arousal before exclusion (upper) and after exclusion (lower).



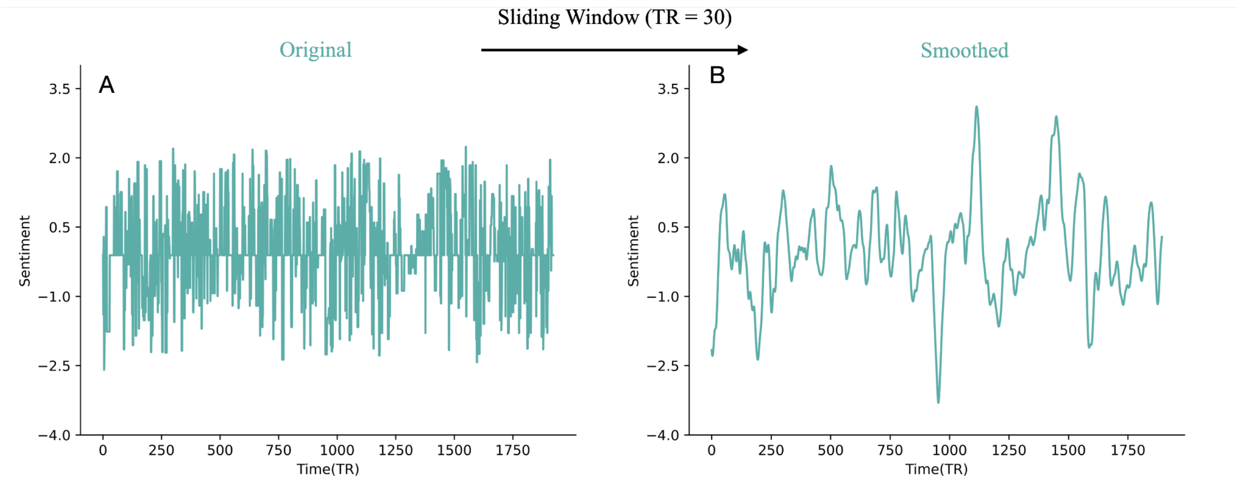
Subjective Valence is Predicted by Automated Sentiment on Scene-level, Not on Sentence-level

After the behavioral ratings of affective experiences had been obtained, we conducted fine-grained sentiment analysis using VADER on scene details (see examples in Table 1) to detect sentiment of the annotated descriptions of the movie. Figure 3A shows sentiment scores of 879 pieces of scene details that had been resampled on a time series with 1924 TR time points.

By smoothing the data using a sliding window with a size of 30 TRs, the original time series was fitted into a new time series with 1894 TR time points (Figure 3B).

Figure 3

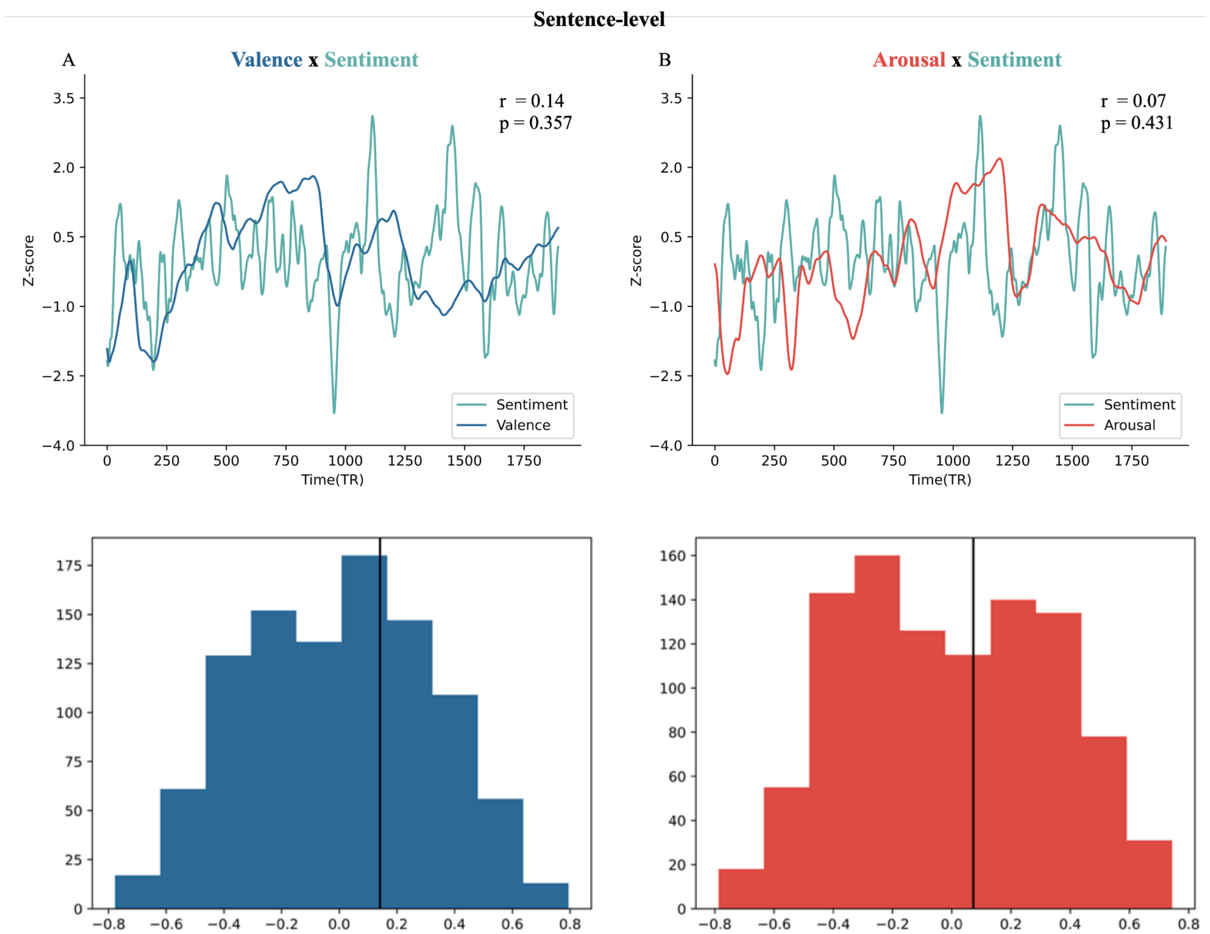
Sentiment scores automated by fine-grained sentiment analysis with VADER.



