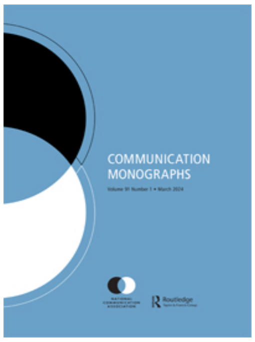

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Moment-by-moment tracking of audience brain responses to an engaging public speech: Replicating the reverse-message engineering approach

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ABSTRACT
Public speaking engages and entertains audiences. Through neuroimaging, we can examine responses to speeches in real time. Replicating an earlier study, this study carries out two kinds of analyses – forward and reverse correlations. First, we examine how the soundwave carrying the speech relates to brain responses, finding that bilateral auditory cortex responses track with the speech signal's energy. Second, we use the speech-evoked brain responses to reverse-identify salient moments in the speech. Specifically, we focus on the right temporoparietal junction (TPJ), a region associated with social cognition. We find that TPJ-peaks reverse-identify socially engaging content (defined by the ability to evoke laughter). These results demonstrate new ways to study the relationship between story content and the audience responses it evokes.

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Introduction

Across the world and throughout history, public speakers have used stories to convey messages in a way that can sustain the attention of large audiences to simultaneously inform, influence, and entertain them. Stories are also a format that audiences prefer, benefit from, and enjoy (Bruner, 1986; Grall et al., 2021; Green et al., 2003). As such, it is no surprise that most entertainment products are story-based. These include various forms of mass-mediated entertainment (from written fiction to radio drama and modern TV, cinema, and games) as well as most live performances (from traditional fireside stories to classical theater performances to modern-day events like the popular *The Moth* storytelling events). Extant work in communication has examined the role of stories as a means of persuasion or entertainment, and considerable work has examined which content elements make speeches or stories interesting, engaging, and so forth (on the content side; Green et al., 2003; Lucas & Stob, 2004; McCroskey & Richmond, 2001). Similarly, much work has also focused on the psychological effects (the outcomes

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or effects side) of speeches and stories (Busselle & Cutietta, 2019; Lucas & Stob, 2004). However, between the content of a speech and its effects on listeners lies the human brain, and much less work has focused on how the brain responds to stories and mediates subsequent effects (Floyd & Weber, 2020). Therefore, this study focuses on how the brains of a group of listeners respond to a story.

The brain represents the point where the speech as a physical stimulus (comprising the soundwaves from the speaker) is transformed into neural signals so that we can process and engage with a public speaking performance (Huskey et al., 2020). Over the past decades, neuroimaging has established new ways to examine how stimuli are transformed into psychological phenomena (Grall et al., 2021; Schmälzle & Meshi, 2020; Weber, 2015), enabling us to examine the biological processes that must logically give rise to the effects commonly studied in previous research on public speaking. With neuroimaging, we can follow the causal pathway that goes from message content (e.g., spoken signals from a speaker) to brain activity and psychological effects. In this study, we specifically focus on the links between the story content of a speech and the brain response in regions involved in audition and social cognition, attempting to replicate the findings from an earlier study that took the same approach (but with a different speech and audience; Schmälzle, 2022).

This paper is organized as follows: first, we introduce the topic, speeches and stories, define their core properties, and describe how these forms of communication prompt strong audience responses. In doing so, we point out the gaps in our theoretical understanding, namely that we possess only fragmentary knowledge about how these effects arise from the brains' activities. Second, we introduce neuroimaging as an approach that can fill these gaps in our understanding. Then we introduce the brain systems that are critical in the current context: (1) the auditory cortex, which transforms the spoken story stimulus and carries out basic analyses of the speech sounds, and (2) the temporoparietal junction (TPJ), which is a key hub within the social cognition system. Fourth, we summarize previous work and motivate the need for this study. Finally, we present the design and analysis of the current study in which 54 participants listened to an engaging story presented at a public speaking event.

Background: the causal path from story content to brain responses to subjective experience

A story is a narrative that describes a series of events or experiences, typically involving one or more characters and a plot (Stein, 1982). Stories can be fictional or describe lived experiences. They can be conveyed through different mediums, the most traditional forms being oral storytelling and public speaking, but also through literature or film. Stories are important because they help us understand complex ideas and emotions, and provide a way to connect with others (Bruner, 1986; Schank, 1995). Stories have been a fundamental part of human communication for centuries and continue to play a crucial role in shaping our beliefs, values, and culture (Bartlett, 1932; Green et al., 2003). From childhood fairy tales to modern-day novels and movies, stories are an essential part of our lives.

Stories often evoke strong social and affective responses in their audiences, and these responses are integral to sustaining peoples' attention, aiding their comprehension of the story (above and beyond more text-based factors like coherence), and motivating them to seek out stories as means of entertainment in the first place (Lazarsfeld, 1940; Mosenthal, 1987; West & Turner, 2010). The latter point is particularly relevant to speeches given at large storytelling events (e.g., *The Moth*).

Audiences' social and affective responses to stories have therefore caught the attention of researchers, but many unsolved questions remain. Findings within media and social psychology reveal strong relationships between stories and social cognition, highlighting the impact stories have on audiences (Busselle & Cutietta, 2019; Green et al., 2003; Mar & Oatley, 2008). Such work has often emphasized the role of theory-of-mind processing (or mentalizing), which allows listeners to infer and keep track of characters' mental states and understand social situations (Luyten et al., 2019). Many other fields have also focused on stories, including literary or cultural perspectives, or pragmatics, artificial intelligence, or cognitive science. Within cognitive psychology, for instance, extant work has focused on topics like text comprehension and story grammar (Abelson & Schank, 1977; Kintsch, 1998). While these varied approaches to the study of stories all have value, it is important to highlight the gaps that remain: Specifically, we have only fragmentary knowledge of the causal pathway that ranges from story content to brain responses to psychological effects in individuals and audiences.

Brain imaging: capturing continuous audience responses during reception

Emerging approaches for functional neuroimaging enable to examine how the brain responds to external stimuli (e.g., public speeches and stories) and give rise to psychological effects (e.g., hearing or social cognition; Poeppel et al., 2020). Research in this area began within neuroscience by focusing on the brain basis of auditory processes (hearing sounds, listening to speech, etc.; Belin et al., 1999). It then moved on to examining the basis of linguistic (Hickok & Poeppel, 2007) and even extralinguistic processes involved in social-cognitive and affective functions (Ward, 2016). Although the complex nature of stories initially posed challenges for neuroimaging, a number of studies still focused on stories (Ferstl et al., 2008; Hasson et al., 2004; Mar, 2011) and within the past years, there has been a trend to use narrative stimuli in neuroimaging studies (Nastase et al., 2021).

These trends have also important implications for communication, and they generate new opportunities to test theories and expand to new areas of investigation (Figure 1). In particular, classical neuroimaging approaches, even if using natural messages as stimuli, almost completely ignore the notion of audience because this does not play a significant role in neuroscience or cognitive neuroscience. However, from a communication perspective, an ability to examine how messages affect and engage the brains of audiences has significant implications (Floyd & Weber, 2020). For instance, research on the impact of public speaking, which is clearly a central topic of our discipline, stands to benefit from the ability to capture brain responses in a continuous manner, that is, during the ongoing speech (Schmälzle, 2022). Moreover, because neuroimaging measures can be recorded without having to ask people to verbalize their reactions, or e.g., turn a dial as in continuous response measurement (which is often used in speech evaluation studies; e.g., VanDyke & Callison, 2018).