Our primary result of interest is the relationship between automated sentiment and affective experience. Specifically, we sought to investigate whether there was a correlation between the sentiment scores obtained from sentiment analysis with VADER and the subjective valence and arousal ratings reported by the participants. To this end, the Pearson correlation coefficient (r) was computed to assess the sentence-level and event-level correlation between sentiment and affective experience. The results of the analysis showed that the correlation between sentiment and subjective valence was not statistically significant, $r = 0.14$, $n = 29$, $p = .357$, as illustrated in Figure 4A. This finding suggests that the automated sentiment analysis using VADER may not be a reliable predictor of subjective valence. Meanwhile, the analysis revealed that there was no significant correlation between sentiment and subjective arousal, $r = 0.07$, $n = 27$, $p = .431$, as shown in Figure 4B. This finding implies that the automated sentiment analysis using VADER may not accurately capture the level of arousal experienced by the participants.

Figure 4

Sentence-level correlation between sentiment and subjective valence (A), and between sentiment and subjective arousal (B). Permutation Test on valence (blue) and arousal (red).

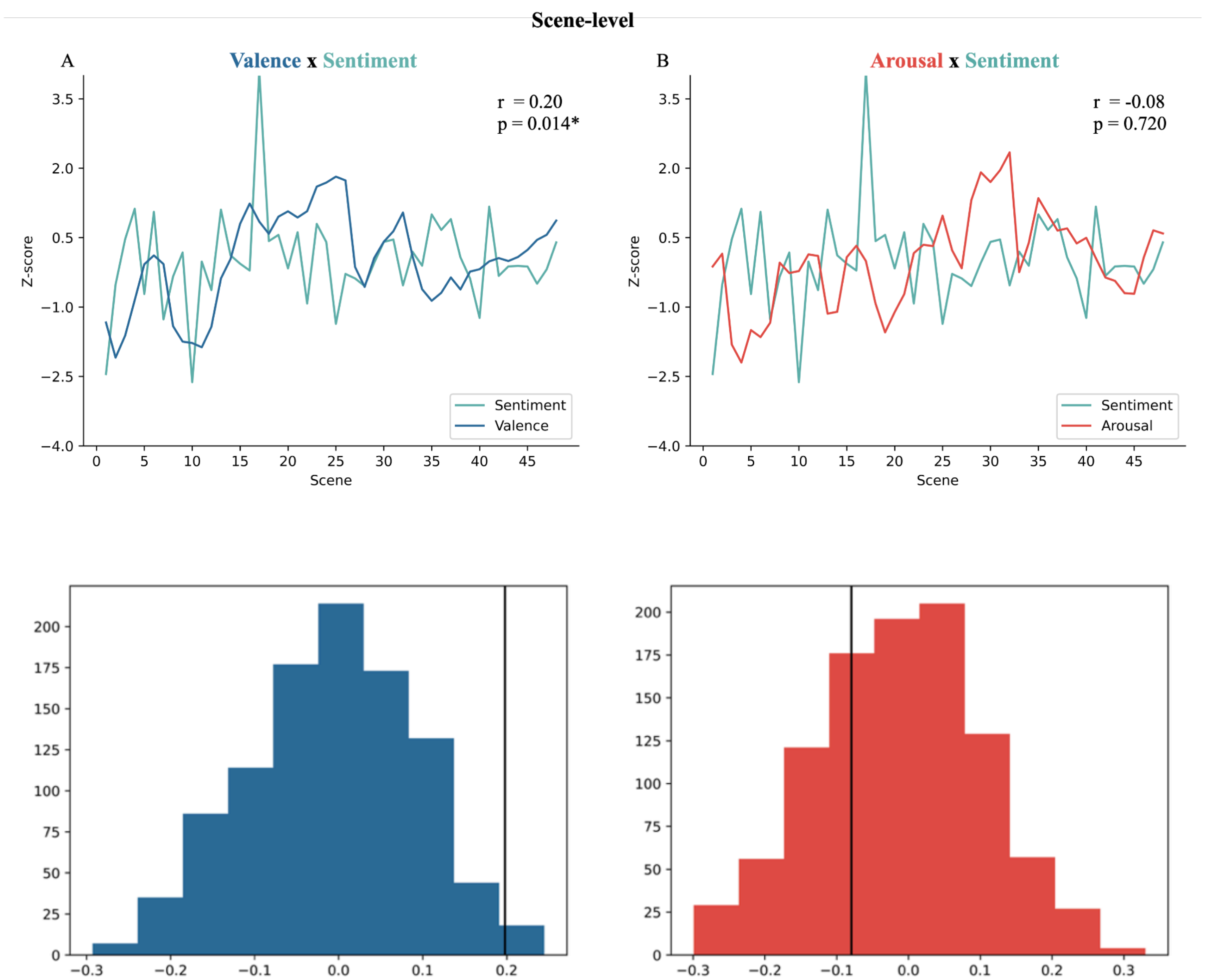


The initial analysis did not yield sufficient statistical evidence to support a significant correlation between sentiment and subjective affective experience on a sentence-level basis. Therefore, we sought to examine the relationship on an event-level basis by averaging the values of sentiment and subjective valence and arousal within each of the 48 events. During this stage of the analysis, we extracted sentiment values from the 879 scene details in the movie script. We had access to the start and end times for each scene detail recorded on the original time series with 1924 TR time points, as well as the corresponding event. Using this information, we utilized a “sentiment” index list to determine which rows of scene details fell within each event. We also located the relevant time information of continuous behavioral ratings for each event using a “behavioral” index list. The sentiment values were segmented, averaged within each event, and z-scored based on their position in the “sentiment” index. Similarly, the behavioral ratings were reorganized in accordance with the “behavioral” index, allowing for both behavioral ratings and sentiment to be temporally aligned in response to the events.

Remarkably, the event-level analysis showed a significantly positive correlation between sentiment and subjective valence ($r = 0.20$, $n = 29$, $p = .014$*), as depicted in Figure 5A. This correlation suggests that subjective valence, i.e., whether an event is perceived as positive or negative, can be predicted by averaging sentiment across events. These findings provide new insights into how individuals’ dynamic feelings of valence during movie-watching can be explored and predicted. In contrast, we did not find sufficient evidence to predict people’s dynamic feelings of arousal from sentiment, neither on the sentence-level nor on the event-level ($r = -0.08$, $n = 27$, $p = .720$), as illustrated in Figure 5B. This lack of correlation suggests that arousal, i.e., the level of emotional intensity, may be influenced by other factors beyond the semantic content of the stimuli. Overall, these results support the use of event-level analysis to predict individuals’ dynamic feelings of valence during movie-watching, rather than sentence-level analysis. Meanwhile, they leave room for further improving the strength of correlation between sentiment and subjective valence and exploring the potential of predicting feelings of arousal during movie-watching from sentiment.

Figure 5

Event-level correlation between sentiment and subjective valence (A), and between sentiment and subjective arousal (B). Permutation Test on valence (blue) and arousal (red).



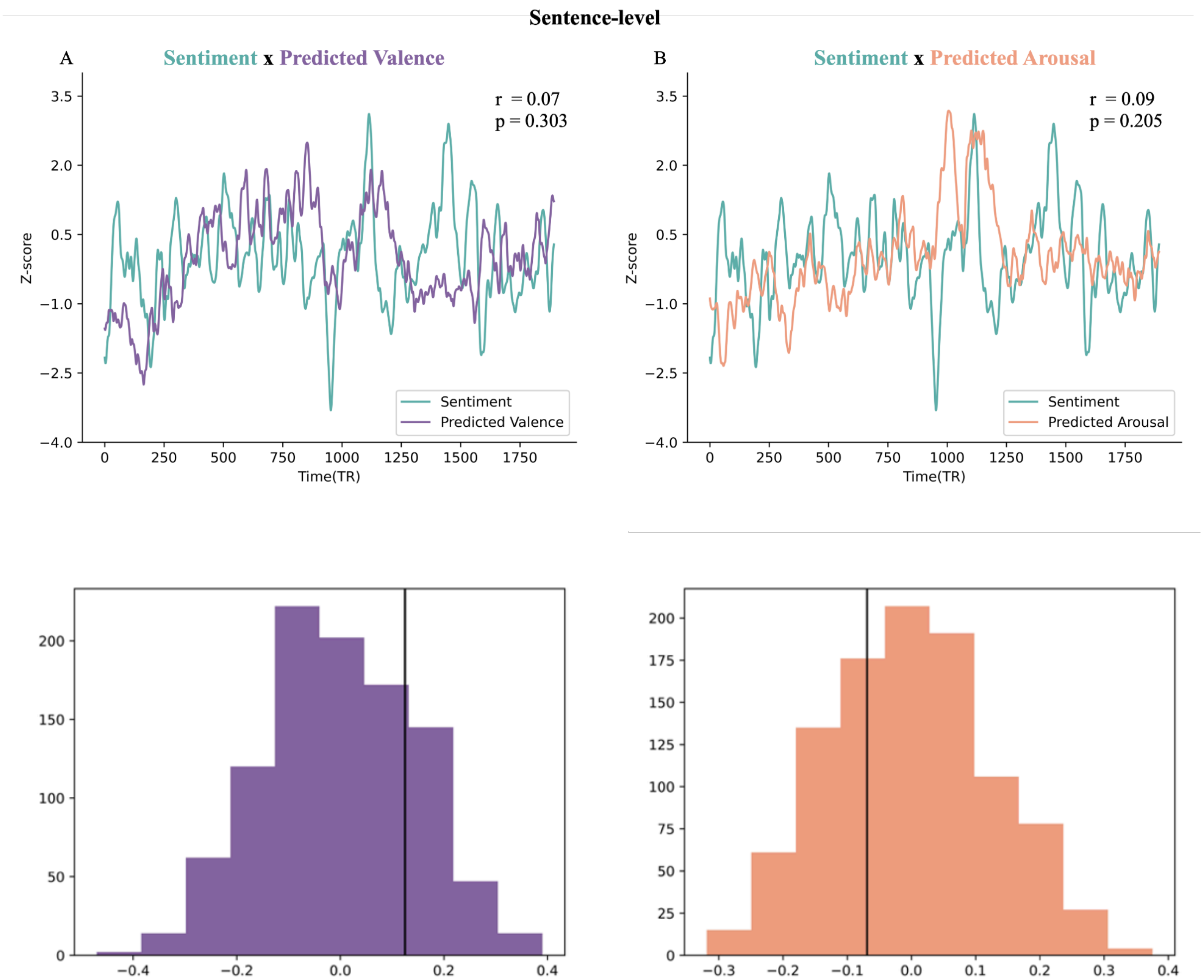
Automated Sentiment is Not Synchronized with Affective Experience Predicted from Brain Functional Connectivity

The CPM was performed using a whole-brain functional connectivity matrix, which was obtained by calculating the pairwise correlation between the time series of all pairs of brain regions in the fMRI data. The CPM was trained to predict the group-average subjective valence and arousal ratings during movie-watching from the functional connectivity patterns. The predicted affective experience was then compared with the actual subjective ratings provided by the participants. Using this information, we examined the relationship between automated sentiment and predicted affective experience generated from brain functional connectivity using CPM. We computed the Pearson correlation coefficient (*r*) between the group-average values of sentiment and predicted valence, and between the group-average values of sentiment and predicted arousal.