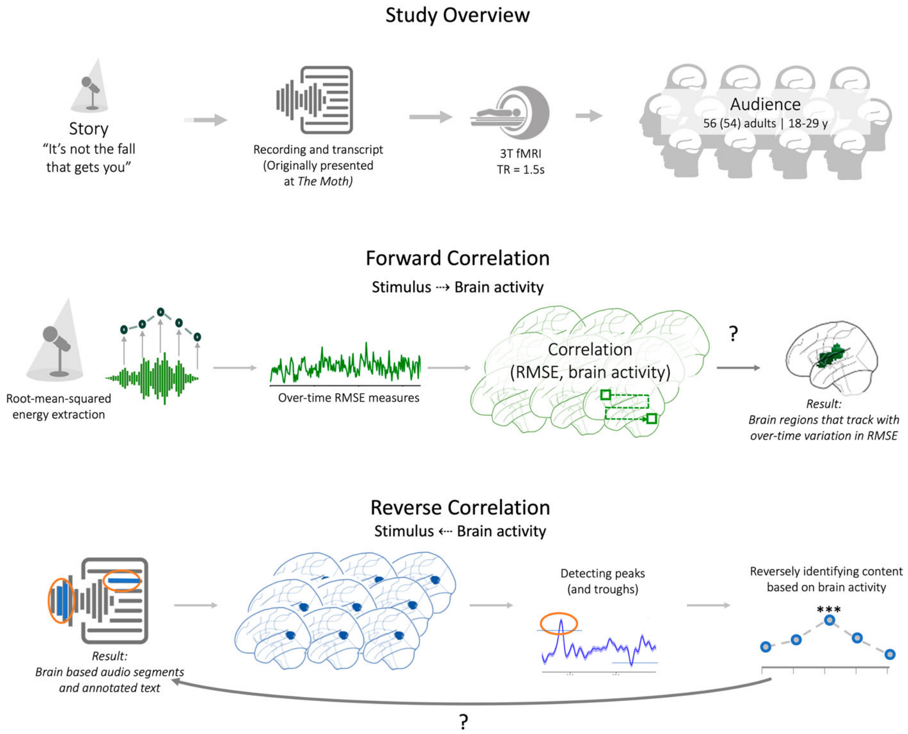

Figure 1. Illustration of key study characteristics and principles of forward and reverse correlations. All participants listened to the same story "It's not the fall that gets you" while they underwent fMRI scanning. The spoken story was transcribed and the onset and offset times of each of the 1601 individual words were coded. Forward correlation "maps out" brain activity that tracks with a pre-specified variable, such as the audio signal's energy (RMSE). Reverse correlation uses salient moments in the story-evoked brain activity to identify content elements, which can be compared based on theory-relevant parameters.

Two brain systems involved in speech reception: auditory cortex and temporoparietal junction

Two brain systems critical for reception are the auditory system (involved in hearing) and the temporoparietal junction (TPJ, involved in social cognition). We do not want to suggest that these systems are "all that it takes" to understand a story-based public speech. Many other brain systems and neurocognitive mechanisms are involved in hearing, language understanding, story understanding, and social-cognitive and pragmatic functions (Castricato et al., 2021; Huskey et al., 2020). However, we focus on these two regions because they provide a gateway to shed light into the neurocognitive black box of the brain as it consumes the rich content conveyed by engaging stories.

Auditory cortex

The auditory cortex refers to regions of the bilateral superior temporal lobe, which instantiate basic auditory-sensory functions (see Figure 2). In brief, the neurocognitive computations that are carried out in these regions produce what we commonly refer to as "hearing," or the processing of incoming information from the perception of hearing sound from the

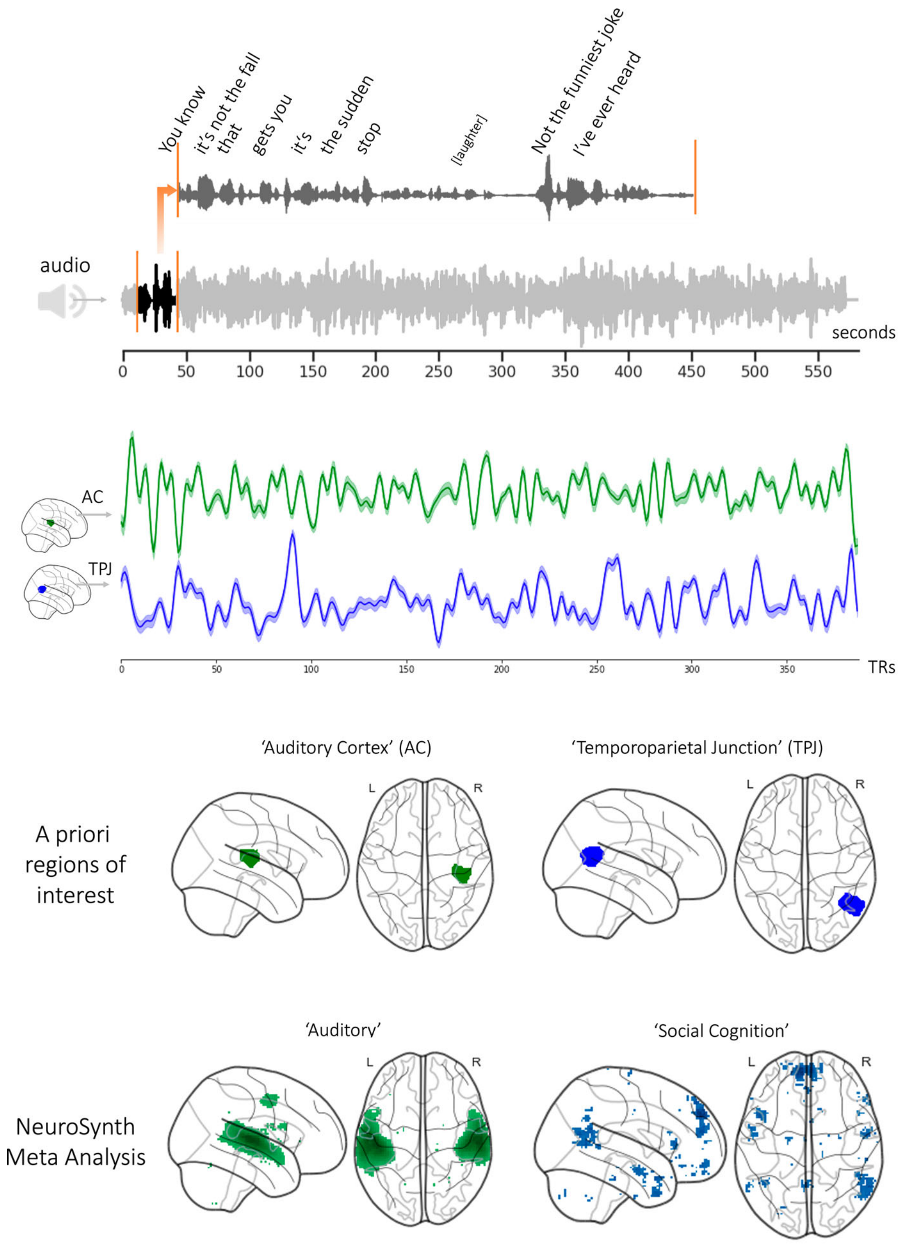

Figure 2. Illustration of the time-aligned nature of story and brain activity recordings and the a priori regions examined in this study. Top panels: The 10-min story recording with its raw sound waveform and a zoomed in version depicting the spoken text. Middle panels: MRI time series from individual regions (auditory cortex and temporoparietal junction). The solid lines represent the group-averaged time course from each region, the shaded corridors around the time series represent the standard error of the mean at each time point. Bottom panels (brain figures): Location of regions labeled "Auditory Cortex" and "Temporoparietal Junction" (right) in this study, which are taken from the 268-node parcellation by Shen and colleagues (2013) as well as meta-analytic maps for the concepts "Auditory" and "Social Cognition"

external environment. These include spectrotemporal analyses (time–frequency decomposition of the sound), filtering (suppressing and amplifying sound elements), and detecting differences between both ears' signals (for echolocation of the sound). Accordingly, damage to the auditory cortex leads to very basic hearing impairments.

Throughout listening to a speech, we can assume that all members of an audience receive the same version of the physical auditory stimulus (i.e., they all listen to the same speech - either live or as a recording). As the incoming auditory signals are transformed into neural signals, they will arrive at each listener's auditory cortex, where they would prompt largely similar processes related to time–frequency analysis, detection of loudness, etc. Similar processing of auditory cortices across individuals promotes orderly communication. Therefore, the auditory cortex clearly represents a cortical entry point to analyze the reception of a speech.

Temporoparietal junction

As the name indicates, the temporoparietal junction is located where the temporal and parietal lobes meet, just behind the Sylvian fissure (see Figure 2). The TPJ has risen to prominence within social and communication neuroscience because it has been implicated in a broad variety of social and affective processes (Decety & Lamm, 2007; Schurz et al., 2017). Specifically, the right temporoparietal junction (rTPJ) has repeatedly been associated with tasks that involve mentalizing, which is among the most fundamental social-cognitive processes (Saxe & Kanwisher, 2003). Critically, however, the underlying studies are often rather artificial and laboratory-based social-cognition paradigms, which differ markedly from the social-cognitive demands that arise during the reception of an engaging public speech with all its multifaceted social content (from prosody of the speaker, to the often social speech content, to processing social feedback signals from the audience). As a result, insights into the TPJ, which is involved in multiple neurocognitive processes (e.g., mentalizing, attention shifts, or contextual integration; Carter & Huettel, 2013; Geng & Vossel, 2013; Nastase et al., 2021) remain limited in many ways, but if listeners follow a speech, then we can expect TPJ responses. In sum, although a dedicated neuroimaging literature on the topic of stories (e.g., Willems et al., 2020), public speaking (e.g., Schmälzle et al., 2015), or even communication and neuroscience as a whole (e.g., Floyd & Weber, 2020; Weber et al., 2008) is still forming, the existing evidence suggests that stories should engage the TPJ, and that particular peak moments within stories (Wilensky, 1983) should prompt TPJ response peaks.

Results from prior research and the importance of replication

The theoretical reasoning laid out above has already motivated an earlier study, and the goal of this study is to replicate and extend that work (Schmälzle, 2022). This earlier study examined how the audience's brains responded to a socially engaging story told at a live event (*The Moth* in NYC), which was recorded and played to a test audience. fMRI data were collected from 68 listeners as they listened to the performance, and the analysis focused on the two regions introduced above, the auditory cortex and rTPJ.

Specifically, this previous study introduced two distinct approaches to link story content, and the brain responses – forward and reverse correlation analysis. The "forward correlation" analysis quantifies a stimulus characteristic (a property of the physical stimulus, such as variations in the soundwave that carries the speech) and asks where in the brain activity "tracks with" over-time variations in that stimulus characteristic. With this forward correlation approach, the previous study confirmed that variations in the root-mean-squared-energy (RMSE) of the speech signal (the story recording) significantly tracked with activity in participants' bilateral auditory cortex.

In addition, this study also carried out a "reverse correlation" analysis: This approach differs by starting with the brain activity in a given region to identify salient moments therein (such as peaks and troughs). Then, researchers "go back" (or reversely identify) the moments in the stimulus (i.e., the story recording) that must have logically prompted those peaks.[1] The authors reasoned peaks in the rTPJ's signal should be associated with more socially engaging moments in the story. They used "audience laughter" as a criterion of social engagement, based on the argument that bursts of laughter among an audience can serve as an implicit, behavioral, and crowd-based annotation of pivotal moments that are collectively expressed among a social group. The reverse-correlation results revealed that rTPJ response peaks pointed back to scenes that contained more audience laughter than the rTPJ response troughs. These findings confirmed the authors' hypotheses, and they align well with the cumulative body of evidence about the neurocognitive functions of the auditory cortex and the rTPJ. As the study itself was the first of its kind, we aimed to replicate these findings.

Over the last decade, the role of replication has been reemphasized across disciplines. Although the underlying debates are much older (Hunter, 2001), there is evidence that findings published in single studies do not necessarily lead to cumulative science. As said, these claims are not really new, but they are severe enough to warrant calls for more replications (Lewis Jr, 2020; McEwan et al., 2018). In addition to the call for replication, limitations within the previous study also support this. In particular, the study used a single story as stimulus. This raises the question to what extent one can use a single message to make generalizations about a broader category of messages (Clark, 1973; Jackson & Jacobs, 1983).

Second, the study used a relatively novel method – reverse correlation analysis – and it relied on in-house code specifically written for this analysis. Although the authors shared all materials and code, it cannot be taken for granted that it would reproduce with another story and another audience. Therefore, these factors motivate the need for a replication study, which is another contribution of this paper.

The current study and hypotheses

The current research replicates the approach of a previous study (Schmälzle, 2022) with a new story stimulus and audience. This new story resembled the old one in that it contained descriptions of funny social events that happened to the character that elicited laughter from the audience (e.g., a skydiving novice being thrown out of an airplane with the farewell call "*wait, wait, your chute*"). Therefore, the same criterion for comparing the content of scenes that prompted TPJ response peaks or troughs could be applied, i.e., using laughter as a criterion that the content of the scenes had produced a significant response in the original audience (when the story was recorded). Like the old story, the new story was also delivered in a similar public speaking setting, and it has a similar length. The story and the transcript can be read at osf.io/nfy64. A further criterion for selecting this story from a set of other candidates (all from a collection of fMRI studies on narratives; Nastase et al., 2021) was that it also had a decent sample size (56 listeners for this study, compared to 68 in the prior study).

As in the previous work, this study examines how two regions of listeners' brains – the auditory cortex and rTPJ – respond to the events conveyed in a story delivered via a public speaking performance. We will focus on the shared activation among all the participants rather than focusing on individual differences, guided by the notion that when listeners process the same narrative stories, they will exhibit similar neural responses. Thus, the theoretical framework laid out above and in the previous paper (Schmälzle, 2022) stays the same. Likewise, the analytical procedures are identical to the previous study except for minor changes commanded by the new stimulus and participant sample. As such, the regions of interest for the analyses (auditory cortex and rTPJ), as well as hypotheses for each of these regions, remain the same.

The first hypothesis concerns the auditory cortex. We know that the auditory cortex responds to the time-varying physical properties of the incoming stimulus, carrying out analyses of sounds. One quantifiable physical property of the sound signal is the root-mean-squared-energy (RMSE), which is roughly related to loudness. We thus expect that over-time variations in this parameter should prompt associated changes in recorded brain activity (i.e., forward correlation content → brain activity) in bilateral auditory cortex (see Figures 1 and 2).

H_1: Variations in RMSE should be associated with brain activity in the superior temporal lobe.