The results of the sentence-level analysis revealed insufficient evidence to support a significant correlation between sentiment and predicted valence, with an $r = 0.07$, $p = .303$, as shown in Figure 6A. Similarly, there was no significant correlation between sentiment and predicted arousal, with an $r = 0.09$, $p = .205$, as indicated in Figure 6A. These findings suggest that the sentiment of individual sentences in the movie script may not be a reliable predictor of the overall affective experience during movie-watching. It is worth noting that the sentence-level analysis has limitations in capturing the complex and dynamic nature of affective experience during movie-watching, which is a multidimensional construct that involves interactions between different movie segments, as well as between affective experience and other cognitive and emotional processes. Alternative methods would allow for a more comprehensive understanding of the temporal dynamics of affective experience and the neural mechanisms underlying this complex phenomenon.

Figure 6

Sentence-level correlation between sentiment and predicted valence (A), and between sentiment and predicted arousal (B). Permutation Test on valence (purple) and arousal (orange).



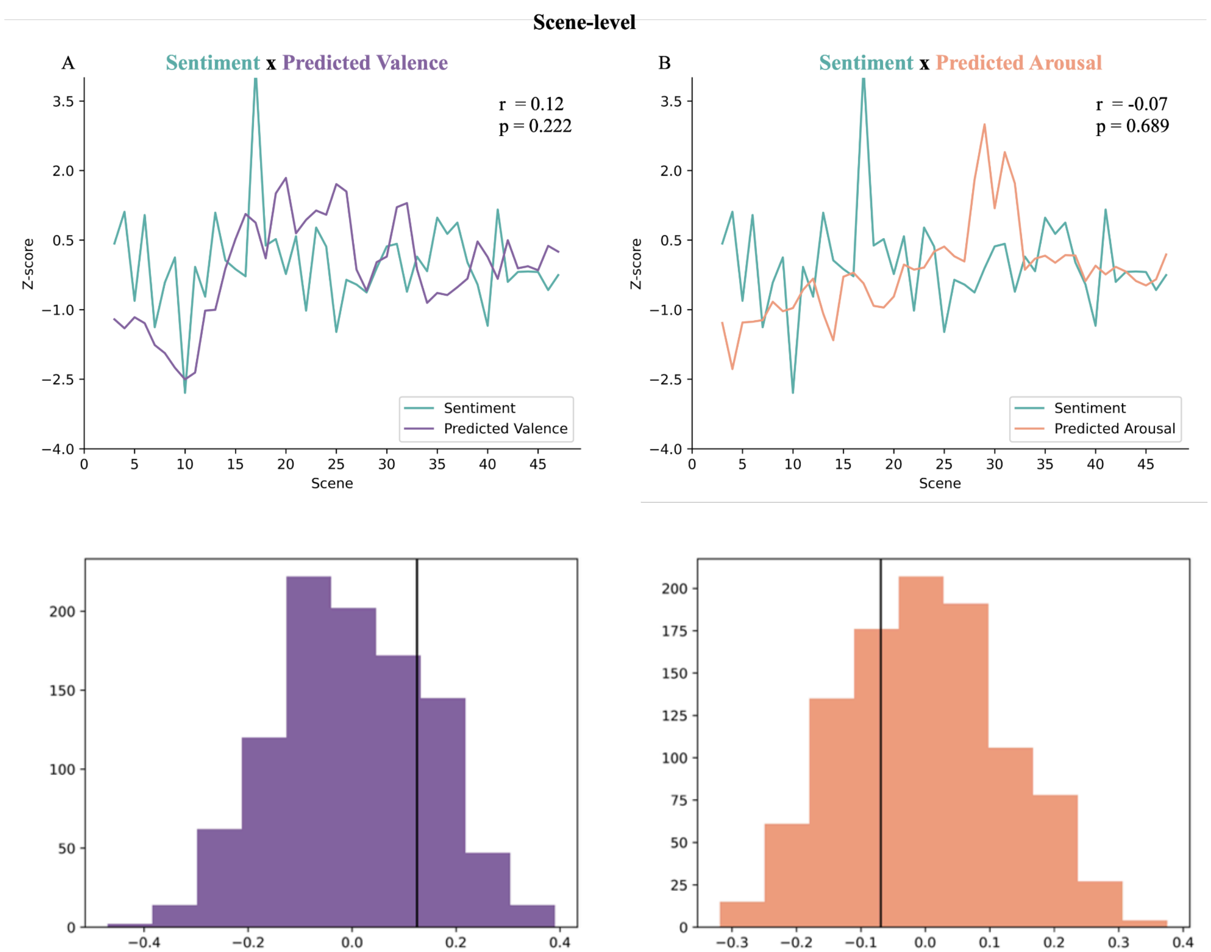
Therefore, we performed an event-level analysis to examine the association between sentiment and predicted affective experience. Specifically, we averaged the group-average values of predicted valence and arousal within each event. As a reminder, the original time series of predicted ratings consisted of 1924 TR time points, which were smoothed using a sliding window procedure to create a new time series with 1894 TR time points. This reduction in the number of time points was due to the averaging of data points within each window, where each window spanned a period of 30 TRs. However, we encountered a discrepancy between the event-level time index of predicted ratings and behavioral ratings, as well as predicted ratings and sentiment, since the index that corresponded to the time interval of events was found on a 1924 time series. To address this issue, we removed the first two events (0 - 8 TRs; 9 - 28 TRs) and the last event (1894 - 1923 TRs) from the original time series that contained the full 48 events, resulting in a shorter time series with 1865 TR time points and 45 events. To maintain consistency with the original time series, we added 15 zeros at both the beginning and end of the predicted ratings that contained 1894 TR time points, resulting in a new time series with 1924 TR time points, including the added zeros. We then removed the values of the 0 - 8 TRs, 9 - 28 TRs, and 1894 - 1924 TRs (i.e., events 1, 2, and 48) from the new time series, resulting in a time series of event-level predicted ratings of 45 events. Similarly, for sentiment, sentences 0 - 7, 8 - 11, and 863 - 878 were removed as being the descriptions of events 1, 2, and 48. This allowed us to examine the association between sentiment and dynamic FC at the event-level, while accounting for the discrepancies between time indices.