The second hypothesis focuses on the temporoparietal cortex as a nexus region for social-cognitive processes. As argued above, the rTPJ is involved in many processes that have been characterized as social-cognitive as well as attention-demanding, although the specific computations it carries out are more fundamental than these labels (see e.g., Nastase et al., 2021 for an integrative review). One key innovation of the previous study was to suggest reverse correlation as a principled approach to examine associations between salient brain activity moments and the content elements that logically evoked this brain activity. In the previous work, the moments at which the rTPJ activity exhibited significant peaks across 68 listeners pointed to those moments in the story that contained punchlines, followed by laughter. The rTPJ-troughs, on the other hand, reverse-identified fewer laughter-evoking scenes. These findings were compatible with the assumed role of the rTPJ for socially engaging content, which was defined here by the ability to produce laughter in an audience (see below for further discussion on using laughter as a social outcome and how laughter relates to the preceding content in this story). However, their generalizability was limited by the fact that they were based only on one particular story stimulus. Thus if the current framework and approach have merit, then we would expect it to apply to other comparable stories as well.

H_2: The TPJ signal peaks will correspond to scenes that describe socially engaging story parts, operationally defined as scenes that contain audience laughter.

Method

This study is a secondary analysis of fMRI data collected in a larger data set about narratives (Nastase et al., 2021). Specifically, it uses the data from the "*It's not the fall that gets* *you"* story, a story originally presented at a *The Moth* live storytelling event. While this dataset has been used before for different purposes (Chien & Honey, 2020), this study seeks to reanalyze the data from the perspective of communication science, which entails a focus on audience responses and social cognitive processing within the TPJ.

Participant sample

A total of 56 participants (31 female) from Princeton University were included in the original study. Participants ranged in age from 18 to 29 ($M = 21$, $SD = 2.4$). All participants provided written consent to the study, which was approved by the local institutional review board. More details about the sample can be found in the data descriptor paper (Nastase et al., 2021). Data from two participants were excluded due to quality reasons, leading to a final sample of 54 participants.

Story stimulus

All participants listened to a recorded story at *The Moth* live storytelling event in New York City in 2009, which was titled "*It's not the fall that gets you"* and was presented by Andy Christie (available at https://themoth.org/stories/its-not-the-fall-that-gets-you). The duration of the clip is 582 s (9.7 min), with 22 s of music and 10 s of silence at the end. The story's recording and written transcript can be found online (*osf.io/nfy64,* also see Figure 5).

In terms of content, the story is told as a personal anecdote of Christie's attempt to learn skydiving during his midlife crisis. He starts out with the shocking and comical, reveal that he was pushed out of a plane, and the instructor said "*wait, wait, your chute …* " before he fell out of their voice. His dramatization of the story, which is full of references to the speaker's own social inadequacies and struggles, leads to a comedic and entertaining story that is enthralling for the audience, prompting many points of laughter.

The file played to participants in the fMRI scanner was 9.7 minutes long (582 seconds). Importantly, this recording contained primarily the story as it was delivered orally by the author, but the recording was done at a live event and thus also included the laughter with which the audience responded to the story.

Data acquisition and analysis

Details on data acquisition and preprocessing can be found in the data descriptor paper (Nastase et al., 2021). In brief, functional MRI data were collected while participants were listening via headphones to a recording of the original "*It's not the fall that gets you"* story. With a TR of 1.5 s, the length of the functional data was 400 samples (TRs, 600 s, including dummy volumes) and the data used for analyses were 388 TRs long. The MRI scanner collecting functional and structural MRI data was a 3T Siemens Magnetom Skyra. Preprocessing was carried out via the fMRIPrep package (Esteban et al., 2019).

Our own analyses were carried out using in-house code leveraging the NiLearn package (Python 3.7, all code available at github.com/nomcomm/narratives_itsnotthefall and/or osf.io/nfy64). Importantly, all code was based on established procedures from the to-be-replicated study, which was only adapted to match the current dataset's specifics (e.g., different length of the story, different number of participants). In brief, we first extracted the fMRI time series (after high-pass filtering, detrending, and *z*-standardization) from the 268-node parcellation by Shen et al. (2013), and stored the resulting neural time series as *NumPy*-arrays (268 regions, 388 samples, 54 participants; specifically containing the two time series from the auditory cortex and the rTPJ region, respectively). Of note, prior research also examined subcortical regions, specifically an exploratory analysis of the N. Accumbens, and it contained a supplementary analysis of all other regions. Here, we focused on the two main hypotheses from the prior study, which were about the auditory cortex and the rTPJ, and we test them via identical procedures.

Forward correlation analysis examining H1 (RMSE → brain activity)

Reflecting prior work, we extracted the RMSE sound energy from the story's recording via the RMSE extractor from the *pliers* package (McNamara et al., 2017). The RMSE time course was then downsampled to match the resolution of fMRI data, shifted to compensate for the HRF delay, and correlated against each of the 268 regional fMRI time series. Because the main forward correlation analysis was carried out via a simple correlative procedure and at the level of averaged brain regions (extracted from the parcellation), we also confirmed these findings when carried out via a conventional GLM-based analysis, which was also done at the level of individual voxels. To this end, we used the NeuroScout platform for automated neuroimaging analysis (de la Vega et al., 2022). Code to reproduce these analyses is available at github.com/nomcomm/narratives_itsnotthefall and on OSF osf.io/nfy64.

Reverse correlation analysis examining H2 (content ← brain activity)

For the reverse correlation analysis, we first group-averaged and plotted the responses from the rTPJ region. We then computed consecutive *t*-scores for each volume/moment across the rTPJ responses from all listeners, yielding a vector of *t*-values that was as long as the dataset. This vector was then thresholded (initially at $t = 2$) to identify peaks and troughs in the response (moments where the fMRI signal is significantly positively or negatively different from zero in the previously standardized time courses, see Figure 4). Of note, this *t*-threshold, which was used in the previous analysis, may not have been optimally applicable to the current dataset: Specifically, we found that it identified rather wide windows around the peaks/troughs and also rather many peaks/troughs (because, strictly speaking, the statistical-threshold-based analysis is not a pure peak-identification procedure, but a procedure that identifies deviations from zero, i.e., moments in which the audience brain response is significantly positively or negatively different from zero). To overcome this, we ran the same analysis using a stricter statistical threshold of 3.29, which resulted in fewer and narrower peaks/troughs being detected.

Having identified the peaks or troughs in the fMRI signal, we then used their temporal location (e.g., interval 20–24.5 s, 34–38 s, …) to go back to the speech stimulus (the sound recording) and identify the corresponding "audio-chunks" from the recording. These "audio-chunks' (peak or trough-based trailers) were then saved to disk. We then listened to and sorted these trailers into groups based on whether they contained audible laughter from the audience or not. Thus, the procedure led to files associated with peaks and troughs, which were sub-grouped based on whether they contained laughter or not, and then statistically tested for differences in the proportion of laughter. In addition to creating these brain-based speech trailers, we also used the transcribed and time-annotated text to carry out the corresponding analysis. Thus, instead of producing an audio trailer, this analysis yields a list of words associated with peaks or troughs.[2] To create a brain-based visualization of this story text, we annotated every word based on the brain response associated with this word (after correcting for the HRF delay, see above and see Figure 5). Again, all code to reproduce these analyses is available at github.com/nomcomm/narratives_itsnotthefall or osf.io/nfy64.

Additional control analyses

In addition to the reverse correlation analysis (which used the rTPJ to go back to the original content), we also conducted a conventional forward correlation analysis, i.e., an analysis that uses a quantified content feature and seeks to "map out" the brain regions that track with variations in this content feature. Carrying out such a forward analysis thus requires to specify the content feature of interest, so that its variations in content can be quantified. This could obviously be done in multiple ways because what we commonly call content actually consists of multiple and hierarchically nested features (Grall et al., 2021; Hopp et al., 2021; Schmälzle & Huskey, 2023): On the one hand, the argument about the socially engaging nature of the previous (as well as the current) story was what led to the operationalization of laughter; instances of laughter can also be coded very clearly and used in a forward analysis. Thus, to create a feature time series of laughter instances, we went through the entire story and annotated for every TR (unit or sample of the fMRI recordings) whether the audio track contained a laughter scene or not. However, while this operational definition of laughter as a social response as well as a content feature of the recording itself is straightforward and complements the main reverse correlation analysis, there are other ways in which the socially engaging character of the speech could be quantified.

Another, albeit rather narrow definition could be to code for all interaction-scenes, i.e., occurrences verbal (e.g., "Wait, wait, your chute!") and nonverbal (e.g., " … and she put her arm through mine") interactions between the protagonists. A similar approach has already been used in animal neuroscience, where researchers annotated videos to delineate so-called social interaction networks in primate brains (Sliwa & Freiwald, 2017). Inspired by this work, we created a second annotation in which every sentence of the story was annotated based on whether it contained a description of "character-interactions."

Obviously, between the "laughter"-based annotation and the "character-interaction"-annotation, there is room for other conceptions of social content that lie in between. In particular, the mere character-interaction descriptions themselves may not prompt much laughter in the audience, which rather seemed to depend on higher-level content features like the speaker's constant reference to his own social inadequacies, the surprising violations of social norms, or the sexual references (see Supplementary Table as well as the discussion in the prior study, Schmälzle, 2022). However, given the "reverse" nature of the rc-procedure (which goes back from response to content that must have evoked these responses), it is also informative to contrive the phenomenon in question via forward correlation procedures. Thus, in addition to the main reverse-correlation analysis, we also ran two forward correlations using (i) the laughter/no-laughter annotation and (ii) the (narrowly defined) character-interaction annotations. Specifically, we used the NeuroScout framework (de la Vega et al., 2022) to run standard fMRI "forward" analyses that identify which brain regions' activity tracks with each of the two quantified content parameters.

Results

Forward correlation between sound energy and brain response

H_1 predicted that RMSE should be correlated to the intensity of BOLD signals in the superior temporal lobe, which is the site of the primary auditory cortex. As reviewed insofar, the soundwave can be analyzed by its physical properties, such as the energy (which roughly translates into the psychophysical notion of loudness). As expected, we found that regressing the over-time variations in loudness onto the fMRI signal fluctuations identifies a significant relationship between the two in the bilateral superior temporal cortex (Figure 3). These results support H1.

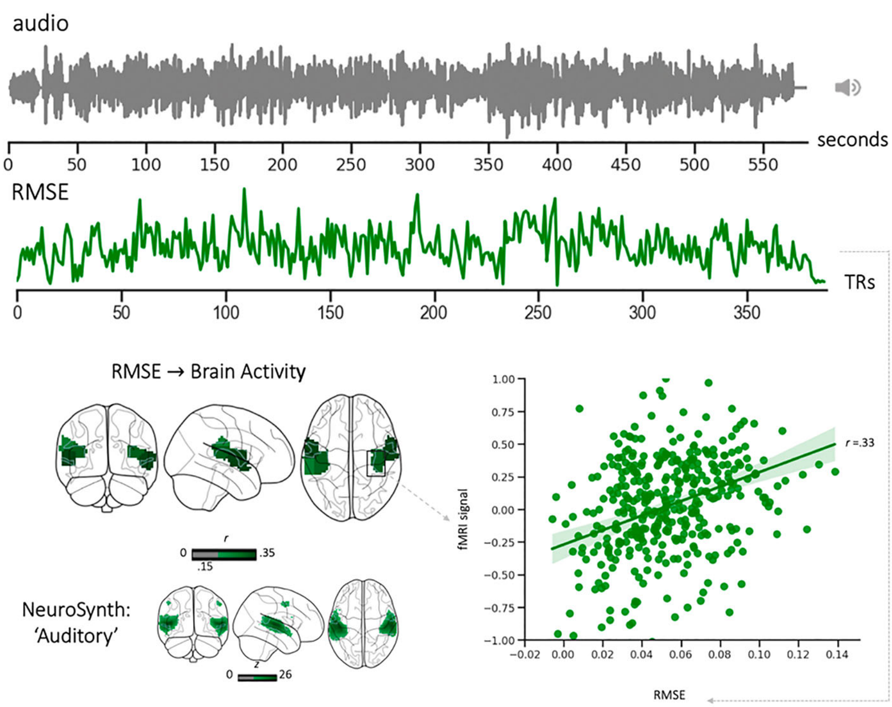

Figure 3. Result for the forward correlation analysis. Shown are the raw waveform from the story's recording along with the extracted RMSE parameter. The brain image illustrates the result of the forward correlation analysis. Specifically, it shows where in the brain the over-time variations of the RMSE parameter track with fMRI activity. As can be seen, the regions that emerge from this analysis encompass the bilateral auditory cortex.

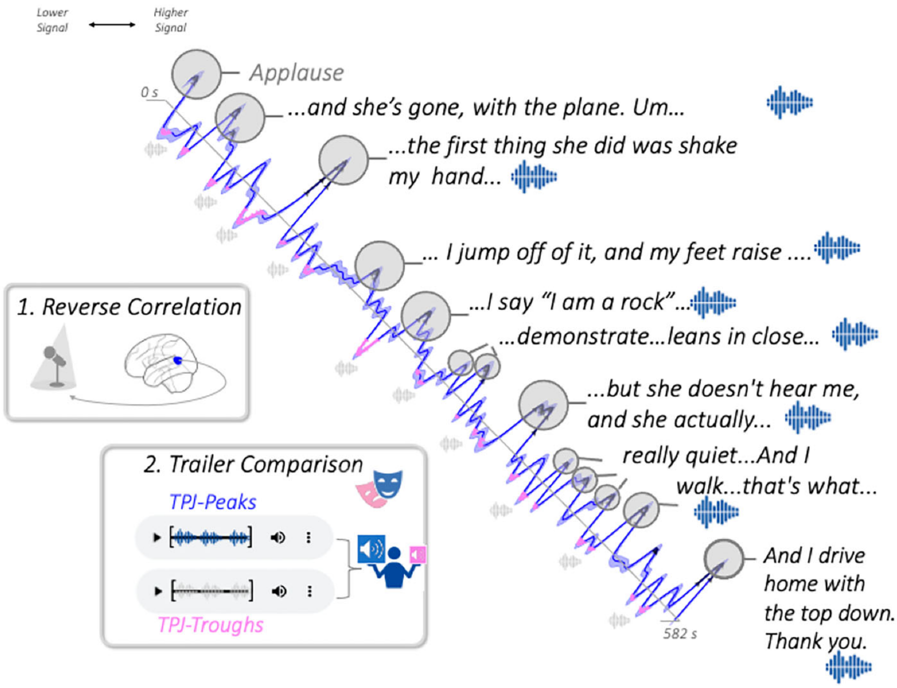

Figure 4. Results for the reverse correlation analysis of TPJ responses. Peaks and troughs in the rTPJ's time course are identified and used to identify points in the original story recording (scene-by-scene audio chunks, or "TPJ-based trailers') that must have logically produced these brain reactions. Both peak and trough-based trailers are then analyzed in terms of how much laughter they contain.