However, contrary to our expectations, the event-level analysis still did not provide sufficient evidence to detect a correlation between sentiment and predicted valence, with an r = 0.12, p = .222, as shown in Figure 7A. Likewise, we did not find a significant correlation between sentiment and predicted arousal, with an r = - 0.07, p = .689, as depicted in Figure 7B. These results suggest that at the event-level, the relationship between sentiment and predicted affective experience may be weaker than anticipated.

Therefore, both the sentence-level and event-level analyses failed to find a significant correlation between sentiment and predicted affective experience in this study. It is important to note that although the event-level analysis was designed to address some of the limitations of the sentence-level analysis, it still did not yield stronger evidence of the hypothesized association.

Figure 7

Event-level correlation between sentiment and predicted valence (A), and between sentiment and predicted arousal (B). Permutation Test on valence (purple) and arousal (orange).

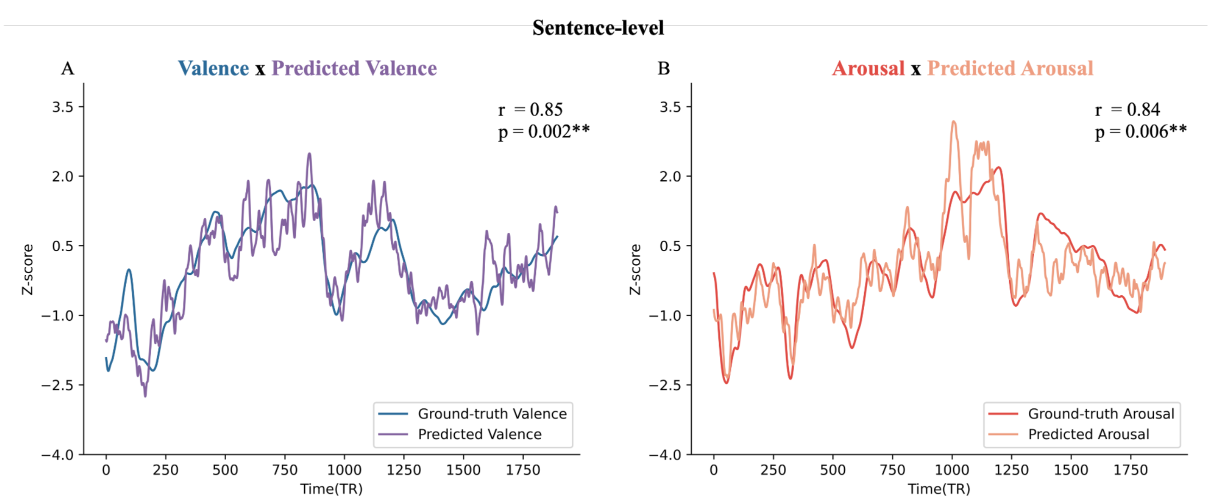


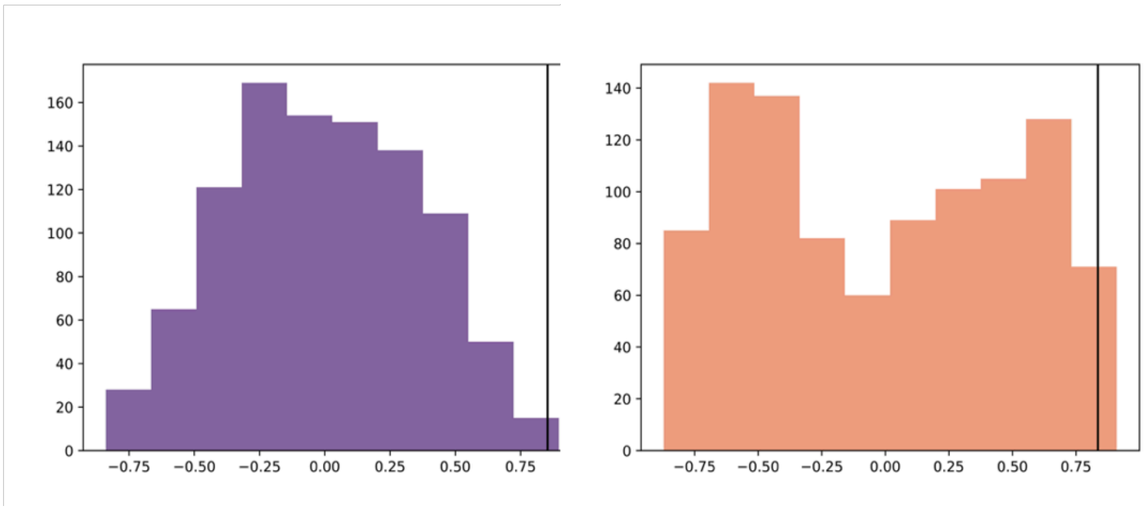
Group-level Affective Experience Predicted from Brain Functional Connectivity is Synchronized with Behavioral Ratings

The following analyses aimed to explore the relationship between subjective valence and arousal ratings provided by the participants and the predicted valence and arousal generated by CPM. Results indicated a very strong and significantly positive correlation between subjective valence and predicted valence, with an $r = 0.85$, $p = .002^{**}$, as well as a very strong and significantly positive correlation between subjective arousal and predicted arousal, with an $r = 0.84$, $p = 0.006^{**}$. These findings suggest that CPM accurately predicts group-average values of affective experience during movie-watching from brain functional connectivity. Furthermore, the high correlation between the predicted and actual affective experience supports the validity of subjective ratings as a measure of affective experience during movie-watching.