Reverse correlation from brain response to story stimulus

H_2 predicted that the scenes that prompt higher TPJ activity (peak-associated scenes) would contain more laughter (as an indicator of socially engaging content) compared to scenes that result in troughs in the TPJ activity. The results of this analysis are overall positive, but with an important caveat: The peak-identification used in the original study relied on a specific *t*-score based on thresholding procedure, and inspection of the peaks and troughs identified using this threshold revealed some issues (identifying too many and too broad peaks/troughs). When using this original threshold to compare laughter scenes associated with peaks and troughs, we found that while the pattern of results was nominally in the expected direction (peaks: laughter: 11, no-laughter: 6, troughs: laughter: 11, no-laughter: 13), statistically they were not significantly different ($\chi^2 = 1.43$, *n.s.*). However, using an improved, more conservative peak/trough-thresholding procedure (using a $t = 3.29$ to identify fewer and narrower peak-scenes), the results were compatible with H_2 (peaks: laughter: 10, no-laughter: 5 (66% laughter), troughs: laughter: 7, no-laughter: 14 (33% laughter), $\chi^2 = 3.90$, $p < .05$. We note, however, that the decision to use a different peak/trough identification procedure was made after the fact and this needs to be taken into account when interpreting the results. A complementary impression can be gained by inspecting the visualization of the TPJ peaks with textual annotations (Figure 4) and the continuous brain-based content annotation as this does not rely on any thresholding (Figure 5).

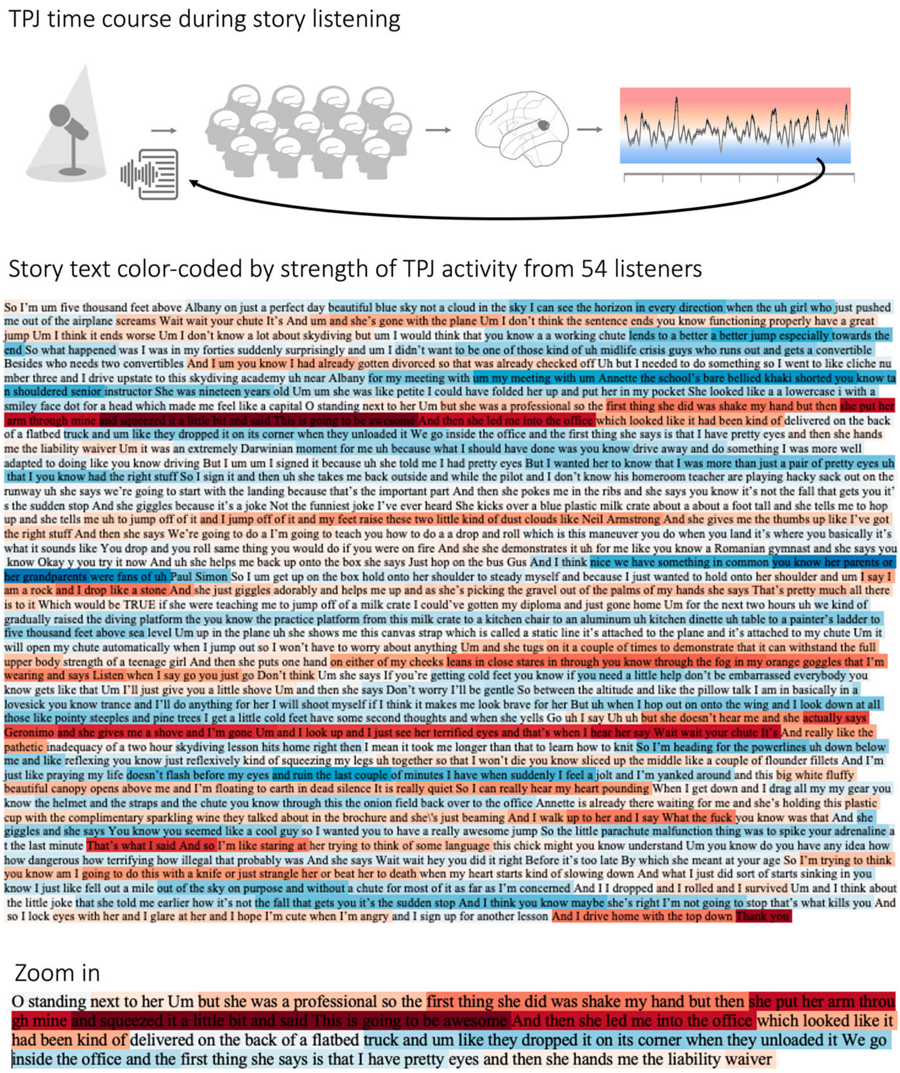

Figure 5. Brain-based annotation of story content. The figure is produced by using the group-averaged fMRI time course of the rTPJ and using the extent of rTPJ activity as an annotation to colorize the story transcript's source text. Thus, reddish colors indicate stronger story-evoked brain activity, whereas blueish colors indicate lower brain activity. See details for text. (Of note, the image shows a left-side view of the translucent brain, but the highlighted region refers to the rTPJ).

Results from additional analyses

We conducted several additional analyses to further examine these results. First, for the forward correlation analysis between the RMSE audio parameter and brain activity, we also carried out a control analysis in which we randomly shuffled the RMSE signal to demonstrate that this destroys the relationship to auditory cortical responses, confirming that the results were only obtained with the unshuffled RMSE predictor. Next, we also confirmed that the results (which were based on an analysis that averaged over broad regions within the parcellation) were also obtained when using a more fine-grained, voxel-level analysis, and a more conventional analytic approach based on the GLM. These results are provided in the Supplementary File.

Second, as described above, we wanted to further hone in on the relationship between story content and TPJ responses, but this time via a forward approach instead of the main reverse correlation analysis. To this end, we quantified two well-defined content features – scenes of audience laughter (same as the coding criterion for reverse-correlation results) and a narrower definition of "character-interaction" content. With these annotated content features, we then carried out a standard GLM-based (forward) analysis.

For the laughter regressor (social-evaluative response to preceding content that is funny and thus socially engaging), we find that this analysis identifies regions of the default mode network (statistically corrected for multiple comparisons via the FDR procedure), encompassing the medial prefrontal cortex, the precuneus, and also the TPJ. Thus there is convergence between the forward and reverse correlation procedures, which strengthens our confidence in findings from the reverse correlation approach. The brain activation maps corresponding to this control analysis are presented in Supplementary Figure S2 and result files are uploaded to the online repository (*osf.io/nfy64*).

For the analysis focused on "character-interaction" (coded as having direct or indirect speech, or descriptions of social interactions between the two protagonists), the forward correlation procedure identified primarily the auditory/language network. This makes sense insofar as descriptions of direct and indirect speech are likely to prompt enhanced auditory attention. Of note, there was some evidence for engagement of the default mode network in this analysis as well, but the results were clearly weaker compared to the auditory/language activity, much weaker than for the laughter analysis, and they did not survive correction for multiple comparisons. The associated brain maps are shown in Supplementary Figure S2 and uploaded to the online repository (*osf.io/nfy64*). In sum, both forward and reverse correlation analyses confirm a relationship between laughter and TPJ activation.

Discussion

Ever since antiquity, communication scholars have been interested in the impact of stories on audiences. However, it has remained difficult to study how audience members respond to stories as they unfold because these responses are largely occurring inside their brains and thus hidden from view. Therefore, this study examined how the brains of 54 listeners responded to an engaging story on a moment-to-moment basis.