Figure 8.

Sentence-level correlation between subjective valence and predicted valence generated by CPM (A), and between subjective arousal and predicted arousal generated by CPM (B). Permutation Test on valence (purple) and arousal (orange).



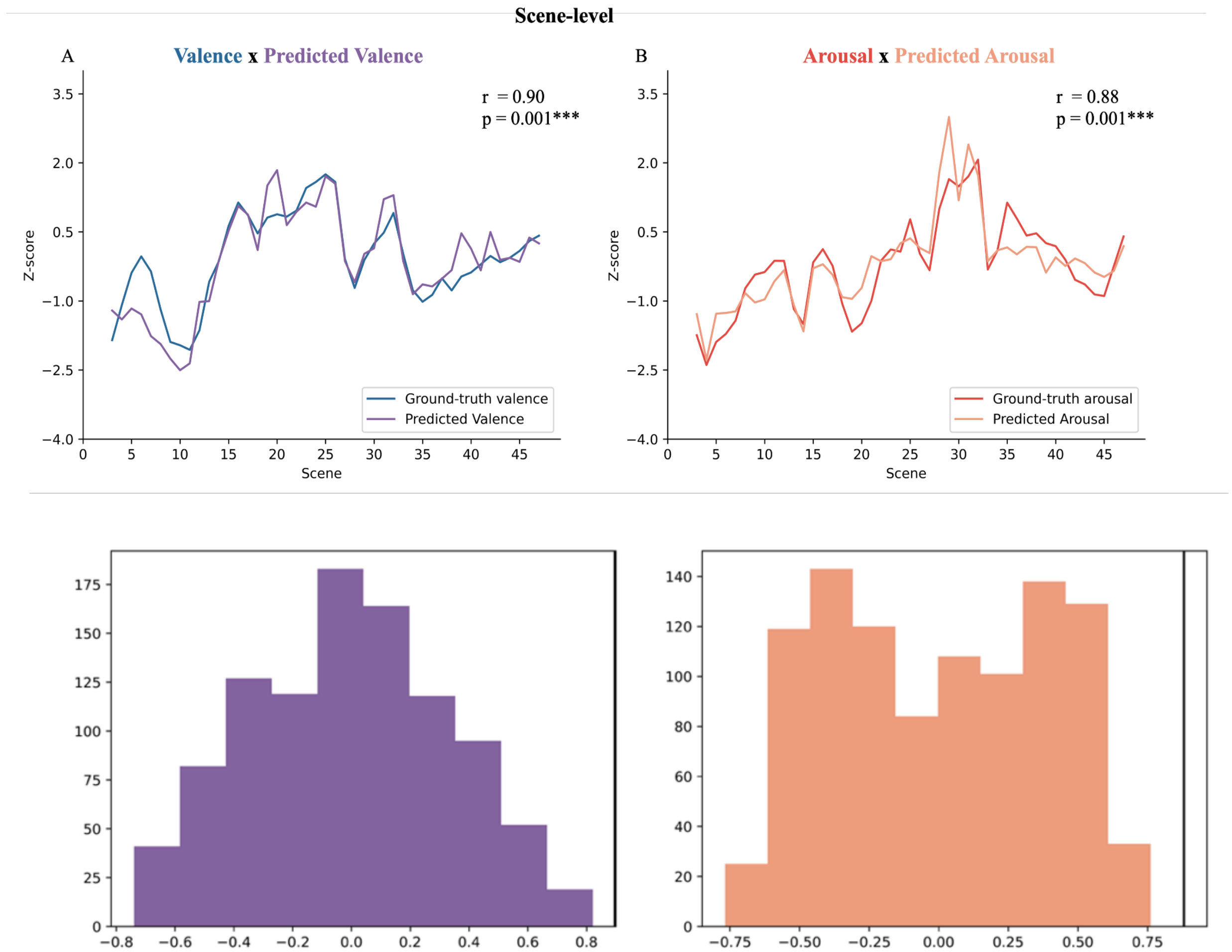


Consistent with our hypotheses, the results of our study revealed strong and significant event-level correlations between subjective valence and predicted valence (r = 0.90, p = .001***, Figure 9A) as well as subjective arousal and predicted arousal (r = 0.88, p = .001***, Figure 9B). These findings provide robust evidence that the affective experience during movie-watching can be accurately predicted from brain functional connectivity using CPM at the event-level. The strong correlations between the predicted and actual affective experience further underscore the validity of subjective ratings as a measure of affective experience and suggest that CPM can be used as a valuable tool to predict affective experience in real-time settings.

Overall, the results demonstrated strong and significant correlations between the subjective ratings and predicted values, indicating that CPM accurately predicts group-average affective experiences during movie-watching both on sentence-level and event-level.

Figure 9.

Event-level correlation between subjective valence and predicted valence generated by CPM (A), and between subjective arousal and predicted arousal generated by CPM (B). Permutation Test on valence (purple) and arousal (orange).



Discussion

As we navigate the rich and dynamic environments we inhabit, our affective experiences fluctuate in response to a myriad of internal (e.g., feelings of positivity and mental activation) and external emotional stimuli (e.g., semantic information, facial expressions, auditory, and somatosensory stimuli), which shape our feelings and behavior. However, the nature of real-world situations makes it challenging to understand and predict affective experience. At the core of this study is to explore the feasibility of predicting individuals' dynamic affective experience during naturalistic movie-watching tasks using semantic information extracted from annotated descriptions of the movie, as well as brain functional connectivity. Here, using fine-grained sentiment analysis and data from independent behavioral and fMRI studies, we tested our theoretical proposals that sentiment that, which exists in emotional laden content of the movie as detected through automated sentiment analysis, will be positively associated with people's affective experience as measured by behavioral ratings and CPM decoding.