Discussion of main results

First, starting with the "forward analysis," the current results confirm H_1. As shown in Figure 3, the RMSE correlates with (i.e., predicts) brain activity in bilateral auditory cortex. These results correspond with well-known findings from auditory neuroscience, serve as an important validity check of the analysis procedure, and are compatible with the theoretical framework. Moreover, it should be noted that many earlier neuroimaging studies have used relatively artificial experimental stimuli that are very different from the current analysis of naturally running speech. In addition, as the fMRI scanner itself makes a rather loud noise, which could have masked effects, the fact that we still reveal significant findings demonstrates the strength of these relationships.

Second, regarding the main "reverse correlation" analysis, the results generally support our hypothesis, but with one caveat: The procedure used to identify peaks and troughs in the fMRI response time course used a threshold that had been adopted in the prior analysis. Using this threshold to identify the peaks and troughs, the results were not significantly different, although the general pattern is still supportive. Specifically, the peak scenes do contain nominally more laughter than the trough scenes, but the difference fails to reach statistical significance. However, we noticed that the original *t*-threshold led to rather wide windows around the peaks, and also to many peaks - suggesting that this threshold may have been too liberal for this particular story stimulus and sample. Therefore, we ran the same procedure, but with a more conservative threshold to identify peaks and troughs ($t = 3.29$). Running the identical analysis with this more restrictive way to identify narrower and fewer peaks and troughs did identify significant differences in terms of laughter-evoking content segments. Thus we interpret these results as in support of H_2, but with the caveat that future work needs to work towards better ways to identify peak and trough scenes that generalize across different stories, with different lengths, different sample sizes, and so forth.[3] Despite these outstanding matters, the current study aligns with the prior one by showing that "going back" from rTPJ response peaks leads to scenes that contain frequent audience laughter, suggesting that the reverse correlation procedure can be used to identify content that engaged the audience.

The supplementary forward correlation analysis of quantified content elements further adds to these results. This analysis utilized the audience laughter as a sort of crowd-based annotation of the story (taken from the original *The Moth* audience), asking which brain regions track with this content feature (in the audience that listened to the recording while lying in the fMRI scanner). The main result was that this analysis identified the default mode network, of which the TPJ is a part (see Supplementary Figure S2). Thus, there is convergence between procedures in the sense that laughter scenes identify the TPJ, and that going back from the TPJ identifies scenes that contain laughter.

Notably though, this does not mean that it is per se the laughter that activates the TPJ. While laughter clearly represents a social communication signal, we used laughter here more like a crowd-based annotation to operationally define socially engaging points (see, e.g., Provine, 1993; Wilensky, 1983). Thus there could be other content features that may not evoke laughter, but might still also prompt peak TPJ reactions. Yet, the largely negative results for the more restrictively defined character-interaction content (comprising direct/indirect speech and described direct interaction between protagonists) suggest that the "active ingredient" in the story's content lies at a higher level than mere character-interaction descriptions. Instead, we believe that likely candidates for such content elements are the laughter-evoking norm violations, sexual references, and the perpetual social awkwardness and inadequacies that the speaker uses strategically to make fun of himself. This interpretation aligns well with the social functions of humor and the ways in which speakers deploy humor to connect with and engage the audience (Lynch, 2002; Meyer, 2015).

Moreover, this reasoning is also in line with Wilensky's story point theory (Wilensky, 1983), which suggests that how humans understand and respond to stories is critically linked to "human dramatic situations" (broadly similar to the content elements listed above). Such situation are, in turn, often realized by expectation breaks in jokes (see Abelson, 1983; Amir et al., 2015), which is quite compatible with the nature of the current story (as well as the story in the previous study, which were both humorous). However, we note that this remains somewhat speculative because we did not experimentally manipulate laughter (nor the preceding story content). Going forward, it would seem promising to conduct studies that edit out the laugh-scenes in order to test whether TPJ peaks would still be observed among listeners. Another way to clearly constrain the relationship between story content and TPJ responses would be to create dedicated stimuli that vary along specific dimensions. For instance, the classical work of Heider and Simmel (1944) showed that simple animated shapes prompt consistent social and narrativized interpretations among observers. Previous work (Nguyen et al., 2019) has already used fMRI in that regard, and the finding that shared social interpretations of animated-shape-stories are associated with activity in the default mode network is again compatible with the current results.

Theoretical and practical implications

These findings are theoretically relevant because they help close the explanatory gap that still exists between the story itself (i.e., the transmitted sounds carrying complex conceptual content) and the reception mechanism (i.e., the complex transformations the brain makes to decipher the content and to produce various psychological effects). With this in mind, we note that a principled ability to identify peak moments within messages from the responses they evoke among recipients is not only practically promising, but also opens up new theoretical directions for other outcomes (e.g., message strength, effectiveness, and communication success).

Specifically, we argue that indicators of message strength could be derived based on a message's ability to prompt similar responses across recipients(e.g., to command consistent TPJ responses among an audience). In the communication literature, some related discussion has centered on the notion of argument strength, which is defined as the quality or persuasiveness of arguments in particular. However, argument strength is often derived from perceptions of audience members as to how convincing an argument is, although it would perhaps be better linked to objective features like the arguments formal structure, its evidential strength, and so forth (e.g., Areni, 2003; Zhao et al., 2011). With this in mind, the ability to have another objective metric of message impact, in this case a brain response, suggests that one could triangulate measures, and potentially advance theoretical debates about hypothetical "routes" that messages take during processing and where they create impact (e.g., on the auditory cortex due to yelling, on prefrontal cortex because of logical qualities, or on other systems because of other features; Petty & Cacioppo, 1986; Stiff, 1986). Moreover, although there are certainly many ways to define effectiveness or communication success,[4] one precondition for any of this is that messages can evoke specific reactions in multiple recipients (Imhof et al., 2020). From that perspective, the ability of stories to produce consistent TPJ-peaks in audiences points to one promising marker for closing the gap between message content and effects via objective neuroimaging measures.

Beyond these implications, there are also many practical applications of a principled ability to identify convergent audience reactions in responses to messages – whether in health communication, persuasion more broadly, or entertainment media. Indeed, some previous research has already demonstrated that brain-based measures can be used to predict success in the field for varied contents (Dmochowski et al., 2014; Falk et al., 2015). While these existing approaches have largely focused on linking brain activity data to later outcomes, we believe that the reverse correlation procedure could be especially useful for message creators because it can be used to provide direct feedback about the audience impact of specific subsegments of messages (e.g., parts of a story, movie, etc.). Thus it may be possible to use these techniques in the formative stages of message creation, or even for computer-based creation strategy (cf. reinforcement-learning from human feedback, where the feedback could also be brain activity; e.g., Xu et al., 2021).

Another use case could be to identify states of heightened receptivity. For instance, if one could identify TPJ-peaks on-the-fly, then one could foresee that one could make the delivery of the upcoming contingent upon such events. Somewhat relatedly, in the field of childrens' media, there is often debate about whether media produced such that they are appropriate for the developing neurocognitive system of children (e.g., Fisch, 2014; Koolstra et al., 2004; Lorch & Anderson, 1979). A principled ability to ascertain continuous audience responses and without having to rely on self-report could thus help creators optimize their content. Of course, this would also be a highly desirable feat for widely used public speaking trainings, for which feedback about audience responses beyond the subjective impressions of small test audiences is largely absent (Lucas & Stob, 2004; McCroskey & Richmond, 2001).