Specifically, we performed fine-grained sentiment analysis on scene details from the movie, which allowed us to create a continuous time series representation of the movie's sentiment during the movie-viewing experience. The sentiment was analyzed both as independent sentences and meaningful-event clusters, enabling a comprehensive representation of the movie's overall emotional arcs at different levels of granularity. This includes the emotions conveyed by the characters, the tone of the dialogue, the setting and scenery, and other elements that contribute to the overall emotional impact of the movie.

Furthermore, we ran behavioral experiments in which two independent group-level ratings of valence and arousal were obtained from participants while they watched a narrative movie. Continuous, self-reported affective experience fluctuated over time and was synchronized across individuals during the movie-watching task, demonstrating that this experimental paradigm captures states of valence and arousal that are shared across individuals. Importantly, using group-average changes in subjective affective experience, event-level correlation analysis revealed a significantly positive correlation between sentiment and subjective valence but not arousal, suggesting that subjective valence can be predicted by averaging sentiment across events. However, we did not find robust evidence that relates sentiment with subjective valence and arousal ratings on a sentence-level basis. Our findings suggest that while automated sentiment analysis using VADER may not be a reliable predictor of subjective valence and arousal on a sentence-level basis, it can predict subjective valence on an event-level basis. These results provide new insights into how individuals' dynamic feelings of valence during movie-watching can be measured and predicted. However, the lack of correlation between sentiment and subjective arousal suggests that the level of emotional intensity may be influenced by other factors beyond the semantic content of the stimuli.

Lastly, a CPM was performed, which was trained to predict the group-average subjective valence and arousal ratings from the functional connectivity patterns. The predicted affective experience was then compared with the actual subjective ratings provided by the participants, revealing a positive relationship between the group-level predicted and actual ratings for valence and arousal. However, we have insufficient evidence to link predicted ratings with automated sentiment neither on sentence-level nor on event-level.

Our study contributes to the growing body of literature and methods regarding natural language processing, affective computing, emotion processing, and whole-brain functional connectivity. Given the various stimuli presented in the environment, our study describes our initial attempt to explore the features of the naturalistic movie underlying people's dynamic affective experience while watching the movie, and serves as a starting point correlates emotional content in movie scripts with affective experience and with brain activity.

Firstly, although sentence-level sentiment is less reliable, we provide new insights into detecting and visualizing textual sentiment automated by rule-based approach of sentiment analysis within a narrative movie on a continuous basis, and further corresponding sentiment to self-reported behavioral affective experience on event-level. For example, we observed high consistencies between sentiment and subjective valence during around the 28th event, “Crime Scene Intro” (see Figure 5A). During this event, Sherlock and John follow Lestrade into a room where a dead body has been discovered (Chen et al., 2017). This event contains a clear beginning, middle, and end, as well as a transformation, as the discovery of the body marks a significant change in the story’s plot. The impact of this event on participants’ affective experience could vary depending on the context and presentation. Participants may feel suspense, curiosity, or even fear as they follow the characters up the spiral staircase and into the room where the body is found. Also, the use of visual and auditory details, such as the sounds of the characters’ footsteps and the empty, foreboding atmosphere of the room, can heighten participants’ emotional valence and arousal. We suggest that people might perceive and be affected by emotion-laden content within each meaningful narrative event.

Further, we have extended the existing method of calculating sentiment scores by developing a way to cluster sentiment scores into events. Previous research has used a method of calculating sentiment scores based on predefined text segments called “blocks”, which were defined as 20 lines of text (Kim et al., 2018). However, the authors found it difficult to extract scenes as the ideal basic unit due to differences in the way movie scripts distinguish scenes. In contrast, in our current research, instead of using fixed predefined text segments as the basic unit for sentiment analysis, we used a more flexible approach of clustering sentiment scores based on events, which are defined as meaningful changes in the storyline, characters, or setting. This allows for a more accurate and contextualized analysis of sentiment, as the sentiment score for each event can be calculated based on the sentiment expressed within that event, rather than just within a fixed block of text.

Interestingly, even though the overall event-level correlation between sentiment and subjective valence is significantly positive, it is still possible that sentiment of some specific events are not positively associated with people's subjective feelings, which suggests that sentiment analysis can capture the actual emotional intensity of the event information, independent of subjective interpretations. To be specific, during the 31st event, "Sherlock's Conclusion" (Chen et al., 2017), Sherlock deduces various details about the victim's life and her circumstances before her death. The way he makes these deductions and the details he uncovers can have a significant impact on the affective experience of the people involved. For example, John looks at Sherlock in shock and admiration as he realizes the depth of his friend's insights. Lestrade, on the other hand, is initially skeptical, but gradually becomes impressed as Sherlock's deductions pile up. Basically, these emotional reactions help to illustrate the ways in which people are affected by the things they witness, and how they can be influenced by the actions and words of others. More importantly, in terms of the correlation between sentiment and affective experience, our results show how the observation of Sherlock's analytical approach and his ability to uncover hidden details that impress other peoples, such as John, can create positive valenced emotions in people, even in the presence of Sherlock's sharp tongue and sarcastic comments. However, these comments tongue and comments, as well as other details might tend to be interpreted as more negatively valenced sentiment by sentiment analysis. As a result, sentiment that represents this specific event was shown inversely associated with people's subjective valence. Therefore, we suggest that sentiment automated by sentiment analysis using VADER represents the factual emotional intensity of narrative events and positively correlates with individual feelings of valence of those events. This suggestion may help us understand how the narrative structure and emotional content from both perspectives of textual information and subjective interpretations work together to impact people's affective experience and overall response to the movie.

Moreover, we provide empirical evidence that self-reported ratings of affective experience of individuals during naturalistic movie-watching tasks was synchronized across individuals on group-level. This study adds to research that explores how results from controlled experiments extend to more naturalistic settings in which participants freely view movies in the absence of sequential trials or blocks. Benefits of naturalistic stimuli include rich perceptual, affective, and semantic information, yielding a more wide-ranging perception of various real-word stimuli (Klasen et al., 2014). Beyond that, we are able to predict group-average ratings of affective experience across individuals from brain functional connectivity using the machine learning model, CPM, and reveal the involvement of brain regions across multiple large-scale functional brain networks. This occurred despite using affective ratings that were generated by a separate group of participants who had markedly different viewing experiences from the fMRI participants who had no explicit task. Predicting affective experience can improve our understanding of how affective experience affects our perception by providing insight into the specific emotional states that are associated with certain cognitive processes (Trilla et al., 2021). Also, we generalized previous results (Kim et al., 2017, 2016) that identifies the distributed representation of affect to multimodal dynamic stimuli to more naturalistic viewing conditions.

Besides, our study adds to previous research that has used CPM to predict narrative engagement (Song et al., 2021), which is defined as an experience of being deeply immersed in a narrative with heightened arousal and attentional focus (Busselle & Bilandzic, 2009), from time-varying functional brain connectivity by providing reliable measurement and predictions of subjective valence and arousal.

The current work could be improved based on the fact that VADER, the sentiment analysis tool we utilized, may have limitations in interpreting sentiment of semantic information extracted from annotated descriptions of movies (Liu, 2012). Admittedly, as a rule-based approach, VADER does not require training data and can efficiently provide sentiment scores for large volumes of text. However, VADER's reliance on a pre-defined dictionary of words and phrases that are assigned positive or negative scores can lead to inaccuracies in the analysis of texts that contain sarcasm or irony, as well as texts that use words and phrases that are not present in the dictionary (Zhu et al., 2014). In such cases, it is worth noting that words that have no consistent match with the VADER dictionary, whether they are base words or derivatives of the base word, may be transcribed as having an imprecise semantic meaning or may be completely ignored from their original sentence.

Further, we should also keep in mind that while VADER is a useful tool for analyzing sentiment in text, it may not capture the full range of emotional nuances present in the annotated descriptions of the movie (Hutto & Gilbert, 2014; Wilson et al., 2009). This limitation may have an impact on the accuracy of the correlations between sentiment and individuals' affective experiences while watching the movie. In other words, there may be emotional content present in the annotated descriptions that VADER is not able to detect, leading to incomplete or inaccurate representations of the movie's emotional content. One potential consequence of this limitation is that the correlations between sentiment and affective experiences may be weaker than they would be if a more nuanced sentiment analysis approach were used. For example, if VADER is not able to detect subtle changes in emotional content that are present in the annotated descriptions, then it may not accurately capture changes in individuals' affective experiences that are related to those nuances. As a result, the overall strength of the correlations between sentiment and affective experiences may be weakened, leading to potentially misleading or incomplete results. Furthermore, the limitations of VADER in capturing emotional nuances may also be reflected in the nature of the correlations that are observed between sentiment and affective experiences. For example, it may be the case that the correlations that are observed are more strongly related to broad emotional themes that are present in the annotated descriptions, rather than specific nuances of emotion that are present in the movie. This could result in correlations that are less informative or less meaningful than they would be if a more nuanced approach to sentiment analysis were used.

Moreover, according to a study by Taboada et al. (2011), lexicon-based sentiment analysis performs poorly on texts with a higher level of complexity and subjectivity. They found that the performance was especially weak in tasks that required understanding the contextual meaning of words, and in tasks that required analyzing the sentiment of subjective text, such as product reviews or social media posts. In our case, for example, the show includes lots of character dialogues, facial expressions, and actions, which are always complex and may have different meanings based on their contexts. This complexity may make it difficult for VADER to accurately capture the sentiment and emotional nuances present in the annotated descriptions of the movie.

Extensions of our analysis that use a more sophisticated approach of sentiment analysis can improve the feasibility of extracting sentiment from semantic information from the annotated descriptions of the movie. Indeed, previous research has shown that neural network-based approaches outperform traditional rule-based approaches, such as VADER, in sentiment analysis tasks (Reimers & Gurevych, 2019). Specifically, transformer-based models, such as BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019), have been shown to achieve state-of-the-art performance in various natural language processing tasks, including sentiment analysis. Thus, future work can predict dynamic affective experience using a neural-network sentiment analysis using transformers to capture more human-like, contextual-based, and accurate interpretations of emotional content of the movie scripts. However, it is worth noting that neural network-based models may also have limitations. For example, the performance of these models can be influenced by the amount and quality of the training data, the choice of hyperparameters, and the selection of the pre-training corpus (Wang et al., 2021). Additionally, these models may require significant computational resources and time to train and fine-tune, which can limit their practicality in certain applications. Future work may generalize the approach of this study to different narrative datasets, such as the TV show "*Friday Night Lights*" dataset, which has also been collected during our work. Future studies may also try to identify discrete emotions, including fear, anger, joy, and surprise from sentiment, people's affective experience, and brain activity to examine how people feel and respond to the naturalistic stimuli using clusters of integrated emotional feelings.

Conclusion

In sum, we have provided a demonstration of how sentiment analysis of semantic information extracted from annotated description of narrative movies can be used to predict the dynamics of emotional valence based on the event-level correlation during continuous movie-viewing experience. Furthermore, we have also provided empirical evidence for the synchronization of affective experience during movie-watching across individuals and the correlation between group-level affective experience with their large-scale brain functional connectivity. We hope that this work will inspire future innovations in measuring and predicting affective experience using state-of-art sentiment analysis methods.

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