Lastly, studying group differences in responses is an important use case. Obviously, the divided political sphere might be a good example, where populists may use "dog whistles'[5] to appeal to specific audiences. Being able to trace down the mechanisms and effects of such manipulative techniques more clearly could lead to interesting insights. We note, however, that this use case is beyond the scope of our study, which had no political content. However, the interface between politics and humor could be an interesting area of research in the future because many entertainment shows focus on politics (Trevor Noah, John Stewart, Stephen Colbert, etc.), and recent communication research has begun to examine humorous messages using neuroimaging (Coronel et al., 2021).

Overall, we view this replication attempt as successful. While we acknowledge the need for more research regarding the peak/trough identification procedure, we believe that making this change is defensible. Even without this modification, the nominal results were compatible with the predictions.

Strengths, limitations, and avenues for future research

This study contributes to the literature on speeches and stories in several ways. The reverse message engineering approach offers an innovative methodology for examining messages. fMRI allows us to capture multiple processes simultaneously on a moment-to-moment basis, which removes potential ambiguity that can come with assessing hypothetical constructs separate from neuroimaging. Furthermore, utilizing neuroimaging circumvents any self-report biases or filtering that may occur when participants are required to verbalize responses. These characteristics make the study well-situated to make a theoretical contribution pertaining to the social and affective processes that public speeches and stories can elicit.

Another strength is that the study replicated the previous study (using the PieMan story) with a new story (It's not the fall). This replication is beneficial not only for the sake of replicability (McEwan et al., 2018) but also with respect to the generalizability (Jackson & Jacobs, 1983). In this case, it seems that the present procedure would be eminently applicable to e.g., dedicated comedy-club performances or other entertainment-focused communication contexts, although one might also seek to generalize it further to e.g., public speaking in general, or topical contexts like health and political communication.

Despite the notable findings, several limitations deserve mention. First, fMRI's temporal resolution does not capture the speed at which language unfolds fully, and readers should interpret the findings with this in mind. However, more slowly evolving processes such as affective responses and engagement with stories may be more accurately captured. Second, the machinery produces loud noises, which may muffle some of the sounds. These unavoidable fMRI limitations call for other neuroscience methodologies, such as electroencephalography (EEG), which can offer clearer insights into the instantaneous brain reactions that are stimulated by storytelling, such as surprising turns.

Additionally, participants are alone in the scanner throughout the duration of the experiment. Because stories are typically delivered in a social setting with surrounding audience effects, this setting may limit the external validity of our study. Relatedly, we have alluded to the fact that the current study comprises different layers of sociality: On the one hand, the story itself is social in that it describes the social interaction and dialogue between the skydiver and the instructor. However, on another layer, the storytelling event ("The Moth") at which the sound recording was captured was a social event because the speaker told his story to a live audience, and the audience responded with laughter, conveying a social feedback signal to the speaker that they got the joke and found it funny. Yet there is also a third layer of social elements present that might be overlooked: The listeners in the current study (the participants in the scanner) responded to the story, but they also listened to the laughter. We can only speculate about the degree to which listening to laughter (from the original audience) may have affected these participants (although they were alone in the scanner), but work manipulating the laugh tracks of sitcom-TV and related entertainment formats has speculated that laughter can lead to social facilitation of listener/viewer reactions (e.g., Neuendorf & Fennell, 1988). Future work could experimentally test this by editing the laugh tracks. Specifically, if the TPJ exhibited similar responses if laugh tracks were edited out, then this would suggest that the TPJ responses are attributable to the primary layer of social content (e.g. the humorous norm violations, sexual references, and other social elements; Lynch, 2002; Meyer, 2015), whereas the latter would speak more for a role of the laughter itself in signaling a socially important event to the (in scanner) listeners.

Lastly, as we made use of an already publicly available dataset, we are not able to collect any additional data that may advance our findings, such as the participant's subjective report on the story. Indeed, it would be beneficial to know to what extent the participants enjoyed the study or which parts were their favorite.

Going forward, we envision that the increasing availability of large-scale datasets with brain imaging data captured in response to stories, speeches, or media messages will generate further insights. For instance, the current study focused on the TPJ as a key hub of the social-cognition network, but future analyses could refine the regions from which we reverse-correlate back to content. For instance, it is possible that we could gain added sensitivity by combining responses from the TPJ and other regions, such as the wider default mode network.

Likewise, by incorporating machine learning methods over hours of transcribed or annotated story data, one might also further zoom in on specific subelements of social content, such as the narrow "character interaction" content (direct/indirect speech and descriptions of interacting characters), social content like morality and norm violations (e.g., Hopp et al., 2021), or also paraverbal aspects that are central to the delivery of content to audiences. Furthermore, with machine-learning based approaches, one may also entirely forgo the peak-identification procedure that led to complications in the current analysis, and instead link continuously varying measures of content and brain responses to each other in a forward and reverse manner. This would then also help to address questions regarding statistical power, which in the present study were not computed beforehand because sample size (listeners) and stimulus (with the number of TPJ peaks it evoked) were given and could not be changed. Finally, if this approach were further automatized (as, e.g., done with the NeuroScout framework for forward correlations; de la Vega et al., 2022), then this could also help overcome the in-house nature of this open-code replication attempt and equip communication scientists with a versatile, new method to study the impact of speeches and stories.

Conclusion

In sum, this study successfully replicated earlier results, examining the brain responses to an engaging story via forward- and reverse correlation analysis. The forward correlation analysis revealed how the story as a physical stimulus (i.e., the soundwave's RMSE waveform) is transformed into the brain and evokes predictable responses in the auditory-sensory cortex of audience members. The reverse correlation analysis, which started from these message-evoked brain responses in the right temporoparietal junction (a region long associated with social-cognitive responses), showed that peaks in the rTPJ-fMRI signal can identify scenes that lead up to laughter (i.e., are socially engaging). By demonstrating more robustly how one can navigate between message content and the brain responses it evokes in audiences, our study lays the groundwork for future research on how stories and other public speaking performances can collectively touch, engage, and entertain large audiences.

Research Transparency Statement

Code to reproduce and document the analyses is accessible online at osf.io/nfy64 | github.com/nomcomm/narratives_itsnotthefall.

Notes

1. Readers may ask: Why not perform a 'forward correlation' as well? This has to do with the fact that while it is easy to quantify the over-time RMSE characteristic, it is more difficult to

create a continuous theoretical measure of a story's social content or demand – however defined. In the current study, we will also carry out 'forward correlation analyses' using coded content, but the main goal of this study was to replicate the reverse correlation procedure from the rTPJ, which relies on instances in which the audience responds with laughter to the speakers' story.

2. In theory, one could also analyze the sentiment of these words via NLP tools. However, this is not very promising for this story because the narrative-level information develops based on the word context and is not a property of the single words.
3. One option could be to simply drop the t-thresholding procedure and work with a fixed set of peaks/troughs (e.g., the top 10) and a fixed window (e.g., ±5 s) around those peaks. An alternative option would be to present results after running parameter sweeps (e.g., varying the t-threshold continuously and keeping track of the results). Together with these refinements, one might then also compute parameters like precision and recall (see Supplementary Results).
4. That is, in terms of proximal hierarchical processes (Colley, 1961) or different goals, which can differ by the context of the genre (e.g. health: to inform and influence; entertainment: to produce laughter or intellectual stimulation).
5. We thank an anonymous discussant for suggesting this potential to us.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